Can Credit Risk be Hedged in Equity Markets?

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Abstract

We examine whether credit default swaps (CDS) can be hedged effectively using equity. Using CDS data for 207 firms over 2001 to 2009, we find that hedging credit default swaps with equity reduces daily volatility of the unhedged position by only about 10% over our entire sample. The conclusion that hedging credit risk in the equity markets is relatively ineffective is robust across sub-samples of firms of different rating classes as well as across sub-periods. The conclusion holds true whether the hedge ratio is estimated from a structural model, or when the hedge ratio is estimated empirically from the observed sensitivity of spreads to equity returns. Hedging is also relatively ineffective in the tail of the distribution as it reduces the 1% VaR by only about 12%. Lack of integration between equity and credit markets is one explanation as hedging is more effective over longer horizons. Our results also indicate that the RMSE are related to the VIX, indicating that the hedging becomes less effective when markets are more fearful.

Keywords: Hedge Ratio, credit default swap

JEL classification: G14, G12, C31

"In the uproar over AIG, the most important lesson has been ignored. AIG failed because it sold large amounts of credit default swaps without properly offsetting or covering their positions." George Soros
(Wall Street Journal, March 24, 2009)

1 Introduction

Over the last decade, the single name credit default swap (CDS) market has grown tremendously both in terms of trading volume and economic significance. This growth has, however, been accompanied with significant controversy. One major concern has been that the market may lead to concentration of credit risk and, therefore, systemic risk (see, for example, Duffie and Zhu, 2011; Stulz, 2009). The poster child for the latter argument is AIG. By selling protection on a wide range of products, including portfolios of corporate debt, AIG concentrated a short position in credit risk in its portfolio, forcing a US bailout.

An unanswered question in this controversy is whether it is possible for a market maker of corporate credit default swaps to effectively hedge inventory risk in the equity markets. If swaps can be hedged, then credit market shocks can be dissipated through the more liquid equity markets, reducing the concentration of risk on a single counterparty or market maker. If, on the other hand, swaps cannot be effectively hedged, then the CDS markets may pose an ongoing systemic risk problem. Our objective in this paper is to address this question of whether or not credit default swaps can be effectively hedged in equity markets.[1]

Integral to the analysis is the question of whether there exists a stable structural pricing relation between stock prices and CDS spreads. Recent research has noted that traditional structural models of credit risk poorly fit observed credit spreads (Eom, Helwege and Huang, 2004) and that changes in credit spreads are poorly correlated with equity returns (Collin-Dufresne, Goldstein, Martin, 2001). Despite these well-documented limitations, Schaefer and Streublaev (2008) demonstrate that the classic Merton (1974) model provides hedge ratios that are accurate predictors of the sensitivity of corporate bond returns to changes in the value of equity. If time-variation in default risk predominantly determine changes in spreads, then their results indicate that structural models should be useful for hedging

[1] Although in principle a credit default swap can be hedged in the bond market, it is impossible to do so when the total outstanding CDS notional is multiple times the outstanding corporate debt. Similarly, the limited size and liquidity of the equity derivative markets makes it difficult to hedge using deep out-of-the-money puts. Dissipating risk by hedging requires using a deeper, more liquid market.

purposes. By examining the effectiveness to which credit default swaps can be hedged in practice allows us both to contribute to the ongoing debate on the value of structural models of credit risk.

In theory, hedging a credit sensitive security with equity simply requires computing the relative sensitivities of credit and equity to changes in the underlying firm value. In practice, in comparison with other derivative markets, hedging credit derivatives poses special problems. First, there is significant model risk. Although a model is required for determining the hedge ratio in many derivative markets, model risk is especially significant for the credit market because the firm value itself is unobservable. Both the hedge ratio and the value of the underlying asset (the firm value) must be simultaneously estimated through the model. Second, a hedged CDS position is vulnerable to relative pricing errors across equity and CDS markets (Kapadia and Pu, 2011) or lead-lag relation (Acharya and Johnson, 2007). In such circumstances, not only is a hedge ineffective, but the hedge increases the volatility of the position's P&L relative to an unhedged position. Third, there is considerable evidence that changes in credit spreads are impacted by factors other than the asset value of the firm. For instance, credit markets are illiquid (Longstaff, Mithal and Neis (2005), Chen, Lesmond and Wei (2007)), and are correlated with systematic factors such as the market return, the VIX, and the yield curve (Collin-Dufresne, Goldstein and Martin, 2001). The greater the extent to which spreads are impacted by variables not associated with changes in asset value, the less effectively will the swap be hedged through equity markets.

As in Figlewski and Green (1999), we examine hedging effectiveness from the viewpoint of a market maker, whose objective is to minimize the daily volatility of the CDS portfolio position. In our analysis, we address model risk associated with the determination of the hedge ratio by considering four different specifications to determine the hedge ratio. First, we use two regression-based estimates of the sensitivity of spread changes to the equity. The advantage of these estimates is that it is easy to control for variables that impact credit spreads but are not incorporated into structural models. In addition, under a linearity assumption, the hedge ratio from the regression is the minimum variance hedge ratio. Second, we use two hedge ratios from variations of the Merton model. The first is the theoretical hedge ratio from the classic zero-coupon Merton model as used in Strebulaev and Schaefer (2008). The second is a hedge ratio from an extended Merton specification, where the zero-coupon model is extended to allow for coupon bonds. The motivation for using the extended Merton model is that, under reasonable assumptions, the spread on a coupon bond priced at par is equal to that of the CDS spread (Duffie, 1999).

We conduct our empirical analysis on a sample of 207 single name credit default swaps over the period 2001 to 2009. The period ranges from the beginning of the credit default swap market to the Big Bang in April of 2009, when contract specifications for North American credit default swaps were standardized.

Our primary finding from is that credit default swaps are poorly hedged in equity markets. Across our entire sample, depending on the model used to construct the hedge ratio, the root mean square error (RMSE) of a portfolio of credit default swaps hedged by the stock of the firm ranges from about \$16,500 to \$17,500 a day for a CDS notional of \$10 million. In comparison, the RMSE of the *unhedged* CDS portfolio is about \$18,000 a day - not much larger than that of the hedged portfolio. That is, on average, hedging a portfolio of credit default swaps in the equity market reduces daily volatility by only about 10 percent. Disconcertingly, hedging often increases volatility. The Merton model hedge ratios result in greater volatility for investment grade firms, and the empirically estimated hedge ratio results in greater volatility for the riskiest firms with rating B and below.

The finding is robust. First, it holds across sub-samples of rating classes, for both above investment grade firms as well as below investment grade firms. Second, it holds over sub-periods. The best hedging performance is in the financial crisis period of 2008-09, when correlations across all asset classes increase. But even in this period, the reduction in daily RMSE only about 12%. Finally, hedging with equity is about as (in)effective in reducing the tail risk as it is in reducing volatility. The VaR of the hedged portfolio over the entire sample is at best lower by 12% in comparison with the 10% reduction in the RMSE.

Hedging ineffectiveness is not because of model risk associated with the estimation of the hedge ratio. Indeed, consistent with the finding of Schaefer and Strebulaev (2008), the Merton model hedge ratios are not statistically different from the in-sample empirically estimated hedge ratios. Consequently, the effectiveness of the hedge ratio in reducing RMSE is about the same across all four models that are used to construct the hedge ratio.

Why then is hedging ineffective? Our methodology allows us to quantify the relative importance of the two other potential explanations. We provide evidence that the lack of integration between equity and credit markets - either because of mispricing (Kapadia and Pu, 2011) or a lead-lag relation (Acharya and Johnson, 2007), has an important role to play. When we aggregate hedging errors over longer horizons, the volatility of the hedged position relative to the unhedged position decreases. However, even so, the RMSE reduces by only about 21%.

Instead, it is evident that the lack of effectiveness is related to the fact that changes in credit spreads are poorly explained by stock returns. In particular, changes in the VIX have about the same explanatory power as the firm's stock return itself. Across our entire sample, the median R-square of the regression of credit spread changes on the firm's equity return is 13%; in comparison, the median R-square of the regression of credit spreads on changes in the VIX index is 9.5%. The VIX consistently explains variation in RMSE across firms in every rating class, as well as across the entire sample.

What is the implication of our results for structural models of credit risk? Structural models not only indicate which variables are important for pricing credit risk, but as importantly, indicate the set of variables that should *not* enter the pricing kernel. We find it difficult to envisage a formal role for the VIX to enter the pricing kernel within traditional structural models of credit risk. Instead, it appears possible that the credit market incorporates market fears in addition to the risk of default of the underlying firm.

The rest of the paper is as follows. Section 2 discusses the determination of the hedge ratio. Section 3 describes our data and also describes the pricing model used to market the spread to market. Sections 4 present the empirical results. Section 5 provides illustrations on the results. The last section offers brief conclusions.

2 Hedging in Structural Models of Credit Risk

2.1 Hedge Ratio

Let $A_{i,t}$ be the value of assets of a firm i with equity value of $S_{i,t}$. The firm has outstanding debt in the form of a zero-coupon bond of face value F, maturity T, and market value of $B_{i,t}$. From the absence of arbitrage,

$$A_{i,t} = S_{i,t} + B_{i,t}. \tag{1}$$

In the Merton one factor model, equity and debt prices are impacted only by changes in the firm value. From equation (1),

$$\frac{\partial S_{i,t}}{\partial A_{i,t}} + \frac{\partial B_{i,t}}{\partial A_{i,t}} = 1. \tag{2}$$

Following Schaefer and Strebulaev (2008), define the hedge ratio for the bond, $\delta^b_{i,t}$, as the amount of equity required to hedge the bond. From (1) and (2),

$$\delta^b_{i,t} = \frac{\partial B_{i,t}/\partial A_{i,t}}{\partial S_{i,t}/\partial A_{i,t}} \frac{S_{i,t}}{B_{i,t}}, \tag{3}$$

$$= \left(\frac{1}{\Delta_{i,t}} - 1\right)\left(\frac{1}{L_{i,t}} - 1\right) \tag{4}$$

where $L_{i,t}$ is the firm leverage, defined as the market value of debt over the market value of the asset, and $\Delta_{i,t}$ is the sensitivity of equity to the firm value. In the Merton (1974) model, Δ is the "delta" of a European call option with the firm as the underlying asset. In a wide class of models, including Merton (1974), Δ is strictly bounded by 1 prior to maturity of the debt. It follows from (4) that $\delta^b_{i,t}$ is strictly positive, and a long position in the bond can be hedged by shorting the stock.

2.2 Merton Model Hedge Ratios

The spread, $\mathrm{cs}_{i,t}$, over the riskfree rate r^f_t is equal to $\mathrm{cs}_{i,t} = \frac{1}{T}\ln(F/B_{i,t}) - r^f_t$. From equation (4), it follows that the sensitivity of the spread to the equity of the firm is,

$$\frac{\partial \mathrm{cs}_{i,t}}{\partial S_{i,t}/S_{i,t}} = -\frac{1}{T}(\frac{1}{\Delta_{i,t}} - 1)(\frac{1}{L_{i,t}} - 1). \tag{5}$$

From the Merton model (suppressing the dependency on A_t), $\Delta_{i,t} = N(d_1(K_{i,t}, T))$, where $N(\cdot)$ is the cumulative normal distribution, and

$$d_1(K_i, T) = \frac{\ln(A_{i,t}/K_i) + (r^f_t - y_i + \sigma^2_i/2)T}{\sigma_i\sqrt{T}}, \tag{6}$$

where y and σ are the constant dividend yield and the asset volatility, respectively, and K is the default threshold. In the classical Merton model, K is equal to the face value of the bond F.

For the *classical* Merton model, we define the hedge ratio for the credit default swap in the Merton model hedge ratio as $\delta^m_{i,t}$,

$$\delta^m_{i,t} = \frac{\partial CDS_{i,t}}{\partial S_{i,t}/S_{i,t}}, \quad (7)$$

$$= \frac{\partial \text{cs}_{i,t}}{\partial S_{i,t}/S_{i,t}} D_{i,t}, \quad (8)$$

where $D_{i,t}$ is defined as the CDS "duration", the dollar change in the value of the swap for a one bps spread change. $D_{i,t}$ is determined by the pricing model used to mark the swap to market; we defer discussion on the mark to market model to a later section.

In addition, to the classical Merton model hedge ratio, we also construct a hedge ratio from the Merton model extended to price a coupon bond. Duffie (1999) demonstrates that under reasonable assumptions, the spread on a coupon bond priced at par is equal to the CDS spread. Thus, it may be more accurate to compute the hedge ratio from the extended Merton model.

Consider a bond $B_{i,t}$, $t \equiv 0$, of face value F, maturity T and an annual coupon c (as a fraction of the face value) payable semi-annually on dates T_n, $n = 1, 2.., 2T$. If the bond defaults on a coupon date, T_n, then the holder of the bond receives either the firm value or a constant fraction, w, of the contracted cash flow on that date, whichever is less. The firm defaults if the firm value at T_n is below a known threshold K_i. Under these assumptions, treating this coupon bond as a portfolio of zero coupon bonds as in Longstaff and Schwartz (1995), Eom, Helwege and Huang (2004) provide the value of the coupon bond from the extended Merton model as,

$$B_{i,0} = \sum_{n=1}^{2T} e^{-rT_n} \text{E}^Q_0 \left[F \left(\mathbb{1}_{[n=2T]} + \frac{c}{2} \right) \mathbb{1}_{[A_{i,T_n} \geq K]} + \min \left(wF \left(\mathbb{1}_{[n=2T]} + \frac{c}{2} \right), A_{i,T_n} \right) \mathbb{1}_{[A_{i,T_n} < K]} \right], \quad (9)$$

where,

$$\text{E}^Q_0 \left[\mathbb{1}_{[A_{i,T_n} \geq K_i]} \right] = N\left(d_2(K_i, T_n)\right),$$

$$\text{E}^Q_0 \left[\min(u, A_{i,T_n}) \mathbb{1}_{[A_{i,T_n} < K_i]} \right] = A_{i,0} e^{-y_i T_n} N(-d_1(u, T_n)) + u \left[N(d_2(u, T_n)) - N(d_2(K_i, T_n)) \right],$$

where $N(\cdot)$ is the cumulative standard normal distribution, r is the constant riskfree interest rate and

$$d_2(X_i, T_n) = d_1(X_i, T_n) - \sigma_i \sqrt{T_n},$$

and d_1 has been defined earlier in equation (6).

Define $\bar{c}(A_{i,t})$ as the coupon rate that results in the bond being priced at par for a given set of parameters and firm value $A_{i,t}$. The sensitivity $\partial\bar{c}(A_{i,t})/\partial A_{i,t}$ can be computed numerically. From $\partial\bar{c}(A_{i,t})/\partial A_{i,t}$, we can estimate the sensitivity of $\bar{c}(A_{i,t})$ to $S_{i,t}$ as,

$$\frac{\partial\bar{c}(A_{i,t})}{\partial S_{i,t}/S_{i,t}} = \frac{\partial\bar{c}(A_{i,t})/\partial A_{i,t}}{\partial S_{i,t}/\partial A_{i,t}} S_{i,t}. \tag{10}$$

Given the equivalence of the spread on the bond priced at par and the CDS spread, the sensitivity of $\bar{c}(A_{i,t})$ to the stock will equal to the sensitivity of the CDS spread to the stock. Therefore, defining the extended Merton model hedge ratio for firm i as $\delta^{\bar{m}}_{i,t}$, we get the hedge ratio as,

$$\delta^{\bar{m}}_{i,t} = \frac{\partial\bar{c}}{\partial S_{i,t}/S_{i,t}} D_{i,t}, \tag{11}$$

where, as in equation (8), $D_{i,t}$ is the duration of the credit default swap.

2.3 Empirical Hedge Ratio

When a single factor model does not determine relative pricing of equity and credit, then hedging credit in the equity market is no longer an act of undertaking an arbitrage as in the Merton model, but a means of reducing the variance of the hedged portfolio. As in the early literature on the hedging of derivatives with basis risk (e.g. Figlewski, 1984), the optimal hedge ratio under a linearity assumption can be computed from a regression of the change in CDS spread against the stock return.

Let the *empirical* hedge ratio, $\delta^{e}_{i,t}$, for the credit default swap be defined as the dollar amount of stock required to hedge one CDS contract. Consider the linear regression of the change in CDS spread, $\Delta CDS_{i,t} = CDS_{i,t} - CDS_{i,t-1}$ on the stock return,

$$\Delta CDS_{i,t} = \alpha_i + \beta_i r_{i,t} + \tilde{e}_{i,t}. \tag{12}$$

The slope coefficient, β_i, is the sensitivity of the CDS spread to changes in the stock price. To compute the hedge ratio, we convert β_i into a dollar sensitivity as follows,

$$\delta^{e}_{i,t} = \beta_i D_{i,t}. \tag{13}$$

The specification of equation (12) can be extended to include other variables,

$$\Delta CDS_{i,t} = \alpha_i + \beta_i r_{i,t} + \gamma\,\mathbb{X}_t + \tilde{e}_{i,t}, \tag{14}$$

where $\mathbb{X}_t$ are additional variables that might impact the CDS spread. In line with previous research (e.g., Collin-Dufresne, Goldstein and Martin, 2001), we include firm-specific variables (changes in leverage and equity volatility), index equity and option market variables (past S&P 500 return, change in VIX) and interest rate market variables (changes in 10-year Treasury rate and slope of the yield curve).

Below, we will estimate and use the empirical hedge ratio both in-sample and out-of-sample (the latter through a rolling regression). Although the in-sample hedge ratio cannot be used in practice, it will serve as a useful benchmark to understand the potential effectiveness of hedging credit risk in the equity markets.

2.4 Hedging Effectiveness

As in Figlewski and Green (1999), we assume that the objective of the financial institution is to minimize the daily volatility of its hedged CDS portfolio position. Suppose that the market maker holds a portfolio of CDS contracts of N_t names, and each swap is hedged with its corresponding stock. On each date t, the mean portfolio hedging error, e_t, is computed as the average hedging error over the portfolio as follows,

$$e_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\left[(-1)^c\left(\mathrm{CV}_{i,t+1} - \mathrm{CV}_{i,t}\right) + (-1)^c\delta_{i,t}\left((P_{i,t+1} + Div_{i,t+1})/P_{i,t} - 1\right)\right], \tag{15}$$

where $c \in \{1, 2\}$ denotes whether the position holds the CDS short ($c = 1$) or long ($c = 2$). We alternate daily between long and short positions to minimize the impact of non-linearity on the hedge. $\mathrm{CV}_{i,t} \equiv \mathrm{CV}(CDS_{i,t})$ is the cash settlement, or mark to market, value of the swap. $\delta_{i,t}$ is the dollar amount of equity of firm i required to hedge one CDS contract at time t, computed either from empirically observed credit-equity sensitivity or from the Merton model as discussed in previous subsections. $P_{i,t}$ is the stock price at time t and $Div_{i,t}$ is the cash dividend received at time t.

Following Bertsimas, Kogan and Lo (2000), we use root-mean-squared error (RMSE) as the summary statistic for the hedging error, where $\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2}$. The RMSE is equal to the standard deviation when the mean hedging error is zero. For comparison, we also compute the $RMSE$ of the portfolio when the swap is not hedged, i.e., when $\delta_{i,t} \equiv 0$.

3 Data and Implementation

3.1 Data

We get our data on credit default swap spreads (CDS) from Markit. Specifically, we use daily observations for five-year credit default swap on senior, unsecured debt of non-financial firms. The 341 obligors that enter our sample are components of the Dow Jones CDX North America Investment Grade (CDX.NA.IG), the Dow Jones CDX North America High Yield (CDX.NA.HY), CDX North America Crossover (CDX.NA.XO), over 2001 to 2009. Our sample ends on March 31st, 2009, right before the Big Bang of April 2000 which changed pricing conventions in the CDS market. Of the 341 firms, 34 firms could not be matched to CRSP and Compustat, 92 firms were delisted during this period, and 8 firms have less than a year of data, leaving us with a final sample of 207 firms. Of these, 112 obligors have an average rating of investment grade (AAA, AA, A, and BBB), and the remaining 95 obligors are below investment grade (BB, B, and CCC). The data of CDS spread has different DocClauses, including MM, MR, XR, CR, for each firm. For below investment grade firms, we use XR; for investment grade firms, we use MR or XR, if MR is missing.

Stock prices and outstanding number of shares are adjusted for stock dividends and splits, and obtained from CRSP. We take into account cash dividends. Accounting information required to compute leverage and face value of debt is collected from Compustat Quarterly file. If the debt data is missing, we use the closest available quarterly data in the same year, or else use the annual data. Interest rate data including Treasury, LIBOR and swap rates are from the Federal Reserve. Data for the TED spread and LIBOR-OIS spread are obtained from Bloomberg.

Panel A of Table 1 reports the summary statistics of our sample. Across rating classes, the average CDS spread increases from 52.9 bps for $\geqslant$ A rated firms to 605.5 bps for $\leqslant$ B rated firms. As would be expected, higher rated firms are larger and have lower leverage. Market capitalization ranges from 46.8 billion dollars to 3.9 billion dollars, and leverage from 0.14 to 0.38 across the rating classes. Panel B reports the summary statistics of daily changes in CDS spread. The average daily spread change for the whole sample is 0.48 bps.

Daily spread changes are positive on average in line with the overall increase in credit risk over this period. Spread changes for lower rated classes are larger and more volatile.

3.2 Merton Model Implementation

To estimate the asset volatility and firm value, we follow Duffie, Saita and Wang (2007) to jointly solve for the asset value and volatility by iterating the following two equations over a rolling one-year period,

$$\begin{aligned} S_{i,t} &= A_{i,t}N[d_1] - K_i e^{-rT} N[d_2], \\ \sigma_i &= \text{stdev}\left[\ln A_{i,t} - \ln A_{i,t-1}\right]. \end{aligned}$$

As is now standard, the default threshold, K_i, is defined as the sum of the firm's book value of short-term debt [Compustat item 45] and half of its long term debt [Compustat item 51] in the previous quarter. The 1-year Treasury rate is used as the riskfree rate. If the number of observations in the rolling window is less than 30, then the volatility and asset value are set as missing.

Panel A of Table 1 also reports the average asset volatilities estimated through the above procedure. The average asset volatility over our sample period is 31%, ranging from 28% to 35%. As would be expected, the higher rated firms have lower asset volatility.

3.3 CDS Pricing Model

We use the ISDA CDS Standard model to mark the credit default swap to market. Documentation of the model as well as the source code for the model is available at *www.cdsmodel.com.* The provider of our CDS quotes, Markit, maintains an implementation (Markit Converter) as does Bloomberg ("CDSW"). Using the model, we define the duration $D_{i,t}$ as the average change in the mark to market value for a $\pm$ 1 bps change in spread as follows,

$$D_{i,t} = \frac{1}{2}\left(|\text{CV}(CDS_{i,t}+1) - \text{CV}(CDS_{i,t})| + |\text{CV}(CDS_{i,t}) - \text{CV}(CDS_{i,t}-1)|\right). \quad (16)$$

The change in the value of the CDS will depend on the level of the spread. Figure 1 plots the relation between the duration and the level of the spread. For example, when the spread is below 250 bps, a one bps change in an investment grade swap initially at par results in a change in the settlement value of the CDS of between \$4,000 and \$4,500 for a notional of \$10 mm. The computed duration, $D_{i,t}$ is used to estimate the hedge ratio in equations (8), (11), and (13).

4 Results

4.1 Hedge Ratio

We begin by reporting the estimated hedge ratios for each of the four specifications discussed earlier, viz., the classical and extended Merton models, and the empirical hedge ratio from an univariate and multivariate specifications, respectively.

4.1.1 Merton Model Hedge Ratio

On each date, t, we compute the hedge ratio for the rating class as follows. First, we compute spreads and sensitivities on a firm-by-firm basis for the classical and extended Merton models. Then, for each day and each rating class, we calculate the average spread and sensitivities across all firms for the rating class. The hedge ratio is now computed as the product of the average sensitivity and duration, where the duration is calculated at the average observed CDS spread for each rating class on each day. The hedge ratio for the rating class is finally used to determine the daily hedge for each firm in that rating class. Using the hedge ratio for the rating class reduces estimation noise. When we compute the hedge using the firm-specific sensitivity and spread, the RMSE is higher and the hedge is less effective.

Table 2 reports the time-series mean and standard deviation of the spreads, sensitivities and hedge ratios for each rating category. First, consider the estimate of the spreads from the Merton model. Both the classical and extended Merton model underestimate the actual spreads. Consistent with theory, the extended Merton model provides estimates of spreads that are closer to the observed spreads. For example, for BBB rated firms, the observed average CDS spread is 98 bps. In comparison, the average spread from the classical and extended Merton model is 36 bps and 50 bps, respectively. Nevertheless, both models underestimate the spread, consistent with Eom, Helwege and Huang (2004), who also document in their Table 3 that the Merton model underestimates bond spreads by about 50%. The pricing error in our calibration of classical Merton ranges from -47% to -71% across the rating classes, and from -31% to -56% for the extended Merton.

Next, consider the sensitivity of the spread to the stock return, and corresponding hedge ratios. The average sensitivity of the spread to equity computed with the extended Merton model is higher than that from the classical model. The mean sensitivity across all firms in the classical Merton model is 0.69 bps for a 1% stock return, and 0.81 bps for the extended Merton model. The difference in sensitivities impacts the estimated hedge ratios. The corresponding hedge ratios, the amount of equity required to hedge one CDS contract of $10 million notional, are $282,865 and $335,525 for the classical and extended Merton models, respectively. The sensitivity of the spread to the stock return increases monotonically as the rating declines. For example, the hedge ratio for BB firms is about two-fold that for BBB firms.

4.1.2 Empirical Hedge Ratio

Next, we estimate the slope coefficient β in the univariate specification of equation (12) and the multivariate specification of (14), respectively. We estimate β through a panel regression allowing for firm effects using weekly changes in CDS spreads and stock return. β estimated from a weekly regression results in lower hedging errors than if estimated from daily or monthly spread changes. Table 3 reports the results. Across all rating classes, the coefficient on the stock return is negative and statistically significant at the highest levels. The coefficient of determination for the univariate specification ranges from 9.6% to 12.7%, and for the multivariate specification from 10.4% to 16.0%. As first observed by Collin-Dufresne, Goldstein, and Martin (2001) and verified in subsequent literature, it is difficult to explain changes in spreads.

For the univariate model, the sensitivity of spread changes to the stock return ranges from 0.70 bps for firms rated $\geq A$ to 4.22 bps for firms rated $\leq B$. For the multivariate model, excepting firms rated B or below, the magnitude of the sensitivity is lower. For example, the slope coefficient of rating BBB is 0.63 bps for the multivariate regression, only half of 1.29 bps for the univariate specification. Following the procedure in Merton hedge ratio, the duration at the average CDS spread level for each rating class on each day is used to calculate the empirical hedge ratios. Table 3 also reports the time-series mean for the duration and hedge ratio for each rating class. The average amount of equity required to hedge a CDS contract of notional \$10 million is \$1,196,485 using the sensitivity from the univariate specification, and \$1,158,299 for the multivariate specification. Consistent with the sensitivities previously estimated from the Merton models, the absolute magnitude of the sensitivity increases monotonically as the rating of the firm declines.

Although the Merton model consistently underestimates the level of the spread, Schaefer and Strebulaev (2008) find that the sensitivities from the Merton model are not significantly different from those estimated from empirically observed bond spreads. Panel B reports the results of the regression test implemented by Schaefer and Strebulaev (2008) for our data,

$$\Delta CDS_{i,t} = \alpha_i + \beta_j^h \overline{\delta_{j,t}^m} r_{i,t} + \gamma\, \mathbb{X}_t + \tilde{e}_{i,t}. \tag{17}$$

where $\overline{\delta_{j,t}^m}$ is the Merton model hedge ratio for rating j at time t. The null hypothesis that the empirical sensitivity is not statistically different from that estimated from the Merton models, $\beta_j^h = 1$, is not rejected for any rating class for the extended Merton model. The classical Merton model fares slightly worse, rejecting the hypothesis for firms of rating class BB and below. Overall, our results are are consistent with Schaefer and Strebulaev (2008) that the empirically estimated sensitivities are close to those estimated from the Merton models. That is, there does not appear to be significant model risk in the estimation of the hedge ratios.

4.2 Hedging Effectiveness

Table 4 reports RMSE of the daily hedging errors under each of the four hedge ratios. The RMSE of the unhedged position serves as a benchmark. The mean hedging error is close to zero, so the RMSE can also be interpreted as the volatility of the market maker's daily P&L.

4.2.1 RMSE across Models

As shown in panel A of Table 4, the average RMSE across the entire sample ranges from \$16,544 to \$17,497 across the four hedge ratios, with the lowest (highest) hedging error arising from the hedge ratio estimated from the empirical multivariate (classical Merton) specification. Across the entire sample, the maximum reduction in RMSE is 9.8%.

How well does the Merton model perform relative to the empirical multivariate hedge ratio? The RMSE for the extended Merton model over the entire sample is $17,353, only about 5% higher than the RMSE from the multivariate specification. Interestingly, the RMSE from the classical Merton model is also about the same as that for the extended Merton model, differing by less than 1%, even though the hedge ratio for the extended Merton model hedge ratios are closer to that for the multivariate empirical hedge ratio. Overall, on average, both the Merton models are about as useful for hedging purposes, and their hedging effectiveness is close to that of the empirically estimated hedge ratios.

Across rating classes, we see wider differences across the models. The hedge ratio from the multivariate empirical model performs better for higher rating classes than either of the hedge ratios from the Merton models, but its performance deteriorates for the lowest rating class. The empirical hedge ratio results in 9% lower volatility than the Merton model hedge ratios for investment grade firms, but results in 3% higher volatility for firms rated B or below.

Sub-period results reported in Panels B to D are consistent with conclusions based on the entire sample period. Except for the financial crisis period of 2008-09, the Merton model hedge ratios perform about the same, or even better, than the empirically estimated hedge ratios. Moreover, the Merton model always dominates the empirically estimated hedge ratios for riskiest firms.

Overall, our first set of findings supports Schaefer and Streulaev's conclusion that Merton model hedge ratios are not different from those estimated from data. On average, across the entire sample, Merton model hedge ratios result in RMSE of about the same order of magnitude as the empirical hedge ratio, and within sub-samples, often improves upon the latter.

4.2.2 Hedging vs. Non-Hedging

How effective is the hedge from the four models in reducing volatility of the market maker's CDS portfolio? If credit default swaps can be perfectly hedged, then hedging in the equity market would reduce the volatility of the CDS portfolio to zero. We can evaluate the effectiveness of the hedge by considering the extent to which the volatility of the hedged CDS portfolio is lower than the volatility of the *unhedged* portfolio. The volatility (RMSE) of the unhedged portfolio is reported in the first column of Table 4.

Surprisingly, as can be observed from Panel A, the RMSE of the unhedged portfolio of

$18,341 over the entire sample is not much different from that of the best hedged position. At best, across the entire sample, hedging using the multivariate hedge ratio reduces RMSE by only 9.8%. The two Merton model hedge ratios reduce the volatility by around 5%. Results across rating classes in Panel A are consistent with the overall sample. Although hedge ratios tends to perform better for lower rated firms than higher rated for all the four models, the maximum reduction in volatility through hedging is less than 10%. Sub-period results reported in Panels B to D provide consistent results. The maximum reduction in volatility of 12% (using the multivariate hedge ratio) occurs in the 2008-09 - the period corresponding to the most volatility CDS markets. In the least volatile period corresponding to 2004-07, the RMSE reduces at most by 6%.

Indeed, hedging often *increases* volatility in sub-samples. For example, across the entire sample period, the Merton model hedge ratios increase volatility for above investment grade firms. In Panel A, the RMSE for the hedged portfolio for A rated firms is about 6% higher than the unhedged portfolio when the extended Merton model hedge ratio is used to construct the hedge.

In summary, consistently across sub-samples and sub-periods, the equity hedge is of limited effectiveness in reducing the volatility of the CDS portfolio across all models. At best, across sub-samples, the reduction in volatility is 12%. At worst, hedging increases volatility of the CDS portfolio compared with leaving the portfolio unhedged.

4.3 Out of Sample Empirical Hedge Ratio

The empirically estimated sensitivities that we used to construct the hedge cannot be used in practice as these were estimated from in-sample. How do out-of-sample hedge ratios perform? To check, we estimate the hedge ratio from a rolling regression over the previous one year. Using the previous one year not only allows us to check the out-of-sample usefulness of the empirical hedge ratio, but also allows a fairer comparison with the Merton model.

The results, reported in Table 5, are not encouraging. Hedging reduces RMSE across all firms by only 5.38% - less than the reduction observed when the hedge ratio was estimated in-sample. Moreover, there is considerable variation in hedging effectiveness of the sensitivities estimated from the one-year rolling regressions. While the hedge ratio from multivariate regression reduces the volatility by 10% in the subperiod 2008-2009, it results in 32% *higher* RMSE than the unhedged portfolio for subperiod 2002-2003. In comparison, the Merton model hedge ratios provide a more consistent hedging performance across sub-samples.

4.4 Alternative Measure of Risk

The RMSE may not be the appropriate risk measure, especially when the distribution of hedging errors does not follow a normal distribution. In Figure 2, we plot the distribution of the hedging error from Section 4.2. The distribution of hedging error is not normally distributed. Both the distribution of the unhedged and hedged CDS portfolio have fat tails. The Kolmogorov-Smirnoff test rejects the hypothesis of a normal distribution at the 5% significance level. As an alternative to volatility, we consider the Value at Risk (VaR). Investigating whether hedging can reduce the VaR is important especially as regulators often set capital requirements based on this measure.

We construct the VaR at the 99'% by averaging the absolute hedging error at the 0.5% percentile and 99.5% percentile. The daily VaR for the unhedged portfolio is $73,000. Hedging in the equity market is slightly more effective at the tail. Across the entire sample, using the in-sample empirical hedge ratio estimated from the multivariate specification reduces the VaR by 12% as opposed to the 9.8% reduction in volatility. The hedge ratios from the Merton model have less effectiveness than the empirical hedge ratio with the VaR reducing by only about 2.5%. Hedging effectiveness using the Merton model hedge ratios varies across sub-periods, ranging from 2.5% to 9%. Hedging effectiveness also varies across rating classes. Consistent with our previous observations with respect to the RMSE, the Merton model hedge ratios are most effective for the riskiest firms, but can increase the VaR for the higher rated firms. Thus, for example in Panel A, whilst the extended Merton model reduces the VaR by 5% for BB rated firms, it increases the VaR by about the same amount for BBB rated firms.

In summary, the conclusions using VaR are consistent with those using the RMSE. Hedging credit risk in the equity markets is of limited effectiveness across the entire sample, although the Merton model performs creditably in comparison with the in-sample estimated empirical sensitivity.

5 Discussion

Our results indicate that hedging in the equity market is of limited effectiveness in reducing the volatility or VaR of a CDS market-maker. The ineffectiveness of the equity hedge is not because of model risk as the performance of the Merton model is about the same order of magnitude as the in-sample estimated hedge ratio, and is often even superior. We now investigate the relative importance of the two alternative explanations.

5.1 Cumulative Hedging Error

One possible explanation is that equity and credit markets are not well integrated over short horizons. For example, there could be lead-lag relationships between the equity and credit markets (Acharya and Johnson, 2007). In addition, there could be transient mispricing (Kapadia and Pu, 2011).If the lack of integration between equity and credit markets over short horizons is partly responsible for the poor performance of the hedge, then the performance of the equity hedge should improve when errors are aggregated over longer horizons. To investigate, we consider cumulative hedging errors over horizons longer than one day.

Specifically, at a time t, we hedge the equally weighted portfolio of CDS contracts with equity, and make no additional trade until $t+T$. At $t+T$, the position is closed out and the cumulative hedging error over the T-day period is computed as,

$$e_t(T) = \frac{1}{N_t}\sum_{i=1}^{N_t}\left[(-1)^c\left(\mathrm{CV}_{i,t+T} - \mathrm{CV}_{i,t}\right) + (-1)^c\delta_{i,t}\left((P_{i,t+T} + \sum_{\tau=t}^{t+T} Div_{i,\tau})/P_{i,t} - 1\right)\right], \tag{18}$$

Results for horizons corresponding to $T \in \{5, 10, 25, 50\}$ are reported in table 7. As would be expected, the magnitude of RMSE increases with horizon. The rate of increase is slightly greater than $\sqrt{T}$ possibly because the hedge is not rebalanced daily. For example, the RMSE of the unhedged portfolio over a 50 (25) business day horizon is 3.16 (2.42) times that of the RMSE over 5 business days. In contrast to the previous results for daily volatility, each of the four hedge ratios are effective in reducing the RMSE. For example, hedging using the extended Merton model reduces RMSE by around 17% for a horizon of 5 business days, and 21% for the 10-day horizon. The hedge ratio from the classical Merton model also shows similar magnitudes of effectiveness. It is interesting to note that the hedge ratio from univariate regression provide the best performance now, even though it works relatively poorly in daily hedging.

Our results indicate that much of the improvement in hedging effectiveness occurs over a short period. Using the hedge ratio estimated from the univariate regression, the decline in RMSE is about 20% within 5-days, and increases only to 31% over 50-days. Figure 3 plots the RMSE of the cumulative hedging error from one to 10 days in Panel A, and shows the effectiveness of hedge in Panel B. There is a steep improvement in the effectiveness of the hedge from 1-day to 4-days, and then a slower improvement for longer horizons upto 10 days and beyond.

Overall, the results suggest that short-term pricing discrepancies play a role in making the equity hedge ineffective. As equity and credit markets are better integrated over longer horizons, the equity hedge is more effective. However, the equity hedge reduces volatility by only about 30% at best when using empirical hedge ratio. Thus, it is clear that mispricing is not the only explanation of the ineffectiveness of the hedge.

5.2 Low Correlation between CDS spread and stock return

The ineffectiveness of hedging may be because other variables, besides the equity, also impact credit spreads. To compare the relative importance of factors determining credit spread changes, we run the monthly regression of CDS spread change over six sets of variables for each firm. The six sets of independent variabels are stock return, change in quasi-market leverage and equity volatility, change in VIX, change in VIX and market return, change in 10-year treasury rate and slope of yield curve. Panel A in Table 8 reports the median adjusted R^2 across each rating class and the whole sample.

Stock return itself only explains 13% of time-series variation in CDS spread for the whole sample. Across rating classes, the explanatory power ranges from about 9% for the highest rated firms to 21% for the lowest-rated firms. Surprisingly, VIX and market return together are more powerful than the underlying stock return in explaining variation of CDS spreads with an adjusted R^2 is 22% across all firms. Moreover, across all rating classes, the VIX and index have higher explanatory power than the underlying stock return. Indeed, the market return and VIX are together more important than any other set of variables in determining credit spread changes.

Do these additional variables explain hedging ineffectiveness? To address this question, we estimate a time-series regression in the monthly RMSE on changes on a set of market variables, including the two interest rates, the VIX and market return. The monthly RMSE in month m is computed using the daily hedging errors of portfolio during that month as follows,

$$RMSE_m = \sqrt{\frac{1}{|m|}\sum_{t\in m} e_t^2} \tag{19}$$

where $|m|$ is the number of days in month m, e_t is defined in equation 15. Although we report results only for the hedge ratio from the classical Merton model, the extended Merton model hedge ratio gives similar results.

Panel B in Table 8 reports the results. Across the whole sample, these four variables together explain 34.8% variation in the monthly RMSE. The RMSE is significantly related to changes in the slope of the yield curve consistent the predictions of recent structural models that indicate credit spreads should be dependent on the business cycle (e.g., Hackbarth, Miao and Morellec, 2006; Gabaix, 2008; Chen, 2010). In addition, the 10-year Treasury rate is also weakly significant. The significance of the slope of the yield curve and 10-year Treasury rate only exists for investment-grade firms, and not for below-investment grade firms.

The most consistently significant variable, however, are not interests rates but the VIX. Across all firms, changes in the VIX is significant at the highest level. The sign of the coefficient is positive indicating that an increase in the VIX increases the RMSE. Moreover, the VIX is also significant for three of the four categories of rating classes. In summary, it is clear that the VIX plays an important role in explaining both the variability of credit spreads and hedging effectiveness.

It is far more difficult to understand why the VIX plays such an important role. Given that the VIX is related to market fears, the results suggests that the credit markets price in an additional market-wide risk that is not fully captured at the level of the firm.

6 Conclusion

We examine whether credit risk can be hedged in the equity market from the viewpoint of a financial institution making markets in credit default swaps. Our surprising finding is that hedging in the equity markets is of limited effectiveness in reducing the volatility of a CDS portfolio at a daily frequency. Over our entire sample, hedging in the equity market reduce daily volatility about 10%. Moreover, in sub-samples, hedging can *increase* the RMSE. The lack of effectiveness is not because of model risk as the Merton model hedge ratios are similar to the hedge ratios based on the empirical observed sensitivity of CDS spread to stock return.

Instead, we find support for two alternative explanations. First, hedging effectiveness increases over longer horizons, indicating that the lack of integration between equity and credit markets over short horizons plays a role in reducing hedging effectiveness. Although the effectiveness of the equity hedge increases, the reduction in the volatility is only about 30% relative to the unhedged portfolio. Second, we find that the correlation between credit spread and stock return is not only low on average, but that it is lower than the correlation of credit spreads with market return and market volatility. In particular, changes in the VIX index plays an economically and statistically important role in determining not only credit spread changes but also hedging effectiveness. Overall, our results indicate that both explanations are economically important.

Although we have attempted to distinguish between the two explanations, it is possible that both explanations are related. Credit derivatives, as opposed to other derivative markets, appear to be especially sensitive to mispricing because of the significant costs associated with arbitrage. But one significant cost, as we noted, is the risk associated with implementing an arbitrage. Given that credit spread changes are susceptible to market wide fears, there is an increased risk of arbitrage, thus making it more likely to have persistent pricing errors.

In summary, the credit markets appear to be unique in the risks they pose to market-makers. Moreover, given that the increased risk is positively related to market fears, market-makers in the credit default swap markets are also likely to be a source of systemic risk. Regulators need to be cognizant of the special risk posed by market-making in the CDS market.

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Table 1: Summary Statistics

This table reports the summary statistics of five important variables for 207 firms over January 2001 to March 2009. Panel A reports the mean and standard deviation of CDS spread, market cap, asset volatility and leverage. CDS Spread is given in basis points. Market Cap (billion dollars) is the product of the stock price and the outstanding number of shares. Asset volatility is computed as noted in text of paper. Leverage is defined as the ratio of the book value of debt (debt in current liabilities plus long term debt) to the sum of the book value of debt and market equity value. Panel B reports summary statistics of daily changes in CDS spread in basis points. The time-series averages of these variables are calculated first for each firm, and then the statistics in the cross-section for each rating class and the whole sample are reported. 'All' refers to summary statistics of the variables across all firms in our portfolio.

Panel A: Summary Statistics of the Sample

		CDS (bps)		Market Cap (B $)		Asset Volatility		Leverage	
Rating	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD
$\geqslant$ A	33	52.9	22.7	46.8	46.8	0.28	0.06	0.14	0.09
BBB	79	98.1	51.9	15.6	17.4	0.28	0.07	0.20	0.11
BB	56	251.4	132.0	6.1	5.5	0.34	0.10	0.31	0.18
$\leqslant$ B	39	605.5	475.5	3.9	3.9	0.35	0.09	0.38	0.15
ALL	207	228.0	293.2	15.8	25.9	0.31	0.09	0.25	0.16

Panel B: Summary Statistics of Daily Changes in CDS Spread (bps)

Rating	Mean	SD	Skew	Kurtosis	P95	P5
$\geqslant$ A	0.05	0.09	2.13	4.88	0.32	-0.03
BBB	0.10	0.22	1.65	4.78	0.55	-0.14
BB	0.28	0.77	3.80	20.15	1.64	-0.33
$\leqslant$ B	1.88	3.58	3.45	14.06	10.38	-0.33
ALL	0.48	1.73	7.43	68.93	2.77	-0.19

Table 2: Merton Model Hedge Ratio

This table reports summary statistics of spreads, sensitivities and hedge ratios calculated using the Merton models for each rating class and the whole sample. Spread (bps) is the credit spread computed with Merton model. Sensitivity is the spread change per unit of stock return which is computed from equation (5) for the classic Merton, and from equation (10) for the extended Merton. The hedge ratio (dollars) is the amount of equity required to hedge one CDS contract of notional of $10 mm, and is equal to the product of the sensitivity and duration. The time-series mean and standard deviation are reported here.

Rating	Classical Merton		Extended Merton	
	Mean	SD	Mean	SD
	Spread (bps)			
⩾A	15.2	27.9	23.4	35.3
BBB	35.8	47.9	50.2	59.8
BB	131.9	158.0	172.6	187.1
⩽B	191.4	219.8	263.4	264.8
All	69.4	87.5	95.7	105.7
	Sensitivity			
⩾A	0.0021	0.0033	0.0030	0.0041
BBB	0.0042	0.0048	0.0055	0.0057
BB	0.0116	0.0106	0.0128	0.0097
⩽B	0.0159	0.0088	0.0165	0.0112
All	0.0069	0.0062	0.0081	0.0058
	Hedge Ratio ($)			
⩾A	96,390	148,487	133,201	184,748
BBB	184,943	206,094	240,845	244,362
BB	460,051	399,958	515,300	365,081
⩽B	551,403	332,553	592,144	265,388
All	282,865	229,134	335,525	221,346

Table 3: Empirical Hedge Ratio

This table reports the estimate of the empirical hedge ratio, $\delta^e_{j,t} = \beta_j D_{j,t}$. β_j is the slope coefficient from a panel regression of equation (12) and equation (14), respectively, for rating j. Fixed effect is allowed here. The duration $D_{j,t}$ is computed at the average observed CDS spread of rating j on each date. Panel A reports the time-series average of duration ($) and hedge ratios ($). Panel B reports the estimate of the slope coefficient β^h_j in hedge ratio regression 17 for rating j. The null hypothesis is $\beta^h_j = 1$, which means Merton hedge ratio is in line with those empirically observed. t-stat is calculated with the clustered standard error.

Panel A: Empirical Hedge Ratio

		Univariate		Multivariate	
Rating	Duration	$\lvert\beta\rvert$	Hedge Ratio ($)	$\lvert\beta\rvert$	Hedge Ratio ($)
$\geqslant$ A	4,490	0.0070	314,311	0.0018	80,823
BBB	4,411	0.0129	569,070	0.0063	277,918
BB	4,127	0.0252	1,039,982	0.0205	846,017
$\leqslant$ B	3,750	0.0422	1,582,637	0.0431	1,616,390
ALL	4,243	0.0282	1,196,485	0.0273	1,158,299

Panel B: $\lvert\beta\rvert$ in Hedge Ratio Regression

	Classical Merton		Extended Merton	
Rating	Coefficient	t-stat	Coefficient	t-stat
$\geqslant$ A	0.97	-0.16	1.16	0.68
BBB	0.94	-0.70	1.02	0.21
BB	1.22	0.68	1.13	0.41
$\leqslant$ B	1.49	2.05**	1.10	0.47
ALL	1.37	2.18**	1.10	0.61

Table 4: Comparisons of Hedging Effectiveness - RMSE

This table reports the RMSE of the hedging errors under four hedge ratios during the whole sample period and three subperiods. An equally weighted CDS portfolio is formed across each rating class and the whole sample, respectively, and then is hedged dynamically in equity market. The four hedge ratios include two empirical ratios from a univariate and multivariate regression, respectively, and two theoretical hedge ratios from classical and extended Merton models. The position is rebalanced on a daily basis. We also report RMSE of the unhedged portfolio ("No Hedge") for comparison. Number in the table is in dollar terms.

		Empirical		Merton	
Rating	No Hedge	Univariate	Multivariate	Classical	Extended
	Panel A: Whole period 2001-2009				
$\geqslant$ A	8,896	9,002	8,681	9,070	9,463
BBB	13,286	13,261	12,551	13,372	13,756
BB	35,473	34,092	33,251	34,214	33,724
$\leqslant$ B	57,479	53,609	53,784	52,726	52,514
ALL	18,341	17,285	16,544	17,497	17,353
	Panel B: Subperiod 2001-2003				
$\geqslant$ A	10,164	10,946	10,083	10,450	10,954
BBB	14,953	16,116	14,768	15,104	15,556
BB	55,361	52,809	52,082	50,847	50,950
$\leqslant$ B	79,432	73,343	73,538	71,993	72,269
ALL	18,002	17,532	16,603	16,594	16,786
	Panel C: Subperiod 2004-2007				
$\geqslant$ A	2,199	2,916	2,157	2,189	2,182
BBB	4,056	5,178	4,029	3,955	3,946
BB	12,440	13,273	12,437	11,988	11,910
$\leqslant$ B	26,197	26,597	26,770	25,175	24,937
ALL	8,486	8,927	8,175	8,090	8,002
	Panel D: Subperiod 2008-2009				
$\geqslant$ A	16,487	15,489	15,885	16,727	17,432
BBB	24,389	21,990	22,091	24,548	25,293
BB	43,143	41,016	39,297	46,546	44,279
$\leqslant$ B	77,283	71,142	71,357	71,320	70,095
ALL	34,811	31,402	30,582	33,829	33,226

Table 5: Out-of-The-Sample Hedging under Rolling Regression

The table reports RMSE ($) of hedging errors using two out-of-the-sample empirical hedge ratios. The β used to calculate hedge ratio is estimated from weekly rolling regression, in which rolling window is 1 year. which are constructed using short-period β. Since the rolling window starts from January 2001, the first date to compute hedge ratio is January 1st, 2002. Panel A reports the RMSE ($) of hedging errors across the whole sample. Panel B - D reports that for three subperiods. For the convenience of comparison, we also report the RMSE of "No Hedge" and that using Merton hedge ratios.

		Out of the Sample		Merton	
Rating	No Hedge	Univariate	Multivariate	Classical	Extended
	Panel A: Whole period 2002-2009				
$\geqslant$ A	7,779	7,874	7,839	7,915	8,298
BBB	12,431	13,075	11,936	12,312	12,605
BB	23,469	22,864	23,329	24,746	23,921
$\leqslant$ B	44,983	44,651	53,013	42,852	42,356
ALL	17,102	16,420	16,182	16,601	16,373
	Panel B: Sub-period 2002-2003				
$\geqslant$ A	5,604	7,343	6,730	5,953	6,609
BBB	12,544	17,210	13,453	11,701	11,764
BB	23,888	26,304	25,742	24,050	24,561
$\leqslant$ B	52,814	67,084	100,252	54,867	55,097
ALL	10,670	14,376	14,072	10,251	10,495
	Panel C: Sub-period 2004-2007				
$\geqslant$ A	2,203	2,220	2,270	2,193	2,187
BBB	4,059	3,979	4,020	3,958	3,949
BB	12,121	11,338	11,576	11,674	11,605
$\leqslant$ B	25,946	24,645	26,698	24,965	24,752
ALL	8,409	7,686	7,952	8,018	7,935
	Panel D: Sub-period 2008-2009				
$\geqslant$ A	16,495	15,959	16,144	16,708	17,412
BBB	24,398	23,036	22,490	24,596	25,348
BB	42,868	40,953	42,247	46,565	44,270
$\leqslant$ B	77,133	71,247	74,647	71,380	70,096
ALL	34,714	31,899	31,185	33,847	33,228

Table 6: Comparisons of Hedging Effectiveness - Value at Risk

This table reports the Value at Risk (VaR) at 99% confidence interval of the hedging errors under four hedge ratios for the whole sample and each rating class. VaR ($) is measured as the average of the absolute value of hedging errors at 99.5 and 0.5 percentile.

		Empirical		Merton	
Rating	No Hedge	Univariate	Multivariate	Classical	Extended
	Panel A: Whole period 2001-2009				
$\geqslant$ A	39,157	39,270	37,739	40,355	40,445
BBB	57,613	56,553	57,537	62,076	60,265
BB	145,181	131,645	129,543	140,454	137,499
$\leqslant$ B	247,185	222,850	223,442	229,259	245,243
ALL	72,953	67,747	64,156	71,156	71,196
	Panel B: Subperiod 2001-2003				
$\geqslant$ A	43,761	48,174	44,167	46,810	48,886
BBB	65,126	66,939	64,949	66,756	69,107
BB	235,651	187,262	191,561	203,804	197,797
$\leqslant$ B	313,827	290,607	291,341	283,931	284,350
ALL	63,327	57,737	57,156	58,816	57,616
	Panel C: Subperiod 2004-2007				
$\geqslant$ A	8,114	9,338	7,931	8,084	8,075
BBB	14,139	16,015	13,829	13,981	13,937
BB	44,663	37,526	37,078	42,949	42,168
$\leqslant$ B	82,462	67,636	68,630	76,378	75,253
ALL	32,018	29,016	27,494	30,658	30,160
	Panel D: Subperiod 2008-2009				
$\geqslant$ A	56,290	55,626	54,873	51,578	52,302
BBB	85,471	72,589	71,931	75,246	77,000
BB	145,550	132,971	128,654	155,653	148,033
$\leqslant$ B	278,060	240,416	239,387	231,550	247,140
ALL	114,136	104,790	105,168	105,337	106,897

Table 7: Hedging Effectiveness Over Longer Time Horizons

For each rating class and the whole sample, the table reports the RMSE of the cumulative hedging errors of four hedge ratios over 5, 10, 25 and 50 business days, respectively. The number in table is in dollar terms.

	No	Empirical		Merton	
Rating	Hedge	Univariate	Multivariate	Classical	Extended
	Panel A: 5 business days				
$\geqslant$ A	37,190	32,738	35,805	33,951	33,142
BBB	42,839	37,254	39,104	38,617	38,295
BB	101,946	83,938	85,316	86,890	85,761
$\leqslant$ B	147,933	117,447	117,370	122,518	124,058
ALL	60,608	48,058	49,103	50,570	50,164
	Panel B: 10 Business days				
$\geqslant$ A	40,389	35,617	38,751	37,007	36,568
BBB	64,138	54,180	57,974	57,151	56,151
BB	139,177	107,739	110,982	112,730	111,517
$\leqslant$ B	222,432	166,384	165,877	175,554	180,891
ALL	92,834	70,042	72,928	73,770	73,349
	Panel C: 25 Business days				
$\geqslant$ A	62,140	53,118	59,272	58,121	57,027
BBB	100,919	84,491	91,142	92,486	90,429
BB	226,202	167,999	174,959	182,268	180,117
$\leqslant$ B	362,331	260,831	259,697	291,105	294,428
ALL	146,519	107,172	113,250	119,936	118,067
	Panel C: 50 Business days				
$\geqslant$ A	90,866	74,449	86,026	85,943	83,889
BBB	138,446	110,346	122,498	128,297	124,701
BB	320,795	228,295	240,687	265,381	259,789
$\leqslant$ B	479,803	307,965	306,166	381,041	377,348
ALL	201,249	137,900	148,229	170,118	165,590

Table 8: Non-equity Factors

Panel A in this table reports the median Adjusted R^2 in firm-by-firm regression of change in CDS spread on six sets of independent variables. $\Delta r_{E,i,t}$ is the stock return of firm i in month t; $\Delta lev_{i,t}$ is the change in quasi-market leverage; $\Delta vol_{E,i,t}$ is the change in equity volatility; Δr_t^{10} is monthly change in 10-year Treasury rate; $\Delta slope_t$ is the monthly change in slope of the yield curve, which is 10-year Treasury rate minus 1-year Treasury rate; ΔVIX_t is monthly change in VIX; $r_{m,t}$ is the market return, which is measured with $S\&P$ return. Panel B reports the regression result of monthly RMSE over a set of non-equity market variables. The dependent variable is the change in monthly RMSE, which is constructed using the hedging errors of Extended Merton hedge ratios. The Newey-West standard error is used to calculate t-stat and number of lags is 3.

Panel A: Median Adjusted R^2 of Firm-by-firm Weekly Regression

	$\geqslant$ A	BBB	BB	$\leqslant$ B	ALL
$r_{E,i,t}$	0.0914	0.1179	0.2192	0.2083	0.1320
$\Delta lev_{i,t}, \Delta vol_{E,i,t}$	0.1631	0.1301	0.1501	0.3084	0.1667
ΔVIX_t	0.1339	0.0713	0.1215	0.1112	0.0954
$\Delta VIX_t, r_{m,t}$	0.2522	0.1917	0.2172	0.2694	0.2217
$\Delta r_t^{10}, \Delta slope_t$	0.0928	0.0581	0.0250	-0.0010	0.0479
everything	0.3834	0.3117	0.3549	0.4910	0.3631

Panel B: Regression of Monthly RMSE of Classical Merton Model Over Market Variables

	$\geqslant$ A	BBB	BB	$\leqslant$ B	ALL
ΔVIX_t	0.0002	0.0003	0.0009	0.0014	0.0007
	(2.13)**	(2.05)**	(1.56)	(2.02)**	(3.59)***
$r_{m,t}$	-0.0015	-0.0003	-0.0156	-0.0877	0.0102
	(-0.11)	(-0.02)	(-0.18)	(-0.72)	(0.28)
$\Delta slope_t$	0.3629	0.9306	2.8894	2.0223	1.0899
	(2.16)**	(3.3)***	-1.57	-1.53	(2.98)***
Δr_t^{10}	-0.3071	-0.4777	-1.1093	-0.8601	-0.6324
	(-2.41)**	(-2.17)**	(-1.04)	(-0.71)	(-1.77)*
intercept	-0.0001	-0.0002	-0.0002	-0.0001	0.0000
	(-0.51)	(-0.46)	(-0.16)	(-0.07)	(-0.12)
Adjusted R^2	0.168	0.212	0.073	0.131	0.348

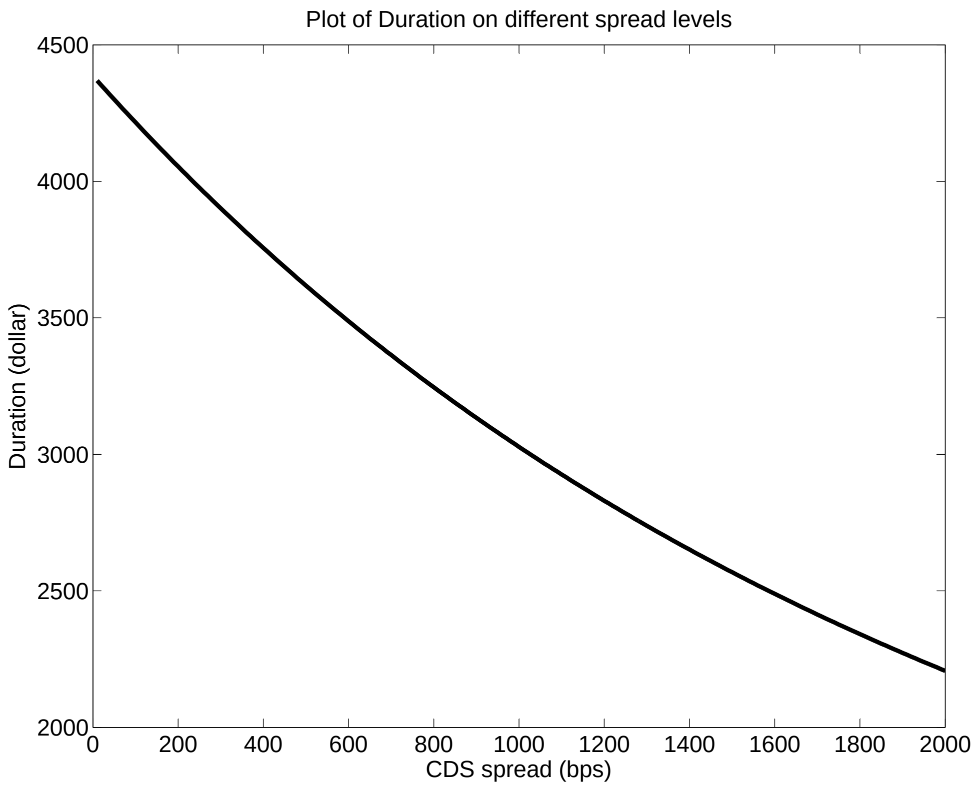

Figure 1: Duration of different spread levels

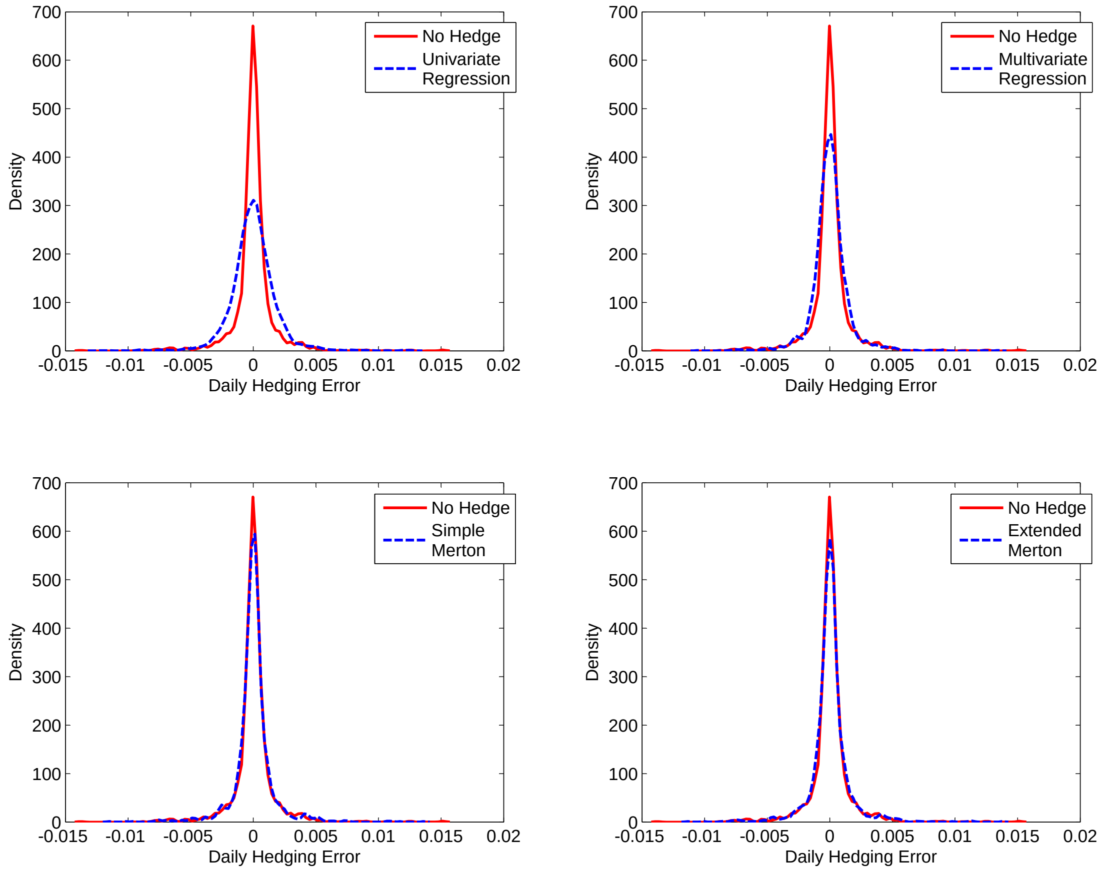

Figure 2: Distributions of Daily Hedging Errors

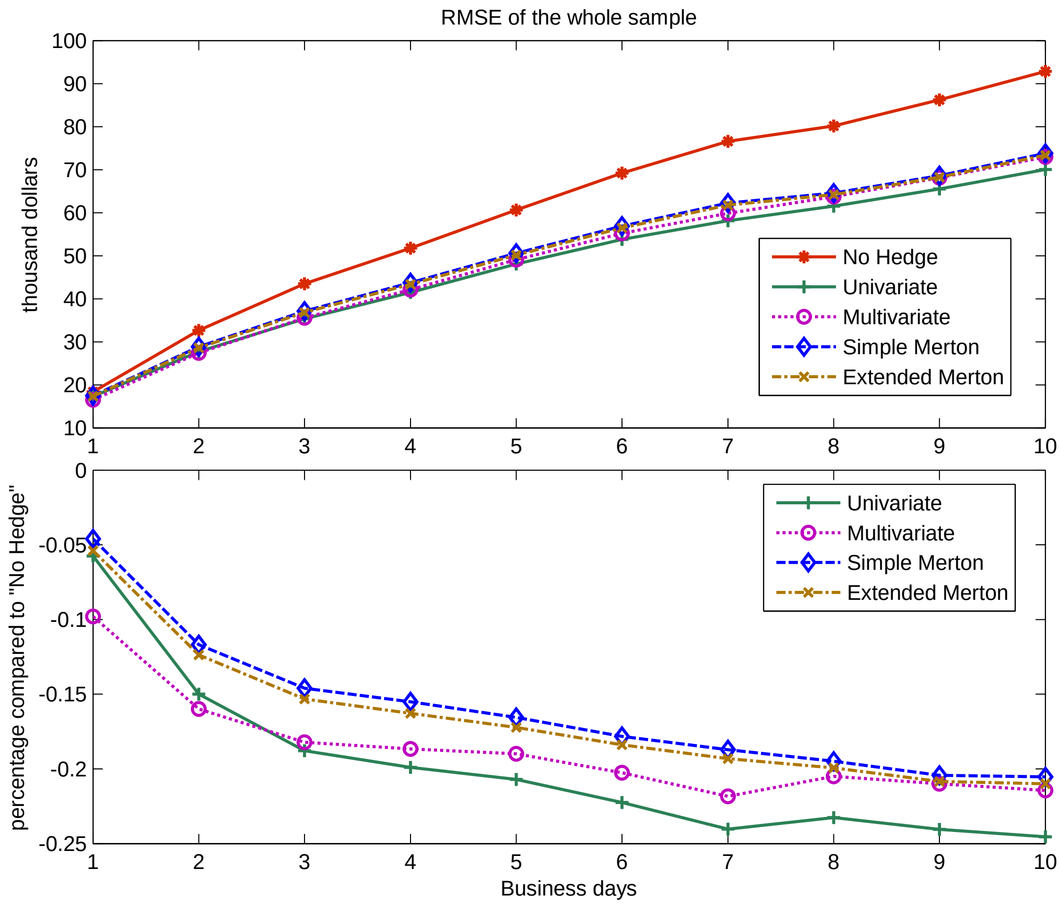

Figure 3: RMSE of four hedge ratios over longer time horizons