Risk and Return in Fixed-Income Arbitrage: Nickels in Front of a Steamroller?

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We conduct an analysis of the risk and return characteristics of a number of widely used fixed-income arbitrage strategies. We find that the strategies requiring more "intellectual capital" to implement tend to produce significant alphas after controlling for bond and equity market risk factors. These positive alphas remain significant even after taking into account typical hedge fund fees. In contrast with other hedge fund strategies, many of the fixed-income arbitrage strategies produce positively skewed returns. These results suggest that there may be more economic substance to fixed-income arbitrage than simply "picking up nickels in front of a steamroller."

During the hedge fund crisis of 1998, market participants were given a revealing glimpse into the proprietary trading strategies used by a number of large hedge funds such as Long-Term Capital Management (LTCM). Among these strategies, few were as widely used—or as painful—as fixed-income arbitrage. Virtually every major investment banking firm on Wall Street reported losses directly related to their positions in fixed-income arbitrage during the crisis. Despite these losses, however, fixed-income arbitrage has since become one of the most popular and rapidly growing sectors within the hedge fund industry. For example, the Tremont/TASS (2005) Asset Flows Report indicates that total assets devoted to fixed-income arbitrage grew by more than $9.0 billion during 2005 and that the total

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amount of hedge fund capital devoted to fixed income arbitrage at the end of 2005 is in excess of $56.6 billion.[1]

This mixed history raises a number of important issues about the fundamental nature of fixed-income arbitrage. Is fixed-income arbitrage truly arbitrage? Or is it merely a strategy that earns small positive returns most of the time, but occasionally experiences dramatic losses (a strategy often described as “picking up nickels in front of a steamroller”)? Were the large fixed-income arbitrage losses during the hedge fund crisis simply due to excessive leverage, or were there deeper reasons arising from the inherent nature of these strategies? To address these issues, this article conducts an extensive analysis of the risk and return characteristics of fixed-income arbitrage.

Fixed-income arbitrage is actually a broad set of market-neutral investment strategies intended to exploit valuation differences between various fixed-income securities or contracts. In this analysis, we focus on five of the most widely used fixed-income arbitrage strategies in the market:

- Swap spread (SS) arbitrage.
- Yield curve (YC) arbitrage.
- Mortgage (MA) arbitrage.
- Volatility (VA) arbitrage.
- Capital structure (CS) arbitrage.

As in Mitchell and Pulvino (2001), our approach consists of following specific trading strategies through time and studying the properties of return indexes generated by these strategies. There are several important advantages to this approach. First, it allows us to incorporate transaction costs and hold fixed the effects of leverage in the analysis. Second, it allows us to study returns over a much longer horizon than would be possible using the limited amount of hedge fund return data available. Finally, this approach allows us to avoid potentially serious backfill and survivorship biases in reported hedge fund return indexes.

With these return indexes, we can directly explore the risk and return characteristics of the individual fixed-income arbitrage strategies. To hold fixed the effects of leverage on the analysis, we adjust the amount of initial capital so that the annualized volatility of each strategy’s returns is 10%. We find that all five of the strategies generate positive excess returns on average. Surprisingly, most of the arbitrage strategies result in excess returns that are positively skewed. Thus, even though these strategies produce large negative returns from time to time, the strategies tend to generate even larger offsetting positive returns.

[1] The total amount of capital devoted to fixed-income arbitrage is likely much larger as the Tremont/TASS (2005) report covers less than 50% of the total estimated amount of capital managed by hedge funds. Also, many Wall Street firms directly engage in proprietary fixed-income arbitrage trading.

We study the extent to which these positive excess returns represent compensation for bearing market risk. After risk adjusting for both equity and bond market factors, we find that the SS and VA arbitrage strategies produce insignificant alphas. In contrast, the YC, MA, and CS arbitrage strategies generally result in significant positive alphas. Interestingly, the latter strategies are the ones that require the most "intellectual capital" to implement. Specifically, the strategies that result in significant alphas are those that require relatively complex models to identify arbitrage opportunities and/or hedge out systematic market risks. We find that several of these "market-neutral" arbitrage strategies actually expose the investor to substantial levels of market risk. We repeat the analysis using actual fixed-income arbitrage hedge fund index return data from industry sources and find similar results.

In addition to the transaction costs incurred in executing fixed-income arbitrage strategies, many investors must also pay hedge fund fees. We repeat the analysis assuming that hedge fund fees of 2/20 (a 2% management fee and a 20% slope above a Libor high water mark) are subtracted from the returns. While these fees reduce or eliminate the significance of the alphas of the individual strategies, we find that equally-weighted portfolios of the more "intellectual capital" intensive strategies still have significant alphas on a net-of-fees basis. On the other hand, however, our results indicate that fees in the fixed-income arbitrage hedge fund industry are "large" relative to the alphas that can be generated by these strategies.

Where does this leave us? Is the business of fixed-income arbitrage simply a strategy of "picking up nickels in front of a steamroller," equivalent to writing deep out-of-the-money puts? We find little evidence of this. In contrast, we find that most of the strategies we consider result in excess returns that are positively skewed, even though large negative returns can and do occur. After controlling for leverage, these strategies generate positive excess returns on average. Furthermore, after controlling for both equity and bond market risk factors, transaction costs, and hedge fund fees, the fixed-income arbitrage strategies that require the highest level of "intellectual capital" to implement appear to generate significant positive alphas. The fact that a number of these factors share sensitivity to financial market "event risk" argues that these positive alphas are not merely compensation for bearing the risk of an as-yet-unrealized "peso" event. Thus, the risk and return characteristics of fixed-income arbitrage appear different from those of other strategies such as merger arbitrage [see Mitchell and Pulvino (2001)].

This article contributes to the rapidly growing literature on returns to "arbitrage" strategies. Closest to our article are the important recent studies of equity arbitrage strategies by Mitchell and Pulvino (2001) and Mitchell, Pulvino, and Stafford (2002). Our article, however, focuses exclusively on fixed-income arbitrage. Less related to our work are a number of important recent articles focusing on the actual returns reported by hedge funds. These papers include Fung and Hsieh (1997, 2001, 2002), Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Park (2000), Dor and Jagannathan (2002), Brown and Goetzmann (2003), Getmansky, Lo, and Makarov (2004), Agarwal and Naik (2004), Malkiel and Saha (2004), and Chan, et al. (2005). Our article differs from these in that the returns we study are attributable to specific strategies with controlled leverage, whereas reported hedge fund returns are generally composites of multiple (and offsetting) strategies with varying degrees of leverage.

The remainder of this article is organized as follows. Sections 1 through 5 describe the respective fixed-income arbitrage strategies and explain how the return indexes are constructed. Section 6 conducts an analysis of the risk and return characteristics of the return indexes along with those for historical fixed-income arbitrage hedge fund returns. Section 7 summarizes the results and makes concluding remarks.

1. Swap Spread Arbitrage

Swap spread arbitrage has traditionally been one of the most popular types of fixed-income arbitrage strategies. The importance of this strategy is evidenced by the fact that swap spread positions represented the single-largest source of losses for LTCM.[2] Furthermore, the hedge fund crisis of 1998 revealed that many other major investors had similar exposure to swap spreads—Salomon Smith Barney, Goldman Sachs, Morgan Stanley, BankAmerica, Barclays, and D.E. Shaw all experienced major losses in swap spread strategies.[3]

The swap spread arbitrage strategy has two legs. First, an arbitrageur enters into a par swap and receives a fixed coupon rate *CMS* and pays the floating Libor rate L_t. Second, the arbitrageur shorts a par Treasury bond with the same maturity as the swap and invests the proceeds in a margin account earning the repo rate. The cash flows from the second leg consist of paying the fixed coupon rate of the Treasury bond *CMT* and receiving the repo rate from the margin account r_t.[4] Combining the cash flows from the two legs shows that the arbitrageur receives a fixed annuity of $SS = CMS - CMT$ and pays the floating spread $S_t = L_t - r_t$. The cash flows from the reverse strategy are just the opposite of these cash flows. There are no initial or terminal principal cash flows in this strategy.

[2] Lowenstein (2000) reports that LTCM lost $1.6 billion in its swap spread positions before its collapse. Also see Perold (1999).

[3] See Siconolfi et al. (1998), Beckett and Pacelle (1998), Dunbar (2000), and Lowenstein (2000).

[4] The terms *CMS* and *CMT* are widely used industry abbreviations for constant maturity swap rate and constant maturity Treasury rate.

Swap spread arbitrage is thus a simple bet on whether the fixed annuity of SS received will be larger than the floating spread S_t paid. If SS is larger than the average value of S_t during the life of the strategy, the strategy is profitable (at least in an accounting sense). What makes the strategy attractive to hedge funds is that the floating spread S_t has historically been very stable over time, averaging 26.8 basis points with a standard deviation of only 13.3 basis points during the past 16 years. Thus, the expected *average* value of the floating spread over, say, a five-year horizon may have a standard deviation of only a few basis points (and, in fact, is often viewed as essentially constant by market participants).

Swap spread arbitrage, of course, is not actually an arbitrage in the textbook sense because the arbitrageur is exposed to *indirect* default risk. This is because if the viability of a number of major banks were to become uncertain, market Libor rates would likely increase significantly. For example, the spread between bank CD rates and Treasury bill yields spiked to nearly 500 basis points around the time of the Oil Embargo during 1974. In this situation, a swap spread arbitrageur paying Libor on a swap would suffer large negative cash flows from the strategy as the Libor rate responded to increased default risk in the financial sector. Note that there is no *direct* default risk from banks entering into financial distress as the cash flows on a swap are not direct obligations of the banks quoting Libor rates. Thus, even if these banks default on their debt, the counterparties to a swap continue to exchange fixed for floating cash flows.[5]

In studying the returns from fixed-income arbitrage, we use an extensive data set from the swap and Treasury markets covering the period from November 1988 to December 2004. The swap data consist of month-end observations of the three-month Libor rate and midmarket swap rates for two-, three-, five-, seven-, and 10-year maturity swaps. The Treasury data consist of month-end observations of the constant maturity Treasury (CMT) rates published by the Federal Reserve in the H-15 release for maturities of two, three, five, seven, and 10 years. Finally, we collect data on three-month general collateral repo rates. The data are described in the Appendix. Figure 1 plots the time series of swap spreads against the expected average value of the short term spread over the life of the swap (based on fitting a simple mean reverting Gaussian process to the data).

To construct a return index, we first determine each month whether the current swap spread differs from the current value of the short term spread. If the

[5] In theory, there is the risk of a default by a counterparty. In practice, however, this risk is negligible as swaps are usually fully collateralized under master swap agreements between major institutional investors. Furthermore, the actual default exposure in a swap is far less than for a corporate bond as notional amounts are not exchanged. Following Duffie and Huang (1996), Duffie and Singleton (1997), Minton (1997), He (2000), Grinblatt (2001), Liu, Longstaff, and Mandell (2004), and many others, we abstract from the issue of counterparty credit risk in this analysis.

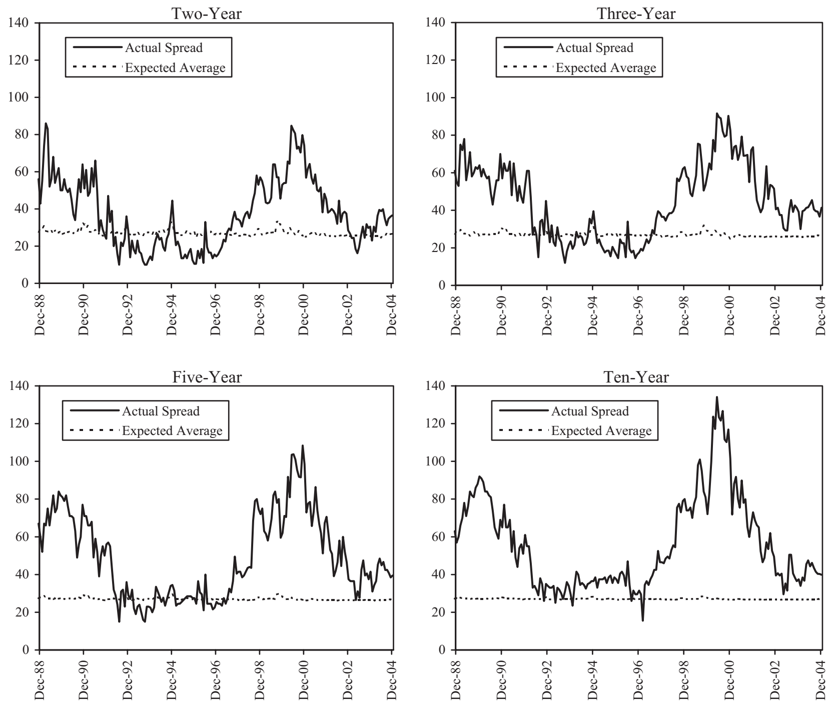

Figure 1
Swap spreads and expected average Libor-Repo spreads
These graphs plot the expected average value of the Libor-repo spread and the corresponding swap spread for the indicated horizons. All spreads are in basis points.

difference exceeds a trigger value of 10 basis points, we implement the trade for a \$100 notional position (receive fixed on a \$100 notional swap, short a \$100 notional Treasury bond, or vice versa if the difference is less than -10 basis points).[6] If the difference does not exceed the trigger, then the strategy invests in cash and earns an excess return of zero. We keep the trade on until it converges (swap spread converges to the short term spread) or until the maturity of the swap and bond. It is useful to think of this trade as a fictional hedge fund that has only a single trade. After the first month of the sample period, there could be one such hedge fund. After two months, there could be two hedge funds (if neither converges), etc. Each month, we calculate the return for each of these funds and then take the equally weighted average across funds as the index return for that month. In initiating and terminating positions, realistic transaction costs are applied (described in the Appendix). As with all strategies considered in

[6] We also implement the strategy with trigger values of five and 20 basis points and obtain very similar results.

this article, the initial amount of capital invested in the strategy is adjusted to fix the annualized volatility of the return index at 10% (2.887% per month). Observe that this swap spread arbitrage strategy requires nothing in the way of complex modeling to implement. Furthermore, as we compare current swap spread levels to current short term spread levels, there is no look-ahead bias in the strategy.

Table 1 provides summary statistics for the excess returns from the swap spread strategies. As shown, the mean monthly excess returns range from about 0.31 to 0.55%. All these means are significant at the 10% level, and two are significant at the 5% level. Three of the four skewness coefficients for the returns have positive values. Also, the returns for the strategies tend to have more kurtosis than would be the case for a normal distribution.

We also examine the returns from forming an equally weighted (based on notional amount) portfolio of the individual hedge fund strategies. As each individual strategy is capitalized to have an annualized volatility of 10%, the equally weighted portfolio will have smaller volatility if the returns from the individual strategies are not perfectly correlated. As shown, considerable diversification is obtained with the equally weighted portfolio as its volatility is only 82% of that of the individual strategies. The t-statistic for the returns from the equally weighted strategy is 2.78. The Bernardo and Ledoit (2000) gain/loss ratio for this equally weighted strategy is 1.643 and the Sharpe ratio is 0.597.[7]

Finally, note that the amount of capital per \$100 notional amount of the strategy required to fix the annualized volatility at 10% varies directly with the horizon of the strategy. This reflects the fact that the price sensitivity of the swap and Treasury bond increases directly with the horizon or duration of the swap and Treasury bond.

2. Yield Curve Arbitrage

Another major type of fixed-income arbitrage involves taking long and short positions at different points along the yield curve. These yield curve arbitrage strategies often take the form of a "butterfly" trade, where, for example, an investor may go long five-year bonds and short two- and 10-year bonds in a way that zeros out the exposure to the level and slope of the term structure in the portfolio. Perold (1999) reports that LTCM frequently executed these types of yield curve arbitrage trades.

While there are many different flavors of yield curve arbitrage in the market, most share a few common elements. First, some type of analysis is applied

[7] We also investigate whether the inclusion of a stop-loss limit affects the results. The stop-loss limit is where an individual hedge fund is terminated upon the realization of a 20% drawdown. As the volatility of returns is normalized to 10% per year (2.887% per month), however, the stop-loss limit is almost never reached. Thus, the results when a stop-loss limit is included are virtually identical to those reported.

Table 1
Summary statistics for the swap spread arbitrage strategies

Strategy	Swap	*n*	Capital	Mean	*t*-Stat	Standard deviation	Minimum	Maximum	Skewness	Kurtosis	Ratio negative	Serial correlation	Gain/loss	Sharpe ratio
SS1	2 years	193	3.671	0.546	2.94	2.887	−9.801	11.552	0.449	2.454	0.326	−0.113	1.758	0.655
SS2	3 years	193	5.278	0.476	3.01	2.887	−8.482	11.209	0.178	2.002	0.326	−0.269	1.629	0.571
SS3	5 years	193	9.047	0.305	1.68	2.887	−10.663	10.163	−0.456	2.269	0.332	−0.135	1.372	0.366
SS4	10 years	193	15.795	0.313	1.69	2.887	−10.761	10.004	0.069	2.711	0.425	−0.114	1.381	0.376
EW SS	–	193	8.448	0.410	2.78	2.378	−8.569	8.439	−0.111	2.505	0.394	−0.148	1.643	0.597

This table reports the indicated summary statistics for the monthly percentage excess returns from the swap spread arbitrage strategies. Swap denotes the swap maturity used in the strategy. The EW SS strategy consists of taking an equally weighted (based on notional amount) position each month in the individual-maturity swap spread strategies. *n* denotes the number of monthly excess returns. Capital is the initial amount of capital required per $100 notional of the arbitrage strategy to give a 10% annualized standard deviation of excess returns. The *t*-statistics for the means are corrected for the serial correlation of excess returns. Ratio negative is the proportion of negative excess returns. Gain/loss is the Bernardo and Ledoit (2000) gain/loss ratio for the strategy. The sample period for the strategies is from December 1988 to December 2004.

to identify points along the yield curve, which are either “rich” or “cheap.” Second, the investor enters into a portfolio that exploits these perceived misvaluations by going long and short bonds in a way that minimizes the risk of the portfolio. Finally, the portfolio is held until the trade converges and the relative values of the bonds come back into line.

Our approach in implementing this strategy is very similar to that followed by a number of large fixed-income arbitrage hedge funds. Specifically, we assume that the term structure is determined by a two-factor affine model. Using the same monthly swap market data as in the previous section, we fit the model to match exactly the one-year and 10-year points along the swap curve each month. Once fitted to these points, we then identify how far off the fitted curve the other swap rates are. Figure 2 graphs the time series of deviations between market and model for the two-year, three-year, five-year, and seven-year swap rates. For example, imagine that for a particular month, the market two-year swap rate is more than 10 basis points above the fitted two-year swap rate. We would

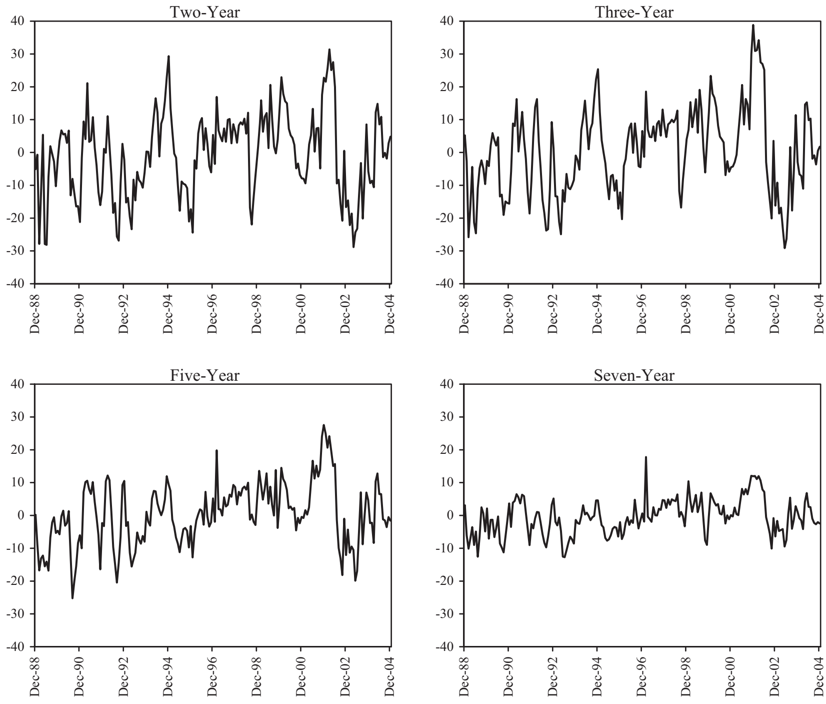

Figure 2
Deviations between market and model swap rates
These graphs plot the difference between the market swap rates for the indicated horizons and the corresponding values implied by the two-factor affine model fitted to match exactly the one-year and 10-year swap rates. All deviations are in basis points.

enter into a trade by going long (receiving fixed) $100 notional of a two-year swap and going short a portfolio of one-year and 10-year swaps with the same sensitivity to the two affine factors as the two-year swap. Thus, the resulting portfolio's sensitivity to each of the two factors would be zero. Once this butterfly trade was put on, it would be held for 12 months or until the market two-year swap rate converged to the model value. The same process continues for each month, with either a trade similar to the above, the reverse trade of the above, or no trade at all being implemented (in which case the strategy invests in cash and earns zero excess return), and similarly for the other swap maturities. Unlike the swap spread strategy of the previous section, this strategy involves a high degree of "intellectual capital" to implement as both the process of identifying arbitrage opportunities and the associated hedging strategies require the application of a multi-factor term structure model.

As before, we can think of a butterfly trade put on in a specific month as a fictional hedge fund with only one trade. Similarly, we can compute the return on this hedge fund until the trade converges. For a given month, there may be a number of these hedge funds, each representing a trade that was put on previously but has not yet converged. The return index for the strategy for a given month is the equally weighted average of the returns for all the individual hedge funds active during that month. As in the previous section, we include realistic transaction costs in computing returns and adjust the capital to give an annualized volatility of 10% for the index returns. The details of the strategy are described in the Appendix.[8]

Table 2 reports summary statistics for the excess returns from the yield curve strategies. We use a trigger value of 10 basis points in determining whether to implement a trade.[9] We implement the strategy separately for two-year, three-year, five-year, and seven-year swaps and also implement an equally weighted strategy (in terms of notional amount) of the individual-horizon strategies. As shown, the average monthly excess returns from the individual strategies as well as for the equally weighted strategy are all statistically significant and range from about 0.4 to 0.6%.

Table 2 also summarizes that the excess returns are highly positively skewed. The positive skewness of the returns argues against the view that this strategy is one in which an arbitrageur earns small profits most of the time but occasionally suffers a huge loss. As before, the excess returns display more kurtosis than would be the case for a normal distribution.

[8] At each date, we fit the model to match exactly the current one- and 10-year swaps. Thus, there is no look-ahead bias in the state variables of the model. While the parameters of the model are estimated over the entire sample, however, they are used only in determining the hedge ratios for butterfly trades. Thus, there should be little or no look-ahead bias in the results. As a diagnostic, we estimated the model using data for the first part of the sample period and then applied it to strategies for the latter part of the sample. The results from this exercise are virtually identical to those we report.

[9] Using a trigger value of five basis points gives similar results.

Table 2
Summary statistics for the yield curve arbitrage strategies

Strategy	Swap	n	Capital	Mean	t-Stat	Standard deviation	Minimum	Maximum	Skewness	Kurtosis	Ratio negative	Serial correlation	Gain/loss	Sharpe ratio
YC1	2 years	193	4.847	0.540	2.76	2.887	−6.878	10.056	0.569	0.902	0.301	−0.059	1.770	0.648
YC2	3 years	193	7.891	0.486	2.31	2.887	−6.365	11.558	0.591	1.172	0.337	0.014	1.643	0.583
YC3	5 years	193	7.794	0.615	3.29	2.887	−8.307	11.464	0.592	2.366	0.212	−0.108	2.102	0.738
YC4	7 years	193	4.546	0.437	2.46	2.887	−10.306	20.032	2.156	14.953	0.088	−0.158	2.355	0.524
EW YC	–	193	6.270	0.519	3.42	2.293	−5.241	11.329	0.995	3.269	0.347	−0.084	1.980	0.785

This table reports the indicated summary statistics for the monthly percentage excess returns from the yield curve arbitrage strategies. Swap denotes the swap maturity used in the strategy. The EW YC strategy consists of taking an equally weighted (based on notional amount) position each month in the individual-maturity yield curve strategies. n denotes the number of monthly excess returns. Capital is the initial amount of capital required per $100 notional of the arbitrage strategy to give a 10% annualized standard deviation of excess returns. The t-statistics for the means are corrected for the serial correlation of excess returns. Ratio negative is the proportion of negative excess returns. Gain/loss is the Bernardo and Ledoit (2000) gain/loss ratio for the strategy. The sample period for the strategies is from December 1988 to December 2004.

Finally, observe that the amount of capital required to attain a 10% level of volatility is typically much less than in the swap spread strategies. This reflects the fact that the yield curve trade tends to be better hedged as all the positions are along the same curve, and the factor risk is neutralized in the portfolio.

3. Mortgage Arbitrage

The mortgage-backed security (MBS) strategy consists of buying MBS passthroughs and hedging their interest rate exposure with swaps. A passthrough is a MBS that passes all the interest and principal cash flows of a pool of mortgages (after servicing and guarantee fees) to the passthrough investors. MBS passthroughs are the most common type of mortgage-related product and this strategy is commonly implemented by hedge funds. The Bond Market Association indicates that MBS now forms the largest fixed-income sector in the U.S.

The main risk of a MBS passthrough is prepayment risk. That is, the timing of the cash flows of a passthrough is uncertain because homeowners have the option to prepay their mortgages.[10] The prepayment option embedded in MBS passthroughs generates the so-called negative convexity of these securities. For instance, the top panel of Figure 3 plots the nonparametric estimate of the price of a generic Ginnie Mae (GNMA) passthrough with a 7% coupon rate as a function of the five-year swap rate (see the Appendix for details on the estimation procedure, data, and strategy implementation). It is clear that the price of this passthrough is a concave function of the interest rate. This negative convexity arises because homeowners refinance their mortgages as interest rates drop, and the price of a passthrough consequently converges to some level close to its principal amount.

A MBS portfolio duration hedged with swaps inherits the negative convexity of the passthroughs. For example, the bottom panel of Figure 3 plots the value of a portfolio composed of a \$100 notional long position in a generic 7% GNMA passthrough, duration hedged with the appropriate amount of a five-year swap. This figure reveals that abrupt changes in interest rates will cause losses in this portfolio. To compensate for these possible losses, investors require higher yields to hold these securities. Indeed, Bloomberg's option-adjusted spread (OAS) for a generic 7% GNMA passthrough during the period from November 1996 to February 2005 was between 48 and 194 basis points with a mean value of 112 basis points.[11]

[10] For discussions about the effects of prepayment on MBS prices, see Dunn and McConnell (1981a,b), Schwartz and Torous (1989, 1992), Stanton (1995), Boudoukh et al. (1997), and Longstaff (2005).

[11] OASs are commonly used as a way of analyzing the relative valuations of different MBSs. As opposed to static spreads, the OAS incorporates the information about the timing of the cash flows of a passthrough with the use of a prepayment model and a term structure model in its calculation. The OAS therefore adjusts for the optionality of a passthrough. For a discussion of the role of OAS in the MBS market, see Gabaix, Krishnamurthy, and Vigneron (2004).

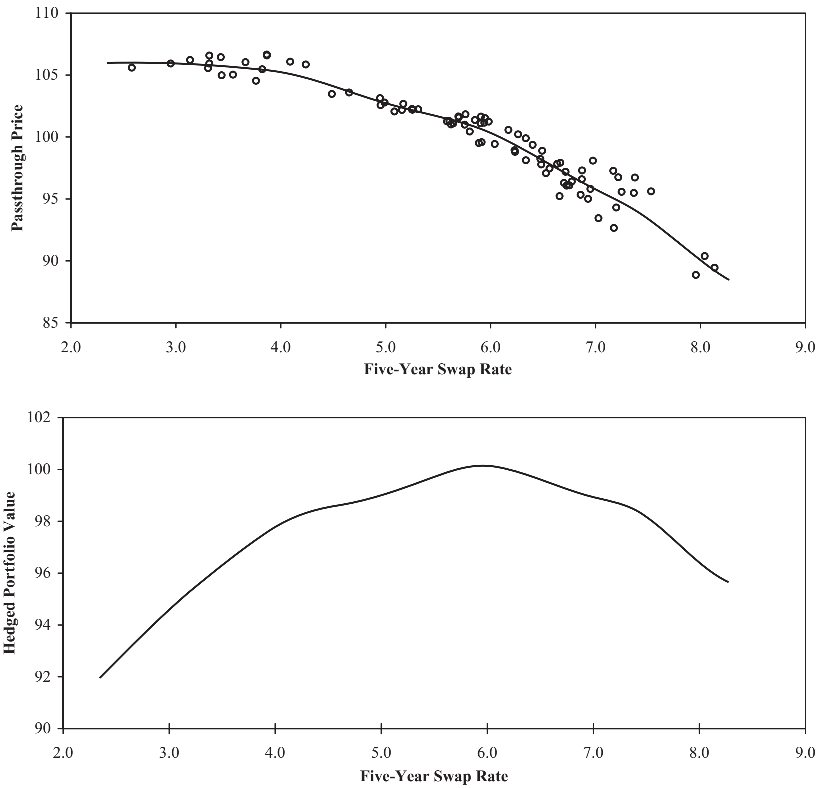

Figure 3
Passthrough price as a function of swap rates
The top panel of this figure displays the nonparametric estimate of the price of the 7% GNMA passthrough as a function of the five-year swap rate. Each point in this figure represents 25 daily observations. The bottom panel displays the value of a portfolio with $100 notional amount of this passthrough duration-hedge with a five-year swap. The hedge is initiated when the swap rate is 6.06%.

Long positions in passthroughs are usually financed with a form of repurchase agreement called a dollar roll. Dollar rolls are analogous to standard repurchase agreements in the sense that a hedge fund entering into a dollar roll sells a passthrough to a MBS dealer and agrees to buy back a similar security in the future at a predetermined price. The main difference between a standard repurchase agreement and a dollar roll is that with the roll, the dealer does not have to deliver a passthrough backed by exactly the same pool of mortgages. Unlike traditional repurchase agreements, a dollar roll does not require any haircut or over-collateralization [see Biby, Modukuri, and Hargrave (2001)]. Dealers extend favorable financing terms because dollar rolls give them the flexibility to manage their MBS portfolios. Assume, for instance, that a MBS dealer wishes to cover an existing short position in the MBS market. To do so, the dealer can buy a passthrough from a hedge fund with the dollar roll. At the end of the roll term, the dealer does not need to return a passthrough backed by exactly the same pool of mortgages. As a result, dollar rolls can be used as a mechanism to cover short positions in the passthrough market.

The overall logic of the strategy of buying MBS passthroughs, financing them with dollar rolls, and hedging their duration with swaps is therefore two-fold. First, investors require larger yields to carry the negative convexity of MBS passthroughs. Second, the delivery option of the dollar rolls makes them a cheap source of MBS financing. To execute the strategy, it is necessary to specify which agency passthroughs are used [Ginnie Mae (GNMA), Fannie Mae (FNMA), or Freddie Mac (FHLMC)], the MBS coupons (trading at discount or at premium), the swap maturities used in the hedge, the model used to calculate the hedge ratios, the frequency of hedge rebalancing (daily, weekly or monthly), and the OAS level above which a long position in the passthrough is taken (the OAS trade trigger).

We use GNMA passthroughs because they are fully guaranteed by the U. S. Government and are consequently free of default risk.[12] The passthroughs we study are those with coupons closest to the current coupon as they are the most liquid. The passthroughs are hedged with five-year swaps. There is a large diversity of models that can be used to calculate hedge ratios. Indeed, every major MBS dealer has a proprietary prepayment model. Typically, these proprietary models require a high level of "intellectual capital" to develop, maintain, and use. We expect that some of these models used in practice deliver better hedge ratios than others. However, we do not want to base our results on a specific parametric model. Rather, we wish to have hedge ratios that work well on average. To this end, we adopt a nonparametric approach to estimate the hedge ratios. Specifically, we use the method developed by Aït-Sahalia and Duarte (2003) to estimate the first derivative of the passthrough price with respect to the five-year swap rate, with the constraint that passthrough prices are a nonincreasing function of the five-year swap rate. We use all the available sample of passthrough prices for this estimation.[13] The hedging rebalancing frequency is monthly. We expect that most hedge funds following this strategy estimate the duration of their portfolios at least daily and rebalance when the duration deviates substantially

[12] All the mortgage loans securitized by GNMA are federally insured. Among the guarantors are the FHA and VA.

[13] Even though the model is estimated over the entire sample, the current five-year swap rate is used to specify the hedging ratio. Thus, there is no look-ahead bias in the state variable of the model. To check whether look-ahead bias is induced by the parameter estimation procedure, we also estimated the model for the 6.5 and 7.0% coupons using only data available prior to the first day that the strategy is implemented. The returns obtained using the hedge ratios implied by this estimation procedure are virtually identical to those obtained when the entire sample period is used in the estimation.

from zero. For reasons of simplicity, we assume that all the trading in this strategy is done on the last trading day of the month. Trade triggers based on OAS may be used to improve the returns of mortgage strategies [see for instance Hayre (1990)]. We, however, take a long position on MBS passthroughs independently of their OAS as we want to avoid any dependence of our results on a specific prepayment model.

The strategy is implemented between December 1996 and December 2004 with a total of 97 monthly observations. The results of this strategy are displayed in Table 3. The first row of Table 3 displays the results of the strategy implemented with passthroughs trading at a discount. The second row displays the results of holding the passthrough with coupon closest to the current coupon, which can be trading at either a premium or a discount. The results using the premium passthroughs with coupons closest to the current coupons are in the third row. We again report results for an equally weighted portfolio (in terms of notional amount) of the individual strategies.

The excess returns of the MBS strategies can be either positively skewed (discount strategy) or negatively skewed (the premium strategy). The excess returns of the strategies are not significantly autocorrelated. The mean excess returns of the discount and par strategies are 0.691 and 0.466%. The mean returns of the discount and par strategies are statistically significant at roughly the 10% level. The performance of the premium passthrough strategy is considerably worse than that of the other strategies. The mean monthly return of the premium strategy is not different from zero at usual significance levels. The relatively poor performance of the premium passthrough strategy is partially caused by the strong negative convexity of the premium passthroughs. Indeed, the passthroughs in the premium strategy have an average convexity of -1.53 compared to -1.44 for the passthroughs in the par strategy and -1.11 for the passthroughs in the discount strategy.

4. Fixed-Income Volatility Arbitrage

In this section, we examine the returns from following a fixed-income volatility arbitrage strategy. Volatility arbitrage has a long tradition as a popular and widely used strategy among Wall Street firms and other major financial market participants. Volatility arbitrage also plays a major role among fixed income hedge funds. For example, Lowenstein (2000) reports that LTCM lost more than $1.3 billion in volatility arbitrage positions before the fund's demise in 1998.

In its simplest form, volatility arbitrage is often implemented by selling options and then delta-hedging the exposure to the underlying asset. In doing this, investors hope to profit from the well-known tendency of implied volatilities to exceed subsequent realized volatilities. If the implied volatility is higher than the realized volatility, then selling options produces an

Table 3
Summary statistics for the mortgage arbitrage strategies

Strategy	Mortgage	*n*	Capital	Mean	*t*-Stat	Standard deviation	Minimum	Maximum	Skewness	Kurtosis	Ratio negative	Serial correlation	Gain/loss	Sharpe ratio
MA1	Discount	97	21.724	0.691	2.08	2.887	−6.794	11.683	0.882	2.929	0.383	0.128	1.999	0.830
MA2	Par	97	19.779	0.466	1.50	2.887	−7.600	11.676	0.330	2.263	0.402	0.059	1.565	0.560
MA3	Premium	97	16.910	0.065	0.23	2.887	−8.274	9.844	−0.274	1.452	0.402	−0.052	1.063	0.078
EW MA	–	97	19.471	0.408	1.39	2.750	−7.556	8.539	0.064	1.027	0.392	0.053	1.489	0.514

This table reports the indicated summary statistics for the monthly percentage excess returns from the mortgage arbitrage strategies. Mortgage denotes the type of mortgage-backed securities used in the strategy—discount, par, or premium. The EW MA strategy consists of taking an equally weighted (based on notional amount) position each month in the individual discount, par, and premium mortgage arbitrage strategies. *n* denotes the number of monthly excess returns. Capital is the initial amount of capital required per $100 notional of the arbitrage strategy to give a 10% annualized standard deviation of excess returns. The *t*-statistics for the means are corrected for the serial correlation of excess returns. Ratio negative is the proportion of negative excess returns. Gain/Loss is the Bernardo and Ledoit (2000) gain/loss ratio for the strategy. The sample period for the strategies is from December 1996 to December 2004.

excess return proportional to the gamma of the option times the difference between the implied variance and the realized variance of the underlying asset.[14]

In implementing a fixed-income volatility arbitrage strategy, we focus on interest rate caps. Interest rate caps are among the most important and liquid fixed-income options in the market. Interest rate caps consist of portfolios of individual European options on the Libor rate [for example, see Longstaff, Santa-Clara, and Schwartz (2001)]. Strategy returns, however, would be similar if we focused on cap/floor straddles instead. At-the-money caps are struck at the swap rate for the corresponding maturity. The strategy can be thought of as selling a $100 notional amount of at-the-money interest rate caps and delta-hedging the position using Eurodollar futures. In actuality, however, the strategy is implemented in a slightly different way that involves a series of short-term volatility swaps. This alternative approach is essentially the equivalent of shorting caps but allows us to avoid a number of technicalities. The details of how the strategy is implemented are described in the Appendix.

The data used in constructing an index of cap volatility arbitrage returns consist of the swap market data described in Section 1, daily Eurodollar futures closing prices obtained from the Chicago Mercantile Exchange, and interest rate cap volatilities provided by Citigroup and the Bloomberg system. To incorporate transaction costs, we assume that the implied volatility at which we sell caps is 1% less than the market midpoint of the bid-ask spread (for example, at a volatility of 17% rather than at the midmarket volatility of 18%). Because the bid-ask spread for caps is typically less than 1% (or one vega), this gives us conservative estimates of the returns from the strategy. The excess return for a given month can be computed from the difference between the implied variance of a caplet at the beginning of the month, and the realized variance for the corresponding Eurodollar futures contracts over the month. The deltas and gammas for the individual caplets can be calculated using the standard Black (1976) model used to quote cap prices in this market. Although the Black model is used to compute hedge ratios, the strategy actually requires little in the way of modeling sophistication. To see this, recall that in the Black model, the delta of an at-the-money straddle is essentially zero. Thus, this strategy could be implemented almost entirely without the use of a model by simply selling cap/floor straddles over time. Note that there is no look-ahead bias in this implementation of the strategy.

Table 4 reports summary statistics for the volatility arbitrage return indexes based on the strategies for the highly liquid two-, three-, four-, and five-yeacap maturities as well as for the equally weighted (based on notional

[14] For discussions of the relation between implied and realized volatilities, see Day and Lewis (1988), Lamoureux and Lastrape (1993), and Canina and Figlewski (1993).

Table 4
Summary statistics for the fixed-income volatility arbitrage strategies

Strategy	Cap	*n*	Capital	Mean	*t*-Stat	Standard deviation	Minimum	Maximum	Skewness	Kurtosis	Ratio negative	Serial correlation	Gain/loss	Sharpe ratio
VA1	2 years	183	0.734	0.389	1.11	2.887	−9.720	6.550	−0.962	1.579	0.383	0.465	1.423	0.467
VA2	3 years	183	0.863	0.609	1.77	2.887	−9.675	6.851	−0.909	1.332	0.355	0.445	1.722	0.731
VA3	4 years	183	0.953	0.682	2.08	2.887	−10.295	7.087	−0.989	1.644	0.311	0.409	1.823	0.819
VA4	5 years	150	1.082	0.488	1.32	2.887	−9.997	6.654	−0.988	1.772	0.347	0.423	1.543	0.586
EW VA	–	183	0.908	0.584	1.79	2.280	−9.592	6.674	−0.925	1.392	0.344	0.425	1.709	0.720

This table reports the indicated summary statistics for the monthly percentage excess returns from the fixed-income volatility arbitrage strategy of shorting at-the-money interest rate caps of the indicated maturity. The EW VA strategy consists of taking an equally weighted (based on notional amount) position each month in the individual-maturity volatility arbitrage strategies. *n* denotes the number of monthly excess returns. Capital is the initial amount of capital required per $100 notional of the arbitrage strategy to give a 10% annualized standard deviation of excess returns. The *t*-statistics for the means are corrected for the serial correlation of excess returns. Ratio negative is the proportion of negative excess returns. Gain/loss is the Bernardo and Ledoit (2000) gain/loss ratio for the strategy. The sample period for the strategies is from October 1989 to December 2004 (but is shorter for some strategies because cap volatility data for earlier periods are unavailable).

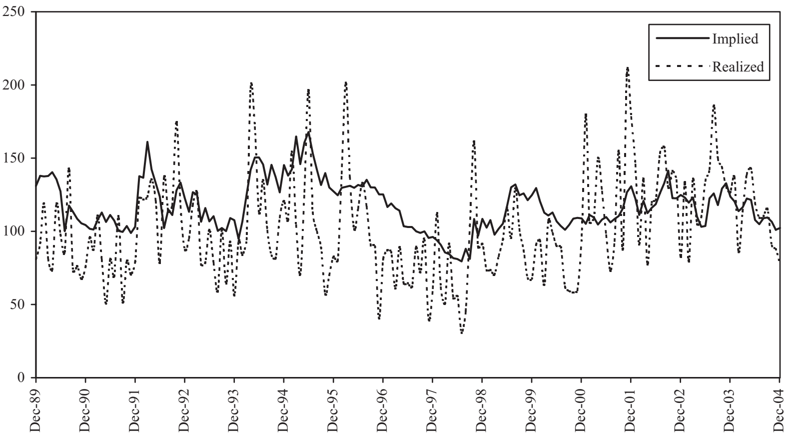

Figure 4
Implied and realized basis point volatility of four-year interest rate caps
This graph plots the implied annualized basis point volatility for a four-year interest rate cap along with the average annualized realized basis point volatility over the subsequent month of the Eurodollar futures contract corresponding to the individual caplets of the cap.

amount) strategy. As shown, the volatility arbitrage strategy tends to produce positive excess returns. The average excess returns range from about 0.40 to nearly 0.70% per month. The average excess return for the three-year cap strategy is significant at the 10% level, and the average excess return for the four-year cap strategy is significant at the 5% level. The average excess return for the equally weighted strategy is also significant at the 10% level. As an illustration of why this strategy produces positive excess returns, Figure 4 graphs the implied volatility of a four-year cap against the average (over the corresponding 15 Eurodollar futures contracts used to hedge the cap) realized Eurodollar futures volatility (both expressed in terms of annualized basis point volatility). In this figure, the implied volatility clearly tends to be higher than the realized volatility. Unlike the previous strategies considered, volatility arbitrage produces excess returns that are highly negatively skewed. In particular, the skewness coefficients for all the strategies are negative. Thus, these excess returns appear more consistent with the notion of "picking up nickels in front of a steamroller." The excess returns again display more kurtosis than would normally distributed random variables. These strategies require far less capital for a $100 notional trade than the previous strategies.

5. Capital Structure Arbitrage

Capital structure arbitrage (or alternatively, credit arbitrage) refers to a class of fixed-income trading strategies that exploit mispricing between a company's debt and its other securities (such as equity). With the exponential growth in the credit default swap (CDS) market in the last decade, this strategy has become increasingly popular with proprietary trading desks at investment banks.[15] In fact, Euromoney reports that some traders describe this strategy as the "most significant development since the invention of the CDS itself nearly ten years ago" [Currie and Morris (2002)]. Furthermore, the *Financial Times* reports that "hedge funds, faced with weak returns or losses on some of their strategies, have been flocking to a new one called capital structure arbitrage, which exploits mispricings between a company's equity and debt" [Skorecki (2004)].

This section implements a simple version of capital structure arbitrage for a large cross-section of obligors. The purpose is to analyze the risk and return of the strategy as commonly implemented in the industry. Using the information on the equity price and the capital structure of an obligor, we compute its theoretical CDS spread and the size of an equity position needed to hedge changes in the value of the CDS or what is commonly referred to as the equity delta. We then compare the theoretical CDS spread with the level quoted in the market. If the market spread is higher (lower) than the theoretical spread, we short (long) the CDS contract, while simultaneously maintaining the equity hedge. The strategy would be profitable if, subsequent to initiating a trade, the market spread and the theoretical spread converge to each other.

More specifically, we generate the predicted CDS spreads using the CreditGrades (CG) model, which was jointly devised by several investment banks as a market standard for evaluating the credit risk of an obligor.[16] It is loosely based on Black and Cox (1976), with default defined as the first passage of a diffusive firm value to an unobserved "default threshold." For CDS data we use the comprehensive coverage provided by the Markit Group, which consists of daily spreads of five-year CDS contracts on North American industrial obligors from 2001 to 2004. To facilitate the trading analysis, we require that an obligor should have at least 252 daily CDS spreads no more than two weeks apart from each other.[17] After merging firm balance sheet data from Compustat and equity prices from Center for Research in Security Prices (CRSP), the final sample contains 135,759 daily spreads on 261 obligors. Details on the calibration of the model and the trading

[15] CDSs are essentially insurance contracts against the default of an obligor. Specifically, the buyer of the CDS contract pays a premium each quarter, denoted as a percentage of the underlying bond's notional value in basis points. The seller agrees to pay the notional value for the bond should the obligor default before the maturity of the contract. CDSs can be used by commercial banks to protect the value of their loan portfolios. For a more detailed description of the CDS contract, see Longstaff, Mithal, and Neis (2005).

[16] For details about the model, see Finkelstein et al. (2002).

[17] This criterion is consistent with capital structure arbitrageurs trading in the most liquid segment of the CDS market. On the practical side, it also yields a reasonably broad sample.

strategy are provided in the Appendix. This strategy clearly requires a high level of financial knowledge to implement.

To illustrate the intuition behind the trading strategy, we present the market spread, the theoretical spread, and the equity price for General Motors (GM) in Figure 5. First, we observe that there is a negative correlation between the CDS spread and the equity price. Indeed, the correlation between changes in the equity price and the market spread for GM is −0.32. Moreover, the market spread appears to be more volatile, reverting to the model spread over the long run. For example, the market spread widened to over 440 basis points during October 2002, while the model spread stayed below 300 basis points. This gap diminished shortly thereafter and completely disappeared by February 2003. The arbitrageur would have profited handsomely if he were to short CDS and short equity as a hedge during this period. Note, however, that if the arbitrageur placed the same trades two months earlier in August 2002, he would have experienced losses as the CDS spread continued to diverge. The short equity hedge would have helped to some extent in this case, but its effectiveness remains doubtful due to the low correlation between the CDS spread and the equity price.

Incidentally, a similar scenario played out again in May 2005 when GM's debt was on the verge of being downgraded. Seeing GM's CDS becoming ever more expensive, many hedge funds shorted CDS on GM and hedged their exposure by shorting GM equity. GM's debt was indeed downgraded shortly afterwards, but not before Kirk Kerkorian announced a $31-per-share offer to increase his stake in GM, causing the share price to soar. According to *The Wall Street Journal*, this "dealt

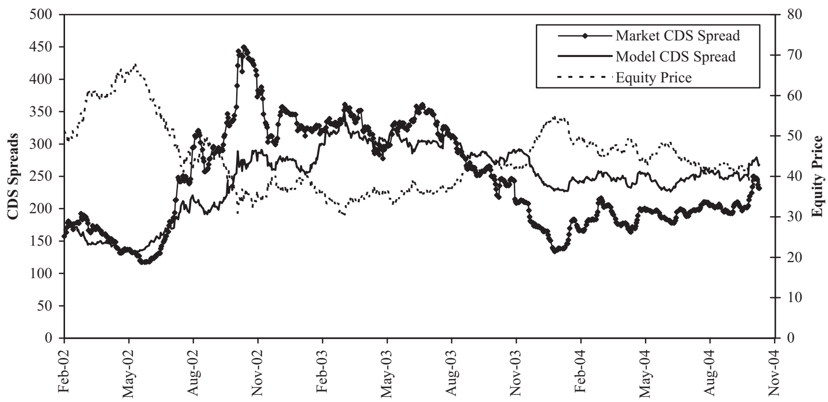

Figure 5
General Motors CDS spreads and equity price
This figure displays the market CDS spread, the model CDS spread, and the equity price for General Motors. The CDS spreads are in basis points.

the hedge funds a painful one-two punch: their debt bets lost money, and the loss was compounded when their hedge lost out as the stock price rose" [Zuckerman (2005)]. Overall, the GM experience suggests that the risk for individual trades is typically a combination of rapidly rising market spreads and imperfect hedging from the offsetting equity positions.

We implement the trading strategy for all obligors as follows. For each day t in the sample period of an obligor, we check whether $c_t > (1 + \alpha)\ c_t'$, where c_t and c_t' are the market and model spreads, respectively, and α is called the trigger level for the strategy. If this criterion is satisfied, we short a CDS contract with a notional amount of \$100 and short an equity position as given by the CG model.[18] The positions are liquidated when the market spread and the model spread become equal, or after 180 days, whichever occurs first. We assume a 5% bid-ask spread for trading CDS. This is a realistic estimate of CDS market transaction costs in recent periods.

As there are 261 obligors in the final sample, we typically have thousands of open trades throughout the sample period. We create the monthly index return as follows. First, as the CDS position has an initial value of zero, we assume that each trade is endowed with an initial level of capital, from which the equity hedge is financed. All subsequent cash flows, such as CDS premiums and cash dividends on the stock position, are credited to or deducted from this initial capital. We also compute the value of the outstanding CDS position using the CG model and obtain daily excess returns for each trade. Then, we calculate an equally weighted average daily return across all open trades for each day in the sample and compound them into a monthly frequency. This yields 48 numbers that represent monthly excess returns obtained by holding an equally weighted portfolio of all available capital structure arbitrage trades. As all information used in implementing the strategy is contemporaneous, there is no look-ahead bias in strategy returns.

Table 5 summarizes the monthly excess returns for six strategies implemented for three trading trigger levels and for investment-grade or speculative-grade obligors. Also reported are the results for an equally weighted portfolio (based on notional amounts). First, we notice that the amount of initial capital required to generate a 10% annualized standard deviation is several times larger than for any of the previous strategies. This is an indication of the risk involved in capital structure arbitrage. In fact, results not presented here show that convergence occurs for only a small fraction of the individual trades. Furthermore, although Table 5 does not show any significant change in the risk and return of the

[18] We also consider the strategy of buying CDS contracts and putting on a long equity hedge when $c_t' > (1 + \alpha)\ c_t$. This strategy yields slightly lower excess returns.

Table 5
Summary statistics for the capital structure arbitrage strategies

Strategy	Rating	Trigger	n	Capital	Mean	t-Stat	Standard deviation	Minimum	Maximum	Skewness	Kurtosis	Ratio negative	Serial correlation	Gain/ loss	Sharpe ratio
CS1	Investment	1.00	48	47.000	0.768	1.95	2.887	−8.160	10.570	0.223	5.337	0.271	−0.055	2.621	0.922
CS2		1.50	48	52.300	0.613	1.25	2.887	−8.020	12.770	0.266	8.682	0.375	0.162	2.435	0.735
CS3		2.00	48	44.900	0.731	1.30	2.887	−4.640	13.790	0.342	10.075	0.417	0.296	3.341	0.877
CS4	Speculative	1.00	48	86.900	0.709	2.30	2.887	−8.680	7.680	0.331	2.646	0.167	−0.298	2.513	0.851
CS5		1.50	48	90.500	0.669	2.17	2.887	−7.250	10.920	0.358	4.661	0.146	−0.306	2.921	0.802
CS6		2.00	48	75.900	0.740	1.03	2.887	−1.730	15.210	0.448	15.889	0.104	0.505	12.738	0.887
EW CS	–	–	48	66.250	0.705	1.70	2.029	−1.955	9.650	2.556	8.607	0.333	0.343	4.117	1.203

This table reports the indicated summary statistics for the monthly percentage excess returns from the capital structure arbitrage strategies. Rating denotes whether the strategy is applied to investment-grade or speculative-grade CDS obligors. Trigger denotes the ratio of the difference between the market spread and the model spread divided by the model spread, above which the strategy is implemented. The EW CS strategy consists of taking an equally weighted (based on notional amount) position each month in the individual capital structure arbitrage strategies. n denotes the number of monthly excess returns. Capital is the initial amount of capital required per \$100 notional of the arbitrage strategy to give a 10% annualized standard deviation of excess returns. The t-statistics for the means are corrected for the serial correlation of excess returns. Ratio negative is the proportion of negative excess returns. Gain/loss is the Bernardo and Ledoit gain/loss ratio for the strategy. The sample period for the strategies is from January 2001 to December 2004.

strategies when the trade trigger level is increased from 1 to 2, the mean return can in fact become 0 or negative at lower values of α, say 0.5. This suggests that the information content of a small deviation between the market spread and the predicted spread is low, and capital structure arbitrage becomes profitable only when implemented at higher threshold levels. Three of the six strategies have average monthly excess returns that are statistically significant at the 5% level. The equally weighted strategy has significantly lower volatility than the individual strategies, indicating that the individual strategies are not perfectly correlated with each other. Finally, these excess returns all display positive skewness and have more kurtosis than would a normally distributed random variable.

6. Fixed-Income Arbitrage Risk and Return

In this section, we study the risk and return characteristics of the fixed-income arbitrage strategies. In particular, we explore whether the excess returns generated by the strategies represent compensation for exposure to systematic market factors.

6.1 Risk-Adjusted Returns

The five fixed-income arbitrage strategies we study are often described in hedge fund marketing materials as "market-neutral" strategies. For example, as the swap spread strategy consists of a long position in a swap and an offsetting short position in a Treasury bond with the same maturity (or vice versa), this trade is often viewed as having no directional market risk. In actuality, however, this strategy is subject to the risk of a major widening in the Treasury-repo spread. Similar arguments can be directed at each of the other arbitrage strategies we consider. If the residual risks of these strategies are correlated with market factors, then the excess returns reported in previous tables may in fact represent compensation for the underlying market risk of these strategies.

To examine this issue, our approach will be to regress the excess returns for the various strategies on the excess returns of a number of equity and bond portfolios. For perspective, Figures 6 and 7 plot the time series of excess returns for the equally weighted SS, YC, MA, VA, and CS strategies. To control for equity-market risk, we use the excess returns for the Fama and French (1993) market (R_M), small-minus-big (SMB), high-minus-low (HML), and up-minus-down (momentum or UMD) portfolios (excess returns are provided courtesy of Ken French). Also, we include the excess returns on the S&P bank stock index (from the Bloomberg system). To control for bond market risk, we use the excess returns on the CRSP Fama two-year, five-year, and 10-year Treasury bond portfolios. As controls for default risk, we also use the excess returns for a portfolio of A/BBB-rated industrial bonds and for a

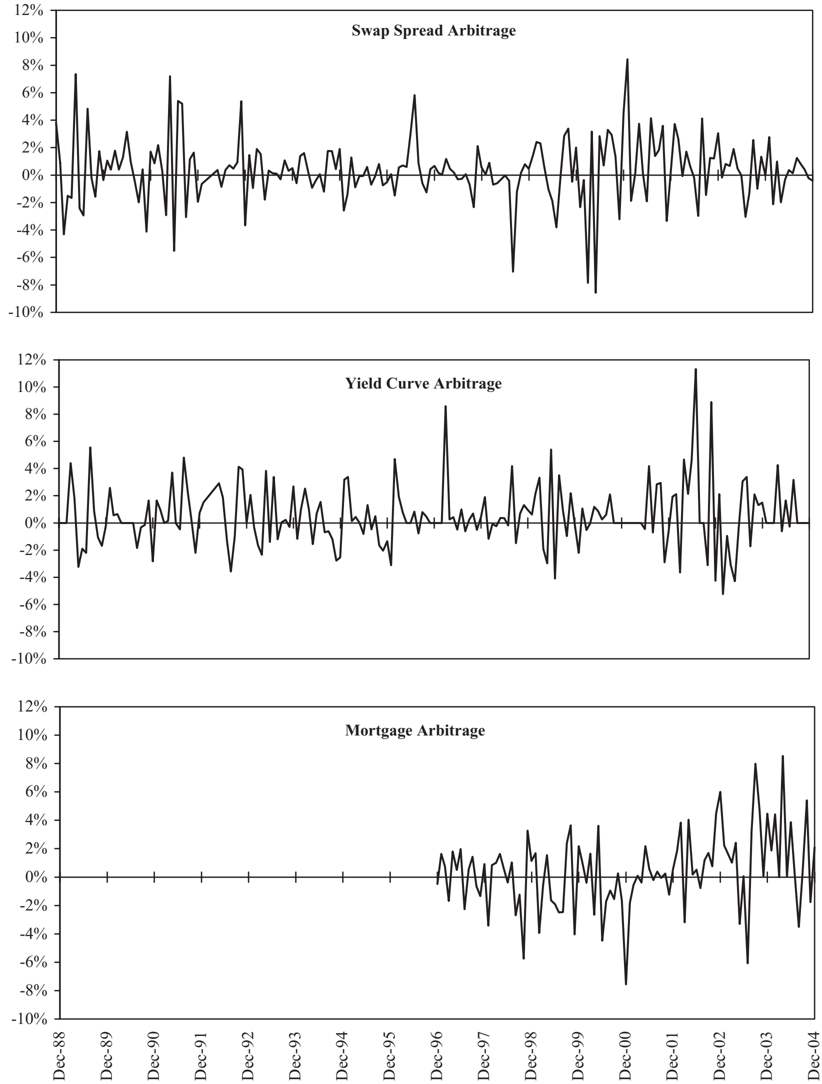

Figure 6
Monthly time series of excess returns
The top panel of this figure displays the monthly time series of excess returns for the equally weighted swap spread strategy. The middle panel displays the time series of excess returns for the equally weighted yield curve arbitrage strategy. The bottom panel displays the excess returns for the equally weighted mortgage strategy.

portfolio of A/BBB-rated bank sector bonds (provided by Merrill Lynch and reported in the Bloomberg system). Table 6 reports the regression results for each of the strategies, including the value of the alpha (the

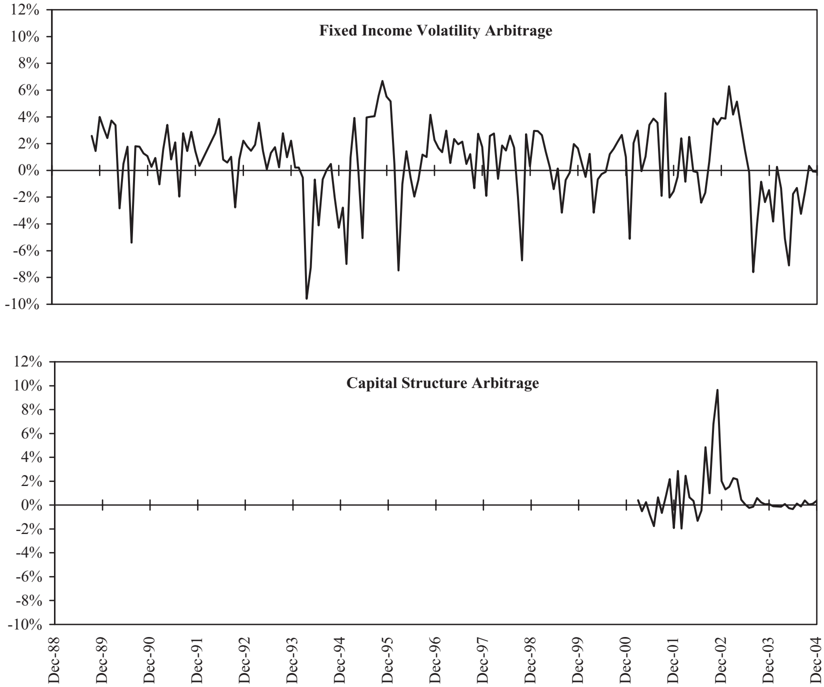

Figure 7
Monthly time series of excess returns
The top panel of this figure displays the monthly time series of excess returns for the equally weighted volatility strategy. The bottom panel displays the excess returns for the equally weighted capital structure arbitrage strategy.

intercept of the regression), along with the *t*-statistics for the alpha and the coefficients of the excess returns on the equity and fixed-income portfolios. Also reported are the R^2 values for the regressions.[19]

It is important to observe that a number of these factors are likely to be sensitive to major financial market “events” such as a sudden flight to quality or to liquidity [similar to that which occurred after the Russian Sovereign default in 1998 that led to the LTCM hedge fund crisis; see Dunbar (2000) and Duffie, Pedersen, and Singleton (2003)]. For example, Longstaff (2003) shows that the yield spread between Treasury and agency bonds is sensitive to macroeconomic factors such as consumer sentiment that portend the risk of such a flight. By including measures such as the excess returns on Treasury, banking, and general industrial bonds, or on banking stocks, we can control for the component of the

[19] We also explored specifications in which these explanatory variables appeared nonlinearly in the regression. The basic inferences about risk-adjusted excess returns were robust to these alternative specifications.

Table 6
Regression results

	Without fees		*With fees*		*t* Statistics										
Strategy	α	*t*-Stat	α	*t*-Stat	R_M	SMB	HML	UMD	R_S	R_2	R_5	R_{10}	R_I	R_B	R^2
SS1	0.350	1.44	0.115	0.59	1.57	0.25	0.41	0.90	−1.52	0.18	0.12	−0.97	−0.85	2.82	0.098
SS2	0.204	0.85	0.019	0.10	2.17	−0.14	1.19	1.04	−2.65	0.52	−0.03	−1.55	−0.02	0.42	0.105
SS3	−0.080	−0.36	−0.194	−1.04	2.56	−1.82	1.37	1.34	−2.64	1.94	−0.36	−3.53	1.84	2.95	0.212
SS4	−0.136	−0.62	−0.286	−1.45	2.71	−1.47	1.42	1.60	−1.81	2.48	1.44	−5.73	2.11	2.21	0.254
EW SS	0.084	0.45	−0.087	−0.55	2.78	−0.94	1.35	1.50	−2.67	1.53	0.34	−3.56	0.89	3.37	0.196
YC1	0.582	2.36	0.322	1.61	−0.81	1.25	−0.25	−0.16	1.03	1.44	0.10	0.23	−1.86	0.27	0.057
YC2	0.521	2.14	0.283	1.38	−1.04	0.93	−0.22	−0.14	0.88	1.98	−0.09	−0.00	−2.02	0.76	0.075
YC3	0.638	2.64	0.373	1.86	−0.85	1.78	0.33	0.86	0.62	0.84	−1.57	2.28	−3.10	2.31	0.094
YC4	0.653	2.74	0.387	1.95	−0.48	−0.56	−0.07	0.21	−0.27	1.27	−1.33	1.11	−2.30	1.44	0.117
EW YC	0.598	3.14	0.341	2.17	−1.01	1.09	−0.05	0.25	0.72	1.76	−0.91	1.14	−2.94	1.51	0.097
MA1	0.725	2.12	0.478	1.56	−1.42	−1.46	−1.33	−0.87	1.05	−0.74	−0.24	−0.39	2.52	−0.61	0.160
MA2	0.555	1.61	0.322	0.99	−1.64	−1.20	−1.68	−1.23	0.72	−0.23	−1.74	1.07	1.82	0.02	0.142
MA3	0.157	0.47	0.016	0.05	−2.08	−1.45	−1.61	−0.91	1.00	0.51	−2.68	1.18	2.41	−0.15	0.191
EW MA	0.479	1.47	0.272	0.89	−1.79	−1.43	−1.61	−1.05	0.96	−0.16	−1.62	0.64	2.35	−0.26	0.157
VA1	0.074	0.29	−0.098	−0.48	0.60	−0.71	0.39	0.92	−1.27	1.44	−0.78	−0.85	1.42	0.56	0.056
VA2	0.305	1.21	0.078	0.38	0.67	−1.29	0.22	0.93	−1.43	1.06	−1.01	−0.41	1.21	0.57	0.064
VA3	0.415	1.65	0.166	0.82	0.53	−1.56	0.03	0.95	−1.34	0.71	−0.93	−0.23	1.65	0.53	0.066
VA4	0.228	0.83	0.005	0.03	0.37	−1.59	0.06	1.09	−1.11	0.80	−0.97	−0.24	0.83	0.55	0.081
EW VA	0.308	1.26	0.084	0.42	0.56	−1.35	0.15	0.95	−1.38	0.92	−0.91	−0.41	1.50	0.58	0.063
CS1	1.073	1.66	0.734	1.35	0.58	−1.94	0.55	−0.59	0.59	0.52	−1.04	1.05	−0.30	−0.12	0.252
CS2	0.803	1.34	0.619	1.06	1.55	−2.06	0.85	−0.32	−0.73	0.32	−1.01	0.96	0.66	−0.68	0.352
CS3	1.076	1.70	0.787	1.41	1.45	−1.78	0.50	−0.38	−1.64	0.11	−0.48	0.44	0.98	−0.91	0.280
CS4	0.432	0.69	0.228	0.42	−0.61	−0.71	−1.23	−0.53	0.38	−0.35	−0.40	−0.70	1.80	0.43	0.303
CS5	1.150	1.67	0.817	1.30	−1.47	−0.38	−1.64	−1.46	0.48	−1.08	−0.35	0.11	0.96	−0.11	0.149
CS6	1.235	1.95	0.893	1.64	−0.72	−0.40	−0.50	−0.96	−1.36	−2.14	1.61	−1.03	2.50	−2.03	0.282
EW CS	0.961	2.11	0.680	1.69	0.14	−1.68	−0.38	−1.01	−0.51	−0.63	−0.38	0.19	1.53	−0.79	0.248
EW All	0.375	3.38	0.147	1.62	1.18	−1.41	0.49	0.95	−1.68	1.27	−1.29	−1.22	0.79	2.83	0.109
EW YC,MA,CS	0.525	3.56	0.275	2.28	−1.22	0.52	−0.58	−0.67	1.69	−0.13	−0.63	0.36	−0.16	0.38	0.054
CSFB	–	–	0.412	3.87	−0.80	0.79	−0.09	0.71	0.32	1.06	−2.30	0.17	−0.06	2.69	0.159
HFRI	–	–	0.479	4.22	−1.70	0.73	−0.59	−0.44	0.81	0.20	0.84	−2.76	1.52	0.40	0.139

This table reports the indicated summary statistics for the regression of monthly percentage excess returns on the excess returns of the indicated equity and bond portfolios. Results for the CSFB and HFRI fixed-income arbitrage hedge fund return indexes are also reported. R_M is the excess returns on the CRSP value-weighted portfolio. SMB, HML, and UMD are the Fama-French small-minus-big, high-minus-low, and up-minus-down market factors, respectively. R_S is the excess return on an S&P index of bank stocks. R_2, R_5, and R_{10} are the excess returns on the CRSP Fama portfolios of two-year, five-year, and 10-year Treasury bonds, respectively. R_I and R_B are the excess returns on Merrill Lynch indexes of A/BAA-rated industrial bonds and A/BAA-rated bank bonds, respectively. The sample periods for the indicated strategies are as reported in the earlier tables.

$$R_{it} = \alpha + \beta_1 R_{Mt} + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 R_{St} + \beta_6 R_{2t} + \beta_7 R_{5t} + \beta_8 R_{10t} + \beta_9 R_{It} + \beta_{10} R_{Bt} + \varepsilon_t$$

fixed-income arbitrage returns that is simply compensation for bearing the risk of major (but perhaps not-yet-realized) financial events. This is because the same risk would be present, and presumably compensated, in the excess returns from these equity and bond portfolios.

The excess returns from the various strategies presented in the previous sections include realistic estimates of the transactions costs involved with implementing the strategies. Thus, these returns are relevant from the perspective of an investor directly implementing these strategies or, equivalently, investing their own money in his or her own hedge fund. In general, however, many investors may not have direct access to these strategies and would instead invest capital in a fixed-income arbitrage hedge fund. Thus, hedge fund fees would need to be subtracted from the strategy returns to represent the actual returns these investors would achieve.

To address the implications of hedge fund fees in the analysis, we will also estimate the regression using an estimate of the net-of-fees excess returns from the various strategies as the dependent variable. Specifically, we assume that the investor must pay a standard 2/20 hedge fund fee (in addition to the transaction costs that are already incorporated into the strategy returns). This 2/20 fee structure means that the investor must pay an annual 2% fund management fee plus a 20% slope bonus for any excess returns (above a Libor-based high-water mark). This 2/20 fee structure is very typical in the hedge fund industry (although many funds are beginning to offer smaller fees in light of the increased competition and smaller returns in recent years). We note that as most of the strategies are above their high water marks throughout the sample period, this results in net-of-fees excess returns for the strategies that are nearly linear functions of the original excess returns (subtract 2% and multiply excess returns by 0.8). Thus, when the net-of-fees excess returns are regressed on the 10 explanatory variables, the *t*-statistics for these explanatory variables are virtually the same as when the original excess returns are regressed on these explanatory variables. Accordingly, to simplify the exposition, Table 6 reports the results for both the alpha based on the excess returns and the alpha based on the net-of-fees excess returns and the *t*-statistics for the explanatory variables from the excess return regressions.

We turn first to the results for the swap spread arbitrage strategies. Recall that each of these strategies generates significant (at the 10% level) mean excess returns. Surprisingly, Table 6 reports that after controlling for their residual market risk, none of the excess returns for the strategies results in a significant alpha. In fact, two of the individual swap spread strategies have negative alphas. When hedge fund fees are subtracted, the alphas are even smaller and even the equally weighted strategy results in a negative alpha.

Intuitively, the reason for these results is that the swap spread arbitrage strategy actually has a significant amount of market risk, and the excess returns generated by the strategy are simply compensation for that risk. Thus, there is very little "arbitrage" in this fixed-income arbitrage strategy. This interpretation is strengthened by the fact that the R^2 values for the swap spread strategies range from about 10 to 25%. Thus, a substantial portion of the variation in the excess returns for the SS strategies is explained by the excess returns on the equity and bond portfolios. In particular, Table 6 reports that a number of the strategies have significant positive loadings on the market factor, significant negative loadings on the SMB and bank equity factors, significant loadings on the Treasury factors, and significant positive loadings on both the corporate bond factors.

The fact that these strategies have equity market risk may seem counterintuitive given that we are studying pure fixed-income strategies. Previous research by Campbell (1987), Fama and French (1993), Campbell and Taksler (2002), and others, however, documents that there are common factors driving returns in both bond and stock markets. Our results show that the same is also true for these fixed-income arbitrage strategies. These results are consistent with the view that the financial sector plays a central role in asset pricing. In particular, the swap spread strategy has direct exposure to the risk of a financial sector event or crisis. The commonality in returns, however, suggests that both the stock, Treasury, and corporate bond markets have exposure to the same risk. Thus, "financial-event" risk may be an important source of the commonality in returns across different types of securities.

Turning next to the yield curve arbitrage strategies, Table 6 reports that the results are almost the opposite of those for the swap spread arbitrage strategies. In particular, the excess returns for all four of the yield curve strategies, along with the excess returns for the equally weighted strategy, have significant alphas. These alphas are all in the range of 0.50 to 0.65% per month. In some cases, these alphas are even larger than the average value of the excess returns.

Turning to the net-of-fees excess returns for the yield curve strategies, Table 6 reports that at least two of the four individual strategies have alphas that are significant at the 10% level. Furthermore, the alpha for the equally weighted strategy is 0.341% and is significant at the 5% level. Thus, these strategies appear to produce significant risk-adjusted excess returns even after incorporating realistic hedge fund fees into the analysis.

In general, the R^2 values for the yield curve arbitrage strategies are small, ranging from about 6 to 12%. Interestingly, the only significant source of market risk in this strategy comes from a negative relation with the excess returns on general industrial corporate bonds (not from the bank sector bonds). One interpretation of this result may be that while the hedging approach used in the strategy is effective at eliminating the exposure to two major term structure factors, more than two factors drive the swap term structure. This interpretation is consistent with recent empirical evidence about the determinants of swap rates such as Duffie and Singleton (1997) and Liu, Longstaff, and Mandell (2004).

The excess returns from the mortgage arbitrage strategies shown in Table 6 also appear to produce large alphas. The alpha for the discount mortgage strategy is 0.725% per month and is significant at the 5% level. Similarly, the alpha for the par strategy is 0.555% per month and is significant at the 10% level. The alpha for the premium strategy is not significant. When hedge fund fees are subtracted from the returns from these strategies, none of the alphas are significant (the alpha for the discount strategy, however, comes close with a *t*-statistic of 1.56).

Note that these mortgage strategies also have a substantial amount of market risk. In particular, the R^2 values for the regressions range from about 14 to 19%. For example, the strategies tend to have negative betas with respect to the market, but have positive loadings on the general industrial corporate bond factor.

The excess returns from the volatility arbitrage strategies appear to be substantially different from those of the other strategies. In particular, only the alpha from the four-year cap strategy is significant at the 10% level. Also, the strategies do not appear to have much in the way of market risk as the R^2 values are generally quite small. After subtracting out hedge fund fees, none of the alphas for the volatility arbitrage strategies is significant.

Finally, recall that we have only 48 months of excess returns for the capital structure arbitrage strategies as data on CDS contract before 2001 are not readily available because of the illiquidity of the market. Thus, one might expect that there would be little chance of detecting a significant alpha in this strategy. Despite this, Table 6 provides evidence that capital structure arbitrage does provide excess returns even after risk adjustment. Specifically, four of the six capital structure arbitrage strategies have excess returns that result in alphas that are significant at the 10% level. In addition, the *t*-statistic for the alpha for the equally weighted strategy's excess return is 2.11. In some cases, the alpha estimates are in excess of 1% per month. Thus, these alpha estimates are the largest of all of the fixed-income arbitrage strategies we consider.

Not surprisingly, the alphas for the capital structure arbitrage strategies are lower when we use the net-of-fees excess returns in the regression. Although all the alpha estimates are positive, only the CS6 strategy results in an alpha that is significant at about the 10% level. The alpha for the equally weighted strategy, however, is 0.680% which is significant at the 10% level.

Despite the large point estimates of the alphas for these capital structure arbitrage strategies, the R^2 values show that the strategies also have a large amount of market risk. These R^2 values are generally in the range of 15–35%. Interestingly, these strategies have significant positive loadings on the industrial bond factor and significant negative loadings on the SMB factor. As both the industrial bond and SMB factors are correlated with corporate defaults, this suggests that there is an important business-cycle component to the returns on capital structure arbitrage.[20]

The results in this section so far have been either for individual strategies within the five broad classes of fixed-income arbitrage strategies or for equally weighted portfolios of the individual strategies. To extend the analysis, it is also useful to examine the returns to strategies that allocate capital over different types of fixed-income arbitrage.[21] To this end, we report results for the strategy that takes an equally weighted (based on notional) position in each of the 21 substrategies across all five broad classes of fixed-income arbitrage. As shown, this strategy benefits from being diversified over many different substrategies. Without including hedge fund fees, the alpha from this strategy is 0.375% with a *t*-statistic of 3.38. When hedge fund fees are included, however, the alpha is only 0.147% with a *t*-statistic of 1.62 (not quite significant at the 10% level).

As the previous results suggest that there may be economic returns to the strategies that require a higher level of "intellectual capital," we also consider a strategy that takes an equally weighted position in the 13 substrategies in the yield curve, mortgage, and capital structure arbitrage categories. As reported in Table 6, the alpha from this strategy when returns do not include hedge fund fees is 0.525% with a *t*-statistic of 3.56. When returns are taken net of hedge fund fees, the alpha for the strategy declines to 0.275%, but the *t*-statistic for the alpha of 2.28 is still significant at the 5% level.

To summarize, these results indicate that some, but not all, of the fixed-income arbitrage strategies generate significant risk-adjusted excess returns even after incorporating both transaction costs and hedge fund fees into the analysis. The strategies that appear to do the best are those that tend to require a higher level of "intellectual capital" in terms of the modeling requirements associated with the implementation of the strategies.

6.2 Historical Fixed-Income Hedge Fund Returns

We have focused on return indexes generated by following specific fixed-income arbitrage strategies over time rather than on the actual returns reported by hedge funds. As discussed earlier, there are a variety of important reasons for adopting this approach, including avoiding survivorship and backfill biases [see Malkiel and Saha (2004)], holding leverage fixed in the analysis, etc. To provide additional perspective, however, we repeat the analysis using actual fixed-income arbitrage hedge fund return data from several widely cited industry sources.

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[20] For evidence about the relation between the SMB factor and default risk, see Vassalou and Xing (2004).

[21] We are grateful to the referee for suggesting this direction.

In particular, we obtain monthly return data from Credit Suisse First Boston (CSFB)/Tremont Index LLC for the HEDG fixed-income arbitrage index. The underlying data for this index is based on the TASS database. The sample period for these data is from January 1994 to December 2004. To be included in the index, funds must have a track record in the TASS database of at least one year, have an audited financial statement, and have at least $10 million in assets.[22] This index is value weighted. The TASS database includes data on more than 4500 hedge funds.

We also obtain monthly return data for the Hedge Fund Research Institute (HFRI) fixed-income arbitrage index. Although returns dating back to 1990 are provided, we only use returns for the same period as for the CSFB/Tremont Index to insure comparability. This index is fund or equally weighted and has no minimum fund size or age requirement for inclusion in the index. This data source tracks approximately 1500 hedge funds.

The properties of the fixed-income arbitrage hedge fund returns implied by these industry sources are similar in many ways to those for the return indexes described in the previous section. In particular, the annualized average return and standard deviation of the CSFB/Tremont fixed-income arbitrage index returns are 6.46 and 3.82%, respectively (excess return 2.60%). These values imply a Sharpe ratio of about 0.68 [which is close to the Sharpe ratio of 0.72 reported by Tremont/TASS (2004)]. The annualized average return and standard deviation for the HFRI fixed-income arbitrage index are 5.90 and 4.02%, respectively (excess return 2.05%). These values imply a Sharpe ratio of 0.51. On the other hand, there are some important differences between the CSFB/Tremont and HFRI indexes and our return indexes. In particular, the CSFB/Tremont and HFRI display a high level of negative skewness. The skewness parameters for the CSFB/Tremont and HFRI indexes are −3.23 and −3.07, respectively. Recall that with the exception of the volatility arbitrage strategies, most of our return indexes display positive (or only slight negative) skewness. Similarly, the CSFB/Tremont and HFRI indexes display significant kurtosis, with coefficients of 17.03 and 16.40, respectively.[23]

Although the correlations between the CSFB/Tremont and HFRI indexes and our return indexes vary across strategies, these correlations are typically in the range of about −0.10 to 0.30. In particular, the average correlations between the swap spread arbitrage returns and the CSFB/

[22] See Credit Suisse First Boston (2002) for a discussion of the index construction rules.

[23] The effects of various types of biases and index construction on the properties of fund return indexes are discussed in Brown et al (1992), Brooks and Kat (2002), Amin and Kat (2003), and Brulhart and Klein (2005).

Tremont and HFRI indexes are 0.12 and 0.18, respectively. The average correlations between the yield curve arbitrage returns and the two indexes are 0.02 and −0.02, respectively. The average correlations between the mortgage arbitrage returns and the two indexes are 0.22 and 0.30, respectively. The average correlations between the volatility arbitrage returns and the two indexes are 0.15 and 0.29, respectively. The average correlations between the capital structure arbitrage returns and the two indexes are −0.05 and 0.26, respectively. The reason for the slightly negative correlation between the indexes and the capital structure arbitrage returns is possibly because that this strategy is relatively new and may not yet represent a significant portion of the industry fixed-income arbitrage index. In summary, while the correlations are far from perfect, there is a significant degree of correlation between our return indexes and those based on reported hedge fund return data. Furthermore, these correlations are similar to the correlation of 0.36 reported by Mitchell and Pulvino (2001) between their return index and merger arbitrage returns reported by industry sources.

Table 6 also reports the results from the regression of the excess returns from the two indexes on the vector of excess returns described in the previous subsection. As these hedge fund return indexes are net of hedge fund fees, we interpret these results as being most compatible with the results in Table 6 based on net-of-fees excess returns. As shown, both the CSFB/Tremont and HFRI indexes appear to have significant alphas after controlling for equity and fixed-income market factors. The alpha for the CSFB/Tremont index is 0.412% per month; the alpha for the HFRI index is 0.479% per month. Both of these alphas are significant at the 5% level. It is worth reiterating the caution, however, that these indexes may actually overstate the returns of hedge funds. This is because of the potentially serious survivorship and backfill biases in these indexes identified by Malkiel and Saha (2004) and others. Thus, care should be used in interpreting these results. Furthermore, these biases (along with the heterogeneity of leverage across hedge funds and over time) may also be contributing factors in explaining the difference in the skewness between the CSFB/Tremont and HFRI indexes and the return indexes for our fixed-income arbitrage strategies. The CSFB/Tremont index appears to have significant exposure to the returns on five-year Treasuries and on the portfolio of bank bonds. This is consistent with Fung and Hsieh (2003) who find that fixed-income arbitrage strategy returns are highly correlated with changes in credit spreads. The HFRI index has significant exposure to the returns on 10-year Treasuries. The R^2 values for the regressions are similar to those for the individual fixed-income arbitrage strategy regressions.

7. Conclusion

This article conducts the most comprehensive study to date of the risk and return characteristics of fixed-income arbitrage. Specifically, we construct monthly return indexes for swap spread, yield curve, mortgage, volatility, and capital structure (or credit) arbitrage over extended sample periods.

While these are all widely used fixed-income arbitrage strategies, there are substantial differences among them as well. For example, very little modeling is required to implement the swap spread and volatility arbitrage strategies, while complex models and hedge ratios must be estimated for the other strategies. While attempting to be market neutral, some of the strategies have residual exposure to market-wide risk factors. For example, swap spread arbitrage is sensitive to a crisis in the banking sector, and mortgage arbitrage is sensitive to a large drop in interest rates triggering prepayments. These considerations motivate us to examine the risk and return characteristics of fixed-income arbitrage, both before and after adjusting for market risks.

We find a host of interesting results. To neutralize the effect of leverage, we choose a level of initial capital to normalize the volatility of the returns to 10% per annum across all strategies. We find that all five strategies yield positive excess returns. The required initial capital ranges from a few dollars per \$100 notional for volatility and yield curve arbitrage to \$50 or more for capital structure arbitrage. With the exception of volatility arbitrage, the returns have a positive skewness, contrary to the common wisdom that risk arbitrage generates small positive returns most of the time, but experiences infrequent heavy losses.

We also find that most of the strategies are sensitive to various equity and bond market factors. Besides confirming the role of market factors in explaining swap spread arbitrage and mortgage arbitrage returns, we find that yield curve arbitrage returns are related to a combination of Treasury returns that mimic a "curvature factor," and capital structure arbitrage returns are related to factors that proxy for economy-wide financial distress. Interestingly, we find that the three strategies that require the most "intellectual capital" to implement command positive excess returns even after adjusting for market risks and accounting for transaction costs and hedge fund fees.

Appendix A: Swap Spread Arbitrage

The swap data for the study consist of month-end observations of the three-month Libor rate and midmarket swap rates for two-, three-, five-, seven-, and 10-year maturity swaps. These maturities represent the most-liquid and actively traded maturities for swap contracts. All these rates are based on end-of-trading-day quotes available in New York to insure comparability of the data. In estimating the parameters, we are careful to take into account daycount differences among the rates as Libor rates are quoted on an actual/360 basis while swap rates are semiannual bond equivalent yields. There are two sources for the swap data. The primary source is the Bloomberg system which uses quotations from a number of swap brokers. The data for Libor rates and for swap rates from the pre-1990 period are provided by Citigroup. As an independent check on the data, we also compare the rates with quotes obtained from Datastream and find the two sources of data to be very similar.

The Treasury data consist of month-end observations of the CMT rates published by the Federal Reserve in the H-15 release for maturities of two, three, five, seven, and 10 years. These rates are based on the yields of currently traded bonds of various maturities and reflect the Federal Reserve's estimate of what the par or coupon rate would be for these maturities if the Treasury were to issue these securities. CMT rates are widely used in financial markets as indicators of Treasury rates for the most actively traded bond maturities. As CMT rates are based heavily on the most recently auctioned bonds for each maturity, they provide an accurate estimate of yields for the most-liquid on-the-run Treasury bonds. As such, these rates are more likely to reflect actual market prices than quotations for less-liquid off-the-run Treasury bonds. Finally, data on three-month general collateral repo rates are obtained from Bloomberg as well as Citigroup.

We initiate the swap spread strategy whenever the current swap spread is more than ten basis points greater than (or less than) the current short-term Libor-general collateral repo spread. Once executed, the strategy is held until either the horizon date of the swap and bond or until the strategy converges. Convergence occurs when the swap spread for the remaining horizon of the strategy is less than or equal to (greater than or equal to) the short-term spread.

To calculate the returns from the strategy, we need to specify transaction costs and the valuation methodology. For transaction costs, we assume values that are relatively large in comparison to those paid by large institutional investors such as major fixed-income arbitrage hedge funds. In a recent article, Fleming (2003) estimates that the bid-ask spread for actively traded Treasuries is 0.20 32nds for two-year maturities, 0.39 32nds for five-year maturities, and 0.78 32nds for 10-year maturities. To be conservative, we assume that the bid-ask spread for Treasuries is one 32nd. Similarly, typical bid-ask spreads for actively traded swap maturities are on the order of 0.50 basis points. We assume that the bid-ask spread for swaps is one basis point. Finally, we assume that the repo bid-ask spread is 10 basis points. Thus, the repo rate earned on the proceeds from shorting a Treasury bond are 10 basis points less than the cost of financing a Treasury bond. This value is based on a number of discussions with bond traders at various Wall Street firms who typically must pay a spread of up to 10 basis points to short a specific Treasury bond. In some situations, a Treasury bond can trade special in the sense that the cost of shorting the bond can increase to 50 or 100 basis points or more temporarily [see Duffie (1996), Duffie, Gârleanu, and Pedersen (2002), and Krishnamurthy (2002)]. The effect of special repo rates on the analysis would be to reduce the total excess return from the strategy slightly.

Turning to the valuation methodology, our approach is as follows. For each month of the sample period, we first construct discount curves from both Treasury and swap market data. For the Treasury discount curve, we use the data for the constant maturity six-month, one-year, two-year, three-year, five-year, seven-year, and 10-year CMT rates from the Federal Reserve. We then use a standard cubic spline algorithm to interpolate these par rates at semiannual intervals. These par rates are then bootstrapped to provide a discount function at semiannual intervals. To obtain the value of the discount function at other maturities, we use a straightforward linear interpolation of the corresponding forward rates. In addition, we constrain the three-month point of the discount function to match the three-month Treasury rate. We follow the identical procedure in solving for the swap discount function. Treasury and swap positions can then be valued by discounting their fixed cash flows using the respective bootstrapped discount function.

Appendix B: Yield Curve Arbitrage

To implement this strategy, we assume that the riskless rate is given by $r_t = X_t + Y_t$, where X_t and Y_t follow the dynamics

$$dX = (\alpha - \beta X)dt + \sigma dZ_1, \tag{A1}$$

$$dY = (\mu - \gamma Y)dt + \eta dZ_2, \tag{A2}$$

under the risk-neutral measure, where Z_1 and Z_2 are standard uncorrelated Brownian motions. With this formulation, zero-coupon bond prices are easily shown to be given by the two-dimensional version of the Vasicek (1977) term structure model.

To estimate the six parameters, we do the following. We pick a trial value of the six parameters. Then, for each month during the sample period, we solve for the values of X_t and Y_t that fit exactly the one-year and 10-year points along the swap curve. We then compute the sum of the squared differences between the model and market values for the two-, three-, five-, and seven-year swaps for that month. We repeat the process over all months, summing the squared differences over the entire sample period. We then iterate over parameter values until the global minimum of the sum of squared errors is obtained. The resulting parameter estimates are $\alpha = 0.0009503$, $\beta = 0.0113727$, $\sigma = 0.0548290$, $\mu = 0.0240306$, $\gamma = 0.4628664$, and $\eta = 0.0257381$.

With these parameter values, we again solve for the values of X_t and Y_t that fit exactly the one-year and 10-year points along the swap curve. From this fitted model, we determine the difference between the model and market values of the two-, three-, five-, and seven-year swaps. If the difference exceeds the trigger level of 10 basis points, we go long (or short) the swap and hedge it with offsetting positions in one-year and 10-year swaps. The hedge ratios are given analytically by the derivatives of the swap values with respect to the state variables X_t and Y_t. Once implemented, the trade is held for 12 months, or until the market swap rate converges to its model value. The swap transaction costs used in computing returns are the same as those described above for the swap spread arbitrage strategy.

Appendix C: Mortgage Arbitrage

The MBS data used in the strategy are from the Bloomberg system. The mortgage data are for the period between November 1996 and December 2004. The data are composed of the current mortgage coupon, price, OAS, actual prepayment speed (CPR), and weighted-average time to maturity of generic GNMA passthroughs with coupons of 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, 8.0, and 8.5%. The mortgage repo rates are the end-of-month one-month values. The mortgages in the pools are assumed to have initial terms of 30 years. Daily five-year swap rates are used to estimate hedge ratios. The assumed bid-ask spread for passthroughs is 1.28 32nds. This is the average bid-ask spread obtained from the Bloomberg system of generic GNMA passthroughs with coupons of six and seven percent. As before, the repo bid-ask spread is 10 basis points, and the swap bid-ask spread is one basis point. Most of the MBS passthrough trading is on a to-be-announced (TBA) basis. This means that at the time a trade is made, neither party to the trade knows exactly which pool of passthroughs will be exchanged. The TBA trades are settled once a month. The settlement dates are generally around the 21st of the month for GNMA passthroughs and are specified by the Bond Market Association. Settlement dates for trades from November 1996 and December 1999 are from the Bond Market Association newsletter. Settlement dates for trades from January 2000 to December 2004 are from the Bloomberg system.

The hedge ratios are estimated by a nonparametric regression of the prices of each passthrough on the five-year swap rate. The constrained nonparametric estimation follows the method developed by Aït-Sahalia and Duarte (2003), which is composed of an isotonic regression followed by a linear-kernel regression. In this method, passthrough prices are assumed to be a decreasing function of the level of the five-year swap rate. One regression is performed for each passthrough coupon. The kernel used is normal and the bandwidths are chosen by cross-validation over a grid of possible bandwidths. Because swap rates are very persistent, we follow a procedure similar to the one in Boudoukh et al. (1997) and perform the cross validation omitting all the data points in an interval. The bandwidth values are 0.001045 for the 4.5% passthrough, 0.0007821 for the 5.0% passthrough, 0.001384 for the 5.0% passthrough, 0.002926 for the 6.0 and 6.5% passthroughs, 0.002922 for the 7.0, 7.5, and 8.0% passthroughs, and 0.002473 for the 8.5% passthrough. The isotonic regression assumes that for each rate level there is only one observed price. In the sample, however, we observe various prices at the same rate level. To circumvent this problem, we take the average of the observed prices for each rate level before we run the isotonic regression. We note that the method developed by Aït-Sahalia and Duarte also allows for restrictions on the second derivative of the estimated function. In this application, however, we are only imposing restrictions on the first derivative because the price of passthroughs can be either a convex or concave function of the interest rate.

We implement the strategy in the following way. At the end of each month in the sample, a decision is made with respect to holding, buying, or selling a MBS passthrough. The decision is based on the current mortgage coupon and on the previous month's portfolio. Assume for instance that on the last trading day of the month, a hedge fund commits a certain amount of capital C_t to implement the MBS discount strategy. As part of this strategy, the hedge fund buys a \$100 notional amount of the MBS passthrough trading at a discount with coupon closest to the current mortgage coupon. At the same time, the hedge fund enters in a dollar roll and pays fixed in an interest rate swap. At the end of the next month, the hedge fund checks whether the passthrough purchased the previous month still satisfies the requirement of being at a discount with coupon closest to the current coupon. If so, the hedge fund continues to hold it, rebalances the hedge with a new five-year swap, and enters into a new dollar roll. If the passthrough does not satisfy this requirement, then the hedge fund sells it, closes the margin account, and restarts the strategy with a new MBS passthrough. The premium and the par passthrough strategies work in the same way.

The return calculation of the trading strategy is better clarified by means of an example. Assume that the hedge fund buys a \$100 notional amount of a MBS passthrough at P_t^{Ask} for settlement on the date S_1, and, to hedge its interest rate exposure, pays fixed on a five-year interest rate swap. To finance its long MBS position, the hedge fund uses a dollar roll in which the hedge fund agrees to deliver a \$100 notional amount of a MBS passthrough at S_1 in exchange for the dollar amount P_t^{Bid} and to receive a \$100 notional amount of a passthrough at the settlement date S_2 in exchange for the dollar amount P_t^{Roll}. At the end of the following month $t+1$, the hedge fund decides to sell the \$100 MBS position at price P_{t+1}^{Bid} for settlement at S_2 and unwind the five-year swap hedge. The net cash flows of the MBS transactions are $(-P_t^{Ask} - P_t^{Bid})$ at time S_1, and $(P_{t+1}^{Bid} - P_t^{Roll})$ at time S_2. The profit (or loss) of the MBS part of this trade is therefore $PV_{t+1}(P_{t+1}^{Bid} - P_t^{Roll}) - PV_t(P_t^{Ask} - P_t^{Bid})$, where PV_t is the time t value of the cash flows. In addition to the profits related to the MBS, the hedge fund also has profit from the swaps and from the capital invested in the margin account. The monthly return of this strategy is therefore the sum of the profits of all the parts of the strategy divided by C_t. Capital is allocated when a passthrough is purchased and is updated afterwards by the profits (or losses) of the strategy.

Note that the MBS return in the expression $PV_{t+1}(P_{t+1}^{Bid} - P_t^{Roll}) - PV_t(P_t^{Ask} - P_t^{Bid})$ does not depend directly on the actual MBS passthrough prepayment because the counterparty of the hedge fund in the dollar roll keeps all of the cash flows of the passthrough that occur between S_1 and S_2. As a consequence, the value of P_t^{Roll} depends on the dealer forecast at time t of the prepayment cash flows between S_1 and S_2. The value of P_t^{Roll} is calculated as in the Bloomberg roll analysis [see Biby, Modukuri, and Hargrave (2001) for details about this calculation]. We assume that the implied cost of financing for the roll is the mortgage repo rate plus the bid-ask spread. In addition, as in Dynkin et al (2001), we assume that the forecast prepayment level is equal to the prepayment level of the month when the roll is initiated. In reality, the level of prepayments during the month when the roll is initiated is only disclosed to investors at the beginning of the subsequent month.

Appendix D: Volatility Arbitrage

Our approach for computing the returns from volatility arbitrage is based on entering into a sequence of one-month volatility swaps that pay the arbitrageur the difference between the initial implied variance of an interest rate caplet and the realized variance for the corresponding Eurodollar futures contract each month. This strategy benefits directly whenever the realized volatility is less than the implied volatility of interest rate caps and floors. This strategy is scaled to allow it to mimic the returns that would be obtained by shorting caps (and/or floors) in a way that keeps the portfolio continuously delta- and vega-hedged.

To illustrate the equivalence, imagine that the market values interest rate caplets using the Black (1976) model and that the implied volatility is constant (or that vega risk is zero). From Black, it can be shown that the price C of a caplet would satisfy the following partial differential equation,

$$\frac{\sigma^2 F^2}{2} C_{FF} - rC + C_t = 0, \tag{A3}$$

where F is the corresponding forward rate and σ^2 is the implied variance. Now assume that the actual dynamics of the forward rate under the physical measure are given by $dF = \mu_F dt + \hat{\sigma} F dZ$. Form a portfolio ($\Pi$) with a short position in a caplet hedged with a futures contract. Applying Ito's Lemma to the hedged portfolio gives

$$d\Pi = \left(\Pi_t + \frac{\hat{\sigma}^2 F^2}{2} \Pi_{FF} \right) dt. \tag{A4}$$

As the initial value of the futures contract is zero, its derivative with respect to time is zero, and its second derivative with respect to F is zero (we abstract from the slight convexity differences between forwards and futures), we obtain

$$d\Pi = \left(-C_t - \frac{\hat{\sigma}^2 F^2}{2} C_{FF} \right) dt. \tag{A5}$$

Substituting C_t from Equation (A3) in Equation (A5) gives

$$d\Pi = \left(\frac{(\sigma^2 - \hat{\sigma}^2)F^2}{2}C_{FF} + r\Pi\right)dt. \tag{A6}$$

The value of this portfolio today is equal to the capital amount invested in this strategy. The excess profit of this strategy over a small period of time is approximately

$$\frac{(\sigma^2 - \hat{\sigma}^2)F^2}{2}C_{FF}dt. \tag{A7}$$

Thus, the instantaneous excess return on the strategy would be proportional to the gamma of the caplet times the difference between the implied and realized variance of the forward rate process. Note that this quantity is identical to the profit on a volatility swap where the notional amount is scaled by $F^2C_{FF}/2$. This means that we can think of the trading strategy as either a volatility swap strategy or a short delta-hedged position in a caplet (holding implied volatility constant over the month).

We calculate the excess returns from the volatility arbitrage strategy by calculating the quantity in Equation (A7) for each individual caplet. As the implied volatility for the individual caplets within a cap, we use the market-quoted volatility for the cap. A 1% bid/ask spread represents a realistic value for interest rate caps and floors. Alternatively, a 1% transaction cost would also be realistic for a volatility swap (which can be approximated by an at-the-money-forward cap/floor straddle). As the realized volatility for each individual caplet, we use the volatility of the Eurodollar futures contract with maturity corresponding to the caplet. Using a one-month horizon for the strategy minimizes the effects of changes in the "moneyness" of the caps on the time series of returns.

Appendix E: Capital Structure Arbitrage

We provide a brief summary of the CG model, the selection of its parameters, and the use of the model in our capital structure arbitrage trading analysis. For details about the model and the associated pricing formulas, the reader is referred to Finkelstein et al. (2002, CGTD).

CG is a structural model in the tradition of Merton (1974), Black and Cox (1976), and Longstaff and Schwartz (1995). It assumes that the firm value is a diffusion, and default occurs when the firm value reaches a lower threshold called the "default barrier." Deviating slightly from the traditional structural models, however, CG assumes that the default barrier is an unknown constant that is drawn from a known distribution. This assumption helps to boost short-term credit spreads in a way similar to Duffie and Lando (2001).

To generate a predicted CDS spread, CG requires a set of seven inputs: the equity price S, the debt per share D, the mean default barrier as a percentage of debt per share $\bar{L}$, its standard deviation λ, the bond recovery rate R, the equity volatility σ_S, and the risk-free interest rate r. Consistent with the empirical analysis in the CGTD, we define D as total liabilities (taken from Compustat) divided by common shares outstanding, σ_S as the 1000-day historical equity volatility, r as the five-year constant maturity Treasury yield, and let λ be equal to 0.3. However, rather than setting $\bar{L}$ to be 0.5 and taking the bond recovery rate from a proprietary database as in the CGTD, we set R to be 0.5 and estimate the mean default barrier $\bar{L}$ by fitting the first 10 daily market spreads of an obligor to the CG model. This is consistent with the historical recovery rates on senior unsecured debt and the literature on endogenous bankruptcy. For example, in Leland (1994) and Leland and Toft

(1996), the default barrier is chosen by the manager with consideration for the fundamental characteristics of the company, such as the asset volatility and the payout rate.

The CG model is used in the trading analysis in three ways. Properly estimated with the above procedure, we first use it to calculate a time series of predicted CDS spreads for the entire sample period for each obligor. The comparison between the predicted spreads and the market spreads forms the basis of the trading strategy as explained in Section 5. Second, to calculate the daily returns on an open trade, we must keep track of the total value of the positions, notably the value of a CDS position that has been held for up to 180 days. The Markit CDS database used in this study, however, provides only the spreads on newly issued five-year contracts. We note that the value of an existing contract can be approximated by the change in five-year CDS spreads multiplied by the value of a five-year annuity, whose cash flows are contingent on the survival of the obligor. We use the term structure of survival probabilities from the CG model to mark to market the CDS position. Third, we numerically differentiate the value of the CDS position with respect to the equity price to identify the size of the equity hedge.

The trading analysis performed in Section 5 assumes a maximum holding period of 180 days, a CDS bid-ask spread of 5%, and a static equity hedge that is held fixed throughout a trade. It ignores the cost of trading equity because CDS market bid-ask spreads are likely to be the dominant source of transaction costs. We have experimented with setting different holding periods (30 to 360 days), updating the equity hedge daily, and computing the CDS market value using a reduced-form approach [such as Duffie and Singleton (1999)], all with results similar to those in Table 5. In addition, the average monthly excess returns remain positive even when the CDS bid-ask spread increases to 10%.

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