Essays on Empirical Asset Pricing

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ABSTRACT

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My dissertation aims at understanding the dynamics of asset prices empirically. It contains three chapters.

Chapter One provides an estimator for the conditional expectation function using a partially misspecified model. The estimator automatically detects the dimensions along which the model quality is good (poor). The estimator is always consistent, and its rate of convergence improves toward the parametric rate as the model quality improves. These properties are confirmed by both simulation and empirical application. Application to the pricing of Treasury options suggests that the cheapest-to-deliver practice is an important source of misspecification.

Chapter Two examines the informational content of credit default swap (CDS) net notional for future stock and CDS prices. Using the information on CDS contracts registered in DTCC, a clearinghouse, I construct CDS-to-debt ratios from net notional, that is, the sum of net positive positions of all market participants, and total outstanding debt issued by the reference entity. Unlike the ratio using the sum of all outstanding CDS contracts, this ratio directly indicates how much of debt is insured with CDS and therefore, is a natural measure of investors concern on a credit event of the reference entity. Empirically, I find cross-sectional evidence that the current increase in CDSto- debt ratios can predict a decrease in stock prices and an increase in CDS premia of the reference firms in the next week. Greater predictability for firms with investment grade credit ratings or low CDS-to-debt ratios suggests that investors pay more attention to firms in good credit conditions than those regarded as junk or already insured considerably with CDS.

Chapter Three tests the relationship between credit default swap net notional and put option prices. Given motivation that both CDS and put options are used not only as a

type of insurance but also for negative side bets, both contemporaneous and predictive analysis are performed for put option returns and changes in implied volatilities with time-to-maturities of 1, 3, and 6 months. The results show that there is no empirical evidence that CDS net notional and put option prices are closely connected.

Table of Contents

List of Figures

List of Tables

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To Sun Hee

Chapter 1

Asset Pricing Using Partially Misspecified Models

with Jialin Yu

1.1 Introduction

Econometricians constantly face the challenge of imperfect models. For example, a trader of Treasury options listed on the Chicago Board of Trade (CBOT) may have learned the state-of-the-art option pricing formula. Over time, the trader starts to notice that option prices sometimes deviate from the pricing formula and suspects the model is misspecified.[1] Misspecification can take various forms: the model may be accurate along some dimensions but crude along others, or the model may be poor along all dimensions. Even in the latter case, the model can still provide useful restrictions that may be utilized by some investors. For example, in the option pricing context, a model may approximate the option delta well

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[1]E.g., the Black-Merton-Scholes option pricing formula (Black and Scholes (1973) and Merton (1973)) is found by many to have difficulty explaining the Black Monday in October 1987, see for example Rubinstein (1994).

but not the option gamma.[2] Therefore, misspecification is not a binary concept. Rather, there is a continuous middle ground between correct specification and the case of a useless model. A partially misspecified model is a more likely scenario in practice than the two polar cases.

How should the option trader use her partially misspecified model? This paper proposes an estimation method (referred to as "robust parametric method" in this paper) and the resulting estimator has the following properties: (i) robustness – the estimator is consistent and the estimation error is at most that of the nonparametric rate irrespective of misspecification; (ii) adaptive efficiency – the estimation error decreases when the model quality improves, and the rate of convergence approaches the parametric rate in the limit when the model misspecification disappears;[3] (iii) model quality detection – the estimator automatically detects the model quality along various model dimensions and provides clues to future improvement of the model.

To see the potential magnitude of improvement from adaptive efficiency, recall that the estimation error of parametric method, based on a correct model, is in the order of $n^{-1/2}$ with n being the sample size. The estimation error of nonparametric method is in the order of $n^{-2/(4+d)}$ where d is the dimension of the state variables.[4] To reduce the pricing error from \$0.1 to \$0.01, parametric method requires 100 times the sample size and nonparametric method requires 10,000 times the sample size if $d = 4$. Multidimensional state variables are common. For example, option pricing can involve state variables such as the underlying asset price, volatility, option maturity, strike price, etc. That the robust parametric method can, depending on model quality, reduce the estimation error toward that of the parametric method is a nontrivial contribution. Its advantage relative to parametric methods lies in the possibility of model misspecification, in which case the parametric pricing error is difficult to quantify. Therefore, the proposed robust parametric method is especially suitable if a

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[2]Delta refers to the sensitivity of option value to the change in price of its underlying asset. Gamma measures the rate of change in delta when the underlying asset value changes.

[3]See (1.8) on measuring model quality.

[4]See Newey and McFadden (1994) and Fan (1992) on the parametric and nonparametric rates of convergence.

model is partially misspecified.

To see the intuition of the robust parametric method, let $f(X; \theta)$ denote the option trader's state-of-the-art model which may be misspecified, where X is the state variable and θ is the model parameter. Misspecification implies the *nonexistence* of a parameter θ such that $f(X; \theta)$ fits the true model for *all* X. However, misspecification does not rule out the *existence* of a parameter θ such that $f(x; \theta)$ fits the true model for *one* value $X = x$ only. Since a parameter generally varies with x, tracing out this parameter for various x (denote the resulting function $\theta(X)$) implies that $f(X; \theta(X))$ matches the true model. That is, the misspecified model has been turned into a true model. For example, because the out-of-the-money put options tend to be more expensive (i.e., higher implied volatility) than the Black-Scholes price, no single volatility number can match the Black–Scholes prices to observed option prices for all strikes. Nonetheless, these implied volatilities, when plotted against strikes, constitute the smile curve. The Black-Scholes price can fit the option prices using the smile curve. This is an instance where a misspecified model is converted into a correct one. Therefore, this paper captures the intuition used informally in the investment community.

Along the dimensions where the model quality is high, $\theta(X)$ tends to be less variable. This implies that a parameter can adequately approximate the true model even for distant state variables. In the option pricing example, the Black-Scholes model is a better model if the smile curve is flatter. In this case, Black-Scholes price using the at-the-money implied volatility may provide a good approximation for out-of-the-money option prices. Similarly, along other dimensions where the model quality is poor, the increased variability of $\theta(X)$ implies that the model cannot match observations with distant state variables. The proposed estimator automatically detects the model quality and assesses the "region of fit," which denotes the region in which the model is deemed high quality. For example, in a two-dimensional case, the region of fit may take the shape of a rectangle. The side along the dimension of high model quality is longer, while the side along the dimension of poor model quality is shorter.

A poor model tends to require a lot of variation in $\theta(X)$ for $f(X; \theta(X))$ to match reality. This relates to Hansen and Jagannathan (1991) and Hansen and Jagannathan

(1997). These two papers show how security market data restrict the admissible region for means and standard deviations of intertemporal marginal rates of substitution (IMRS) which can be used to assess model specification. Specifically, Hansen and Jagannathan (1991) calculate the lower bound on the standard deviation of IMRS to price the assets. This bound on the variability of IMRS has a natural connection to the variability of $\theta(X)$ in this paper. Therefore, the robust parametric estimator operationalizes the Hansen and Jagannathan (1991) volatility bound for investors who know their model is misspecified but have no better model at the time of decision making.

The robust parametric pricing method can add value even in the unlikely situations where the correct model is known. For example, a true model can be high-dimensional and does not admit closed-form formula. Estimation using numerical procedures can add noise when computing power is finite. In this case, it may sometimes be beneficial to use a simple (yet misspecified) model and explicitly adjust for the misspecification using the proposed method. This echoes the "maxim of parsimony" in Ploberger and Phillips (2003) and is consistent with, for example, the widespread practice of using the Black-Scholes option price despite possible misspecification. Section 1.3.3 illustrates this point using simulation under a realistic setting of Treasury option pricing. The robust parametric estimator using a simple but misspecified model can give pricing precision comparable to that of a true yet complicated model.

We then apply the robust parametric method to the pricing of Treasury options traded on the CBOT. In both in-sample analysis and out-of-sample performance, the robust parametric method consistently performs better than the nonparametric price and the parametric price (based on models in which the short rate follows an affine term structure model). This suggests that such option pricing formulas are misspecified, but they are still informative (otherwise, the robust parametric prices would not perform better than nonparametric prices). The region of fit indicates that these option pricing formulas have poor fit along the dimensions of short rate and bond maturity but are good along the dimension of option maturity. Such information facilitates future development of asset pricing models. Specifically, it suggests that the cheapest-to-deliver (CTD) practice in the CBOT Treasury options market is an important source of model misspecification which is often ignored in bond option

pricing formulas. Jordan and Kuipers (1997) document an interesting event where CTD affected the pricing of those Treasuries used in the delivery. Results in this paper suggest that CTD is also an important feature in day-to-day Treasury options pricing.

The robust parametric estimator is motivated in the context of asset pricing. Asset prices involve expectations of discounted future payoffs conditional on available information. Nonetheless, the estimator can be applied to estimate conditional expectation functions in general when partially misspecified models are available.[5] Model misspecification is an important topic in the econometrics literature and has motivated specification tests (e.g., Hausman (1978)) and nonparametric estimation (e.g., Fan and Gijbels (1996)). Nonparametric estimation achieves robustness by completely ignoring economic restrictions (either right or wrong restrictions). This results in a loss of efficiency (the "curse of dimensionality" illustrated previously). To improve efficiency, nonparametric pricing can be conducted under shape restrictions implied by economic theory (Matzkin (1994), Aït-Sahalia and Duarte (2003)). There is also a literature on semiparametric estimation (Powell (1994)). Gozalo and Linton (2000) propose to replace the local polynomial in nonparametric estimation with an economic model and show that the resulting estimator is consistent and retains the nonparametric rate of convergence. This paper builds on their insight and shows that incorporating model restrictions can improve efficiency toward that of the parametric rate when the model quality improves, hence constituting a continuous middle ground between parametric and nonparametric estimations. The estimator is particularly useful when an available model is partially misspecified — good along certain dimensions yet poor along others.

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[5]This paper focuses on the estimation of the conditional expectation function. In the context of likelihood estimation, quasi-maximum likelihood estimator (White (1982)) and local likelihood estimator (Tibshirani and Hastie (1987)) have been proposed to address misspecification. When the model is correctly specified, the maximum likelihood estimator is optimal under fairly general conditions (e.g., Newey and McFadden (1994)). When the model is misspecified, the quasi-maximum likelihood estimator minimizes the Kullback-Leibler Information Criterion (KLIC) which is the distance between the misspecified model and the true data-generating process measured by likelihood ratio. However, minimal distance measured by likelihood ratio need not translate into minimal distance in price (i.e., conditional expectation function) if the model is misspecified. This also applies to the local likelihood estimator.

This paper is organized as follows. Section 1.2 details the proposed robust parametric method and its properties. Section 1.3 uses simulation to examine its performance. Section 1.4 studies the pricing of CBOT Treasury options using the robust parametric method. Section 1.5 concludes. The appendix contains the proofs and collects the various Treasury options and futures pricing formulas used in the simulation and empirical analysis.

1.2   Asset pricing with misspecified models

Consider an asset whose price is $P(X)$ where X is a d-dimensional state variable. In case a state variable is unobservable, we assume in this paper that the investors observe a proxy of it.[6] We assume that an investor has an economic model which prescribes a possibly misspecified pricing formula $f(X;\theta)$. θ is a p-dimensional parameter. The data consist of observations $\{x_i, y_i\}_{i=1}^n$ where $y_i = P(x_i) + \varepsilon_i$. ε has zero mean and can capture the market microstructure effects (see Amihud et al. (2005) for a recent review) or noises in the proxy of the state variable.

As motivated in the introduction, a misspecified model $f(X, \theta)$ can be turned into a true model if there exists a function $\theta(X)$ such that

$$P(X) = f(X; \theta(X)). \tag{1.1}$$

Correct specification is equivalent to $\theta(X)$ being constant. Given x, a Taylor expansion implies that for X near x,

$$P(X) = f(X; \theta(x)) + b_1(x) \cdot (X - x) + (X - x)^T \cdot b_2(x) \cdot (X - x) + o\left(\|X - x\|^2\right) \tag{1.2}$$

i.e., the model f using parameter $\theta(x)$ (the true parameter at $X = x$) approximates $P(X)$ for X near x. Therefore, we propose to estimate $\theta(x)$ using observations near x,

$$\widehat{\theta}(x) = \operatorname*{argmin}_{\theta} \sum_{\|x_i - x\| \leq h} [y_i - f(x_i; \theta)]^2 \tag{1.3}$$

The reason we include observations at $X \neq x$ in the presence of misspecification is that the additional observations likely reduce estimation noise as long as the misspecification is

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[6]We do not focus on the filtering problem associated with unobservable state variables due to our focus on the conditional expectation.

not severe. This creates a trade-off between estimation efficiency and robustness which is represented in the choice of h in (1.3). We will refer to h as "region of fit" in this paper. When the model misspecification is minor, one can afford to use a larger region of fit to improve efficiency. By contrast, if model misspecification is severe, one might want to use a smaller region of fit to ensure robustness. We will discuss the optimal choice of region of fit shortly. For now, assuming an estimate $\widehat{\theta}(x)$ is obtained using the optimal region of fit, we estimate the asset price by

$$\widehat{P}(X = x) = f\left(x; \widehat{\theta}(x)\right).$$

The (infeasible) optimal choice of region of fit, denoted h^*, can be determined by minimizing the integrated mean squared pricing error

$$h^* = \underset{h}{\operatorname{argmin}} E\left[P(X) - f\left(X; \widehat{\theta}(X)\right)\right]^2. \tag{1.4}$$

Equation (1.4) cannot be directly applied because the true expectation is unknown. In this paper, we follow a method similar to the crossvalidation in nonparametric bandwidth choice. The crossvalidation procedure is asymptotically optimal with respect to the criterion function in (1.4) (see Hardle and Marron (1985) and Hardle et al. (1988)).[7] Specifically, the crossvalidation method has two steps. For a given candidate h, we obtain a first-step estimate $\widehat{\theta}_{-i,h}(x_i)$ of $\theta(x_i)$ using all observations less than h away from x_i except x_i itself,[8]

$$\widehat{\theta}_{-i,h}(x_i) = \underset{\theta}{\operatorname{argmin}} \sum_{0 < \|x_j - x_i\| \leq h} [y_j - f(x_j; \theta)]^2 \tag{1.5}$$

and the optimal choice of the region of fit is set to $\widehat{h}$ that minimizes the sum of residual squared errors from the first-step estimates

$$\widehat{h} = \underset{h}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} \left[y_i - f\left(x_i; \widehat{\theta}_{-i,h}(x_i)\right)\right]^2 \tag{1.6}$$

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[7]There is a large statistics literature on choosing the optimal smoothing parameter h. See Hardle and Linton (1994) for a review.

[8]If x_i itself is included in the crossvalidation, it will result in a mechanical downward bias in the h estimator because a perfect fit is possible by choosing a very small region of fit so that only x_i is included to fit itself.

where, for technical reasons, the minimization is restricted to the compact set

$$O\left(n^{-1/(4+d)}\right) \leq h \leq O\left(n^{-\omega}\right) \tag{1.7}$$

for some $\omega > 0$. The lower bound $n^{-1/(4+d)}$ is the rate of the nonparametric bandwidth. The upper bound, when ω is close to zero, is allowed to decrease at a very slow rate (in the case of a good model). The propositions in this paper will be proved for the feasible region of fit $\widehat{h}$ instead of for the infeasible h^*. In general, $\widehat{h}$ depends on the sample size n. However, the dependence is not made explicit to simplify notations.

Proposition 1. *(Consistency) Under Assumptions 1-5, irrespective of misspecification, when $n \to \infty$,*

$$\widehat{\theta}(x) \xrightarrow{p} \theta(x)$$
$$f\left(x; \widehat{\theta}(x)\right) \xrightarrow{p} P(x)$$

if $\widehat{h} \xrightarrow{n \to \infty} 0$ and $n\widehat{h}^d \xrightarrow{n \to \infty} \infty$.

The asymptotic distribution of $\widehat{\theta}(x)$ varies with the quality of the model. (1.2) implies that the model can locally match the true pricing formula. Therefore, model quality in this paper is measured by the mismatch between the true model and $f(X; \theta(x))$ for state variable X away from x. This relates to the match between the derivatives of $f(X; \theta(x))$ and those of the true model. We say that a model matches the true model up to its $2k$-th derivative if, for any x, (using univariate notation for simplicity)

$$P(X) = f(X; \theta(x)) + b_{2k+1}(x) \cdot (X - x)^{2k+1} + b_{2k+2}(x) \cdot (X - x)^{2k+2} + o\left(\|X - x\|^{2k+2}\right). \tag{1.8}$$

Let $n_{x,h}$ denote the number of observations less than h away from x. When X is d-dimensional, the number of observation less than h away from x is in the order of

$$n_{x,h} = O_p\left(nh^d\right) \tag{1.9}$$

when $n \to \infty$ and $h \to 0$.

Proposition 2. *(Bias-variance trade-off) Under Assumptions 1-5, if the model f matches the true model up to its $2k$-th derivative as in (1.8) for some $k \geq 0$, when $n \to \infty$, $\widehat{h} \to 0$*

and $n\widehat{h}^d \to \infty$,

$$Bias\left(\widehat{\theta}\left(x\right)\right) = O\left(\widehat{h}^{2k+2} + n^{-1}\widehat{h}^{-d}\right) \tag{1.10}$$

$$Var\left(\widehat{\theta}\left(x\right)\right) = O\left(n^{-1}\widehat{h}^{-d}\right).$$

This proposition illustrates the trade-off between estimation efficiency and robustness. When the region of fit $\widehat{h}$ is larger, more observations are used which results in lower variance of the estimate. However, if the model is misspecified, increasing the region of fit leads to a larger bias. When the model quality improves (k increases), the bias becomes smaller. The next proposition shows that the estimator will, depending on model quality, automatically select an appropriate region of fit $\widehat{h}$ to balance efficiency and robustness.

Proposition 3. *(Model quality) Under Assumptions 1-5, when the model f matches the true model up to its $2k$-th derivative as in (1.8) for some $k \geq 0$,*

$$\widehat{h}^{-1} = O_p\left(n^{1/(4+4k+d)}\right) \tag{1.11}$$

$$P\left(x\right) = f\left(x; \widehat{\theta}\left(x\right)\right) + O_p\left(n^{-(2+2k)/(4+4k+d)}\right)$$

Note that $n^{-(2+2k)/(4+4k+d)} \to n^{-1/2}$ when $k \to \infty$.

When $k = 0$ (i.e., if the model can only match the level of the true model), the estimator automatically achieves the nonparametric rate of convergence $n^{-2/(4+d)}$.[9] When the model gives a better fit in the sense of a higher k, the rate of convergence automatically improves towards that of the parametric rate $n^{-1/2}$. Therefore, a continuous middle ground between nonparametric and parametric estimation is achieved depending on the quality of the model. The efficiency gain is due to the valid restrictions imposed by a better economic model. When k increases, (1.11) implies that the region of fit $\widehat{h}$ decreases at a slower rate. Recall that (1.7) implies an upper bound $n^{-\omega}$ for the region of fit. Therefore, full parametric rate of convergence cannot be achieved. This efficiency loss is necessary because we need $h \to 0$ to ensure robustness. However, ω can be made arbitrarily small to make the rate of convergence arbitrarily close to the parametric rate. Further, if one views most models as reasonable approximations (i.e., misspecified) rather than literal descriptions of the reality,

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[9]See Fan (1992) on the nonparametric rate of convergence.

this efficiency loss associated with $\omega > 0$ is likely a small price to pay in practice to ensure robustness.

This efficiency is gained without introducing additional parameters. This contrasts with the local polynomial nonparametric estimators (see Fan and Gijbels (1996)) in which smaller bias can be achieved using a higher-order polynomial to approximate the true model. However, this leads to increased variance due to increased number of parameters. For example, going from a local linear model to a local quadratic model can double the asymptotic variance for typical kernels (Table 3.3 in Fan and Gijbels (1996)).

(1.3) weighs observations equally for ease of illustration and does not explicitly discuss the possibility of weighting the observations as in, for example, GMM estimation (Hansen (1982)) or LOWESS nonparametric estimation (Fan and Gijbels (1996)). This is similar to using a uniform kernel in nonparametric estimation where it is known that the choice of kernel is not crucial (Hardle and Linton (1994)). Equal weighting is also technically convenient. When the model is correct and the sampling errors are homoskedastic, we would like the estimator to use all observations with equal weight just like the parametric nonlinear least-squares estimation. To achieve this using a kernel with unbounded support (such as normal), $h \to \infty$ is required which is inconvenient in numerical implementation. However, weighting implicitly occurs in this paper through the region of fit; observations outside of the region of fit receive zero weight.

1.2.1 Sensitivity analysis

One may be interested in estimating derivatives of the pricing formula for, e.g., risk management purposes. Examples include the various Greek letters of the option pricing formula or other sensitivity analyses. Recall that $\theta(X)$ satisfies $P(X) = f(X; \theta(X))$. Taking derivative with respect to the state variable implies

$$P'(X) = f_X(X; \theta(X)) + f_\theta(X; \theta(X)) \cdot \theta'(X).$$

To simplify notation, f_X is used to denote $\frac{\partial}{\partial X} f$, similarly for f_θ.

In order to estimate $P'(x)$, $\theta'(x)$ needs to be estimated. Otherwise there is a bias if the model is misspecified and $f_X(X; \theta(X))$ alone is used to estimate sensitivity. To estimate

the first derivative of $\theta(X)$, we can use an augmented model

$$f\left(X; \theta_0(x) + \theta_1(x) \cdot (X - x)\right)$$

to approximate the true model for X near a given x. The estimation then proceeds in the same way as in the previous section. From the estimates $\left(\widehat{\theta}_0(x), \widehat{\theta}_1(x)\right)$, the derivative of the true model $P'(X)$ at $X = x$ can be estimated by

$$f_X\left(x; \widehat{\theta}_0(x)\right) + f_\theta\left(x; \widehat{\theta}_0(x)\right) \cdot \widehat{\theta}_1(x).$$

The estimation of higher-order derivative is similar. Counterparts to Proposition 1 – 3 exist for derivative estimation. These propositions and their proofs are similar to Proposition 1 – 3. These results are omitted for brevity and are available from the authors upon request.

1.2.2 Partially misspecified models

A multivariate model may be correctly specified along some dimensions, but misspecified along other dimensions. Even when it is misspecified in all dimensions, its approximation may be better in some dimensions than the others. The robust parametric pricing method is well suited for such models. In fact, Proposition 1 - 3 are derived for the general case of d-dimensional state variables. In this section, we show that the region of fit can be refined for a partially misspecified model. Specifically, we apply a separate region of fit for various model dimensions (this contrasts with the previous sections where the estimation of $\theta(x)$ use observations x_i satisfying $\|x_i - x\| \leq h$ and does not distinguish different model dimensions).

We illustrate using a two dimensional example where the state variable is $x = \left(x^{(1)}, x^{(2)}\right)$. (1.3) can be modified so that the parameters are estimated from

$$\widehat{\theta}(x) = \underset{\theta}{\operatorname{argmin}} \sum_{\substack{\left\|x_i^{(1)} - x^{(1)}\right\| \leq h^{(1)} \\ \left\|x_i^{(2)} - x^{(2)}\right\| \leq h^{(2)}}} [y_i - f(x_i; \theta)]^2. \tag{1.12}$$

The region of fit now takes the shape of a rectangle. I.e., the model is allowed to have different qualities along the first and the second dimensions of the state variable. This

refinement may also be used to reflect different scales of various dimensions (e.g., measured in different currencies). The estimation then proceeds in the same way and the conclusions in Proposition 1 - 3 remain the same.

1.2.3 Numerical implementation

The estimation in (1.3) and (1.5) involves nonlinear least squares which is programmed in many statistical software packages. Nonlinear least squares estimation is quick because it is typically implemented as iterated linear least squares, see Greene (1997). Nonetheless, when the dataset has a large number of observations and when the state variable has many dimensions, there is room for faster implementation of the proposed pricing method.

A potential bottleneck of the robust parametric pricing method is the crossvalidation step (1.5). In principal, it is repeated for all possible candidates of h at all observations to evaluate the model quality. However, this is not necessary; fewer evaluations can be done to trade efficiency gain for computation speed.

First, one can restrict the choice of h by searching over a grid instead of a continuum,

$$h_1 = n^{-1/(4+d)}, h_2 = h_1 + \Delta, h_3 = h_1 + 2\Delta, \cdots, h_m = n^{-\omega} \tag{1.13}$$

where ω is a small positive number as in (1.7). The grid size is $\Delta = (h_m - h_1)/(m-1)$. The number of grid can be increased when additional computing power is available. The downside from searching over fewer grids is that $\widehat{h}$ is away from its optimal choice, which reduces (though does not eliminate) the efficiency gain. For a partially misspecified model in Section 1.2.2, the grid can be applied separately to each dimension.

Next, one can restrict the number of observations at which (1.5) is evaluated. For the purpose of estimating the expectation in (1.4) using its sample analog, the number of evaluations should increase asymptotically towards infinity though the rate of increase can be lower than that of the sample size. This can be implemented, for example, by estimating (1.5) at randomly selected n^v observations for some $0 < v \le 1$. When v is bigger, the expectation in (1.4) is estimated more precisely at the cost of additional computing time.

1.3   Simulation – Treasury options pricing

This section uses simulation to illustrate the proposed robust parametric pricing method in realistic samples, comparing its performance to parametric and nonparametric methods. When a true model is complicated, we also illustrate the potential advantage of using a simple (though misspecified) model.

We illustrate in the context of pricing Treasury options. Specifically, let $C(\tau, T, X)$ denote the price of a call option on Treasury zero-coupon bonds, where τ is time to option expiration, T is bond maturity at option expiration, and X includes other state variables such as the prevailing interest rate, the strike price, etc. This is a multivariate example in that the option pricing formula will be estimated along the dimensions of option maturity, underlying bond maturity, and other state variables using the method in Section 1.2.2. We assume that the true data-generating process follows the Cox et al. (1985) model (CIR model) under the risk-neutral probability

$$dr_t = k(\theta - r_t) dt + \sigma \sqrt{r_t} dW_t \tag{1.14}$$

where r_t is the instantaneous short rate at time t. The short rate mean-reverts to its long-run mean θ. The speed of mean reversion is governed by k. The standard Brownian motion W drives the random evolution of the short rate. The instantaneous volatility of the short rate is determined by the parameter σ and the square root of the short rate (hence the process is also known as the square root process). Under the CIR model, the Treasury zero-coupon bond option has a closed-form expression (detailed in the appendix).

To implement the robust parametric method, we travel back in time to year 1977 where an investor has just learned the Vasicek (1977) model (which delivers a closed-form Treasury option pricing formula detailed in the appendix), but this same investor has yet to learn the Cox et al. (1985) model. In the Vasicek model, the evolution of the short rate under the risk-neutral probability is assumed to follow

$$dr_t = k(\theta - r_t) dt + \sigma dW_t. \tag{1.15}$$

We compare the robust parametric method using the misspecified Vasicek model to four other estimation methods: (i) parametric estimation using the CIR model (true model); (ii)

parametric estimation using the Vasicek model (misspecified model); (iii) nonparametric estimation; (iv) parametric estimation using the correct CIR model but applying numerical integration (instead of the closed-form formula) to obtain option prices. The estimation performance is measured by the sample analog of the root integrated mean squared error

$$RIMSE \equiv \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\widehat{C}_i - C_i\right)^2} \tag{1.16}$$

where $\widehat{C}$ and C are, respectively, the estimated and the true Treasury option prices in each simulation. $RIMSE$ captures the average goodness of fit and smaller $RIMSE$ indicates better fit.

The simulation draws 100 sample paths of short rate, each sample path being equivalent to 5 years of weekly observations. Such samples are common in practice, see for example Duffie and Singleton (1997). For each sample path, to realistically match the contracts traded on the Chicago Board of Trade (CBOT), Treasury call option prices are generated according to the CIR model for the option maturity $\tau =$1, 2, 3, 6, 9, 12, 15 months, underlying bond maturity $T =$2, 5, 10, 30 years. The first short rate is drawn from the stationary distribution of the CIR process. To simplify the illustration, we consider only at-the-money options which also tend to be the most liquid contracts in practice. As a result, our model has a three-dimensional state variable – option maturity, underlying bond maturity, and short rate. In the simulation, the "true" CIR parameters are set to the estimates in Aït-Sahalia (1999)

$$k = 0.145, \theta = 0.0732, \sigma = 0.06521 \tag{1.17}$$

and we add a zero-mean normally distributed noise to generate the observed option price. The standard deviation of the noise is set to 1% of the CIR price and captures effects such as the bid-ask bounce. At the true parameter, the bond option prices average around \$1. Hence the pricing errors can be interpreted either as dollar pricing errors or as proportional pricing errors.

1.3.1 Simulation result: parametric and nonparametric prices

Table 1.1 panel 1 shows the performance of the various option price estimators. When an investor knows the correct model, parametric estimator performs the best, generating an average pricing error of only 0.022 cents.[10] However, the accuracy of the parametric estimator depends crucially on the validity of the model. When the model is misspecified, the parametric pricing error is 4.1 cents which is an increase of about 200 times. Nonparametric prices, on the other hand, do not depend on any model and avoid misspecification. In the simulation, nonparametric prices register an average pricing error of 1.3 cents, about 70% less than the parametric prices when the model is wrong.[11] However, the nonparametric prices ignore all model information (correct or not) and perform much worse than parametric prices when the model is correctly specified.

1.3.2 Simulation result: robust parametric prices

The robust parametric method proposed in this paper aims to achieve a continuous middle ground between parametric and nonparametric methods. Table 1.1 panel 1 shows that the robust parametric method (which uses a misspecified model) has an average pricing error of 0.15 cents. This is about 7 times larger than that of the parametric estimation error using the correct model, yet 27 times smaller than the parametric estimation error using a wrong model. The error is also an order of magnitude smaller than the nonparametric error.

To see the source of the efficiency gain, let us turn to panel 2 in Table 1.1 and Figures 1.1 and 1.2. In panel 2 of Table 1.1, the regions of fit along the option maturity and bond maturity dimensions are both zero, indicating that the Vasicek model provides a poor fit of the CIR prices along these two dimensions.[12] Figures 1.1 and 1.2 further illustrate this. Figure 1.1 plots the true and estimated option prices along the dimension of option maturity.

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[10]The parametric estimation uses nonlinear least squares.

[11]We use the Nadaraya-Watson nonparametric estimator with uniform kernel and cross-validation bandwidth selection, see Hardle and Linton (1994) for more details.

[12]To be exact, the region of fit for option maturity averages to 0.01. However, because the observations come in weekly and the interval between successive observations of option maturity is at least $1/52 \approx 0.02$, the region of fit for option maturity is essentially zero.

The robust parametric method is applied to four maturities (1, 3, 6, and 12 months) and we use the estimates to price options with other maturities. The Vasicek and CIR prices quickly diverge, confirming severe model misspecification along the dimension of option maturity. Similarly, Figure 1.2 illustrates severe misspecification along the dimension of bond maturity, too. Such misspecification is the reason why the robust parametric method outperforms parametric method using a misspecified model. When the model quality is poor along some dimensions, the robust parametric method sets small regions of fit along such dimensions to achieve robustness.

The situation is different along the dimension of short rate. Panel 2 of Table 1.1 shows that the region of fit is 0.026 along this dimension. I.e., if one is estimating the option price at short rate 7%, the robust parametric estimator uses all observations whose short rates are between 4.4% and 9.6%. Figure 1.3 confirms that the Vasicek price approximates the CIR price reasonably well for adjacent short rates (the two option price curves almost overlap). The robust parametric method detects the good fit and uses a larger region of fit for the dimension of the short rate to improve efficiency. This is the intuition why the robust parametric method outperforms the nonparametric method – it retains those model restrictions that are valid.

1.3.3 Simulation result: comparison with using a true but complicated model

The proposed robust parametric method can add value even in the unlikely case where the correct model is known. A true model is likely complicated and may not have closed-form pricing formula. For example, many term-structure models do not render closed-form bond option pricing formula. The Vasicek and CIR models used in the simulation, along with a handful of other models, constitute the exception. For more complicated models, numerical methods can be used to approximate the option prices (e.g., numerical integration in Duffie et al. (2000)).

In this section, we compare the performance of the proposed method to the performance of parametric estimation using numerical methods on a true model. Specifically, the robust parametric estimator still uses the closed-form Vasicek option pricing formula which is mis-

specified. On the contrary, the parametric estimator uses the true CIR model but pretends that this is a model complicated and closed-form option pricing formula is unavailable. Instead, the parametric estimator uses numerical integration to obtain option prices.

We use two ways to model the numerical errors. First, we assume that the option price from numerical integration (denoted by C^{NUM}) satisfies

$$C^{NUM} = C \cdot (1 + \varepsilon)$$

where C is the true option price from the closed-form CIR pricing formula. ε is set to be a uniformly distributed random variable over $[-\omega, \omega]$. I.e., we do not actually use numerical integration. Instead, we start from the closed-form option price and let ω vary to control the degree of numerical error. When $\omega = 0$, numerical error disappears and we return to the case of parametric estimation using the closed-form formula. A larger ω indicates larger numerical error. We repeat the simulation for $\omega = 0.01\%$, 0.1%, 0.2%, 0.3%, 0.5%, and 1%. The results are shown in Panel 3 of Table 1.1. The proposed robust parametric method using the misspecified Vasicek model is comparable in performance to parametric estimation using the true model when the numerical error is between 0.2% and 0.3%. This is remarkable because Vasicek option prices are grossly misspecified relative to CIR option prices.[13] Nonetheless, adjusting for misspecification using the robust parametric method improves the estimation performance to the equivalent of parametric estimation using true model with a numerical error of around 0.25%.

Next, we follow Duffie et al. (2000) and compute CIR option prices by actual numerical integration. The estimation $RIMSE$ is shown in Panel 4 of Table 1.1. The result is comparable to the case of $\omega = 1\%$ in Panel 3. In practice, numerical precision can be improved at the cost of longer computing time. Therefore, the result in Panel 4 should be interpreted with caution. However, even with a relatively tractable model like CIR, there are already non-trivial issues with numerical integration. For example, Carr and Madan (1999) point out that poor numerical precision can result from the highly oscillatory nature of the characteristic function in the integrand. When the true model becomes more complicated,

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[13]Parametric estimation error using the Vasicek model is 200 times the parametric estimation error using the true CIR model, see Panel 1. Panel 2 further shows that the Vasicek model does not fit CIR model along the dimensions of bond maturity and option maturity at all.

the numerical errors are likely more difficult to understand and control. This shows that it may sometimes be preferable to use a simpler model and explicitly adjust for misspecification using the proposed robust parametric method.

1.4 Empirical application – Treasury options pricing

We next apply the robust parametric method to the pricing of Treasury options traded on CBOT to examine its in-sample and out-of-sample performances. We collect weekly call option closing price data from CBOT. The sample period is May 1990 – December 2006. CBOT lists options on 2-, 5-, 10-, and 30-year Treasuries.[14] The 2-year Treasury option does not have much trading volume and is excluded from the analysis. To reduce data error, we eliminate those observations where the recorded option price is less than the intrinsic value, i.e., if $C < \max(F - K, 0)$ where C, F, and K are the observed Treasury call option price, observed Treasury futures price, and option strike, respectively. Further, for each option contract, we use only data for the at-the-money contract (contract whose F is closest to K) which tends to have the most trading volume. There are a few instances where CBOT supplies a closing option price but indicates a trading volume of zero. Such observations are eliminated.

As in Section 1.3, we apply the robust parametric method using the possibly misspecified Vasicek (1977) model.[15] The Vasicek (1977) option pricing formula assumes that a zero-coupon bond underlies the option. This differs from the cheapest-to-deliver (CTD) practice of CBOT listed options where the delivery can be made with different Treasuries.[16] Because

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[14]These options are more precisely options on Treasury futures. However, those option maturities with the most trading volume (March, June, September, and December) coincide with futures expiration. Therefore, upon option exercise, the delivery is essentially made in the underlying Treasuries. We focus on the option maturities of March, June, September, and December and will refer to the options as Treasury options for simplicity.

[15]We have alternatively estimated a model in which the short rate follows the Cox et al. (1985) process. The result is similar. It is suppressed for brevity and available from the authors upon request.

[16]CTD refers to the right to deliver any Treasuries designated eligible by CBOT. For example, for the 10 year contracts, deliverable grades include US Treasury notes maturing at least 6 1/2 years, but no more than 10 years, from the first day of the delivery month. To address the fact that Treasuries vary in their coupon,

we do not have information on the cheapest Treasury for delivery, we use the following procedure to adjust for the coupon of the delivery bond. Specifically, we convert the delivery bond into a zero coupon bond by assuming that the coupons are paid at bond maturity. This assumption ignores the time value between coupon payment and bond maturity. It is an imperfect way to model the cheapest-to-deliver practice and we will discuss more on this issue later. However, since the estimation method permits misspecification, this assumption does not lead to inconsistent estimators. Now the problem of unknown coupon is translated to the new problem of unknown face value at maturity which we back out using the observed Treasury futures price from CBOT. Specifically, let M denote the unknown par value, then M can be computed from

$$M = \frac{F}{F(\tau, T, r)}$$

where F is the observed CBOT Treasury futures price, $F(\tau, T, r)$ is the Vasicek (1977) implied futures price on a zero coupon bond with face value \$1 (see appendix 1.5 for the futures price formula).[17] This implies the following pricing formula for the CBOT options

$$C^{adj}(\tau, T, r, K) = M \cdot C(\tau, T, r, \frac{K}{M}) \tag{1.18}$$

where C^{adj} is the call option price adjusted for the cheapest-to-delivery practice, C is the Vasicek (1977) pricing formula for call option on a Treasury zero coupon bond with \$1 face, τ is the option maturity, T is the bond maturity, r is the short rate which is measured by one month Treasury bill rate, and K is the option strike price.

We compare both in-sample and out-of-sample performances of three pricing methods: the robust parametric method proposed in this paper, the parametric method, and the nonparametric method.[18]

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maturity, and other features, CBOT uses a system known as the conversion factor to equalize various bonds. According to CBOT, the conversion factor is the price of the delivered note (\$1 face value) to yield 6 percent and the invoice price equals the futures settlement price times the conversion factor plus accrued interest. The conversion system usually makes some bonds less costly to deliver than others.

[17]The CBOT Treasury futures price data are from Datastream.

[18]We use nonlinear least squares in the parametric estimation. We use the Nadaraya-Watson nonparametric estimator with uniform kernel and cross-validation bandwidth selection, see Hardle and Linton (1994) for more details.

1.4.1 Misspecification of Treasury option pricing models

We use the root integrated mean squared error (RIMSE) defined in (1.16) to measure the in-sample performance of various estimators. The result is in Panel 1 of Table 1.2. The model is so misspecified that the nonparametric prices do better than parametric prices in the sample. Nonetheless, the model contains useful information because the proposed robust parametric method does better than either parametric or nonparametric methods. The robust parametric method also produces the highest R-square in the regression of observed option prices on fitted option prices – 90.2% versus 49.8% and 74.4% from parametric and nonparametric estimators, respectively. The improvement in R-square is consistent with the scatterplots shown in Figure 1.4.

The robust parametric method selects a region of fit separately for each dimension (see Section 1.2.2). Figure 1.5 shows the RIMSE for various regions of fit along the dimensions of option maturity, bond maturity, and short rate.[19] In the sample, the Vasicek (1977) model performs poorly along the dimensions of bond maturity and short rate. This can be seen by the increase in RIMSE when the regions of fit for these two dimensions increase. Therefore, the robust parametric estimator selects small regions of fit for these two dimensions. The model, however, provides useful restrictions along the dimension of option maturity. In Figure 1.5, the RIMSE bottoms out when the region of fit is set to 3 weeks for the dimension of option maturity.[20] This implies that the Vasicek option pricing formula provides a good approximation for observations with adjacent option maturity.

The information provided by the regions of fit along various dimensions of the state variable can be used to triangulate model misspecification which is useful for the development of pricing models. In this case, the model fits well along the dimension of option maturity but not along bond maturity or short rate. Pinpointing the exact cause of bond options mis-

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[19]When plotting for one of the three dimensions, the regions of fit for the other two dimensions are held the same as those in the estimation.

[20]The optimal region of fit along the dimension of option maturity is 2 weeks if the Cox et al. (1985) process is used instead of the Vasicek (1977) process to model the short rate. The optimal regions of fit along bond maturity and short rate remain the same. This suggests better fit of Vasicek (1977) process for the purpose of modeling CBOT Treasury option prices.

specification requires a separate study, though the evidence is suggestive that the cheapest-to-deliver (CTD) practice associated with the CBOT Treasury futures/options plays a role. The CTD practice usually makes some bonds less costly to deliver than others, which is not typically captured by bond option pricing formulas. The actual cheapest-to-deliver bond varies across contracts involving different bond maturities and across different interest rate environments (see, for example, Kane and Marcus (1984) and Livingston (1987)) which is consistent with the misspecification along the dimensions of bond maturity and short rate indicated by the regions of fit. The region of fit for option maturity, on the contrary, shows good fit up to 3 weeks. Observations less than 3 weeks apart are likely consecutive weekly observations of the same contract for which the cheapest-to-deliver bonds are likely similar or even identical. Therefore, the evidence suggests that the cheapest-to-deliver feature is an important source of misspecification for Treasury option pricing.

1.4.2 Out-of-sample performance

To confirm that the improved fit is not due to in-sample overfitting and can be extrapolated out of the sample, Panel 2 of Table 1.2 shows the out-of-sample comparison of the proposed robust parametric method to parametric and nonparametric methods. Specifically, model parameters are estimated using five years of weekly observations which are then used in out-of-sample pricing in the subsequent year. RIMSE and regression R-square are computed in the subsequent year out-of-sample. Because the sample period starts in May 1990, the first year of out-of-sample comparison is 1996. Panel 2 shows the RIMSE for each year separately. It also shows the R-square in the regression of observed option prices on predicted option prices. The robust parametric method has the best out-of-sample performance in all years. Overall, the robust parametric method has a reduction of 46.6% and 33.9% in RIMSE, and an increase of 39.6% and 16.5% in R-square relative to parametric and nonparametric methods, respectively.

1.5 Conclusion

Misspecified models is a fixture in decision making. This paper proposes a robust parametric method which extracts valid information yet explicitly controls for possible misspecification of a model. The resulting estimator provides a continuous middle ground between parametric and nonparametric precision. Though the simulation and empirical analysis are in the context of asset pricing, the method can be applied to the estimation of conditional expectation function in general.

Model restrictions also help to alleviate the concern of overfitting. As pointed out by Campbell et al. (1997) (page 524), "... perhaps the most effective means of reducing the impact of overfitting and data-snooping is to impose some discipline on the specification search by *a priori* theoretical considerations." The estimator in this paper does exactly that; it confronts the data with an a priori model. This is confirmed by the out-of-sample performance in Section 1.4.2.

Using an approximate (i.e., misspecified) model may also provide other advantages. For example, the true model can be complicated and it may sometimes be preferable to use a simple yet misspecified model. As pointed out by Fiske and Taylor (1991) (page 13), "... People adopt strategies that simplify complex problems; the strategies may not be normatively correct or produce normatively correct answers, but they emphasize efficiency." Interestingly, one of the simulations shows that applying the proposed estimator on a good parsimonious model can sometimes outperform fully parametric estimation using a complicated model even if the complicated model is the true model. This echoes the "maxim of parsimony" in Ploberger and Phillips (2003) and allows wider applications of the proposed estimator.

Assumptions, Proofs, and Option Pricing Formulas for Chapter One

Assumptions

First, we collect the regularity conditions assumed in this paper. Recall that we want to estimate the pricing formula $P(X)$ where $X \in \mathbb{R}^d$ is the state variable. We assume an investor has an economic model which implies a possibly misspecified pricing formula $f(X;\theta)$ for $P(X)$. $\theta \in \mathbb{R}^p$.

Assumption 1. *There exists a unique function $\theta(X)$ such that $f(X;\theta(X)) = P(X)$. The range of $\theta(X)$ is in a compact set Θ.*

Assumption 2. $P(X)$ *and* $f(X;\theta)$ *are infinitely differentiable with respect to X and θ. $P(X)$, $f(X;\theta)$, and their derivatives are uniformly bounded over X and θ.*

Assumption 3. *(Sample) The sample consists of independent observations $\{x_i, y_i\}_{i=1}^n$ where*

$$y_i = P(x_i) + \varepsilon_i.$$

$E[\varepsilon_i | X = x_i] = 0$, $Var[\varepsilon_i | X = x_i] = v(x_i) > 0$. $v(\cdot)$ *is continuously differentiable. $v(\cdot)$ and $v'(\cdot)$ are bounded.*

Assumption 4. $\inf_{X,\theta} \| f_\theta(X;\theta) f_{\theta^T}(X;\theta) \| > 0$. *There exist $H > 0$, a non-random function $G(\theta, x, h)$, and random variables $Z(\theta, x, h) \sim N(0, \Sigma(\theta, x, h))$ such that*

$$\sup_{\theta \in \Theta, x \in \mathbb{R}^d, h < H} \left\| n^{-1} \sum_{i=1}^n f_\theta(x_i; \theta) f_{\theta^T}(x_i; \theta) - G(\theta, x, h) \right\| = O_p\left(n^{-1/2}\right)$$

$$\sup_{\theta \in \Theta, x \in \mathbb{R}^d, h < H} \left\| n^{-1/2} \sum_{i=1}^n f_\theta(x_i; \theta) \varepsilon_i - Z(\theta, x, h) \right\| = o_p(1)$$

for the observations $\{x_i\}_{i=1}^n$ satisfying $\|x_i - x\| \leq h$ for all i. The functions $\|G(\theta, x, h)\|$ and $\|\Sigma(\theta, x, h)\|$ are continuous and bounded.

Assumption 4 is a standard uniform convergence condition in large sample asymptotics (see Newey and McFadden (1994)) except that it requires stronger uniformity because the "true" parameter $\theta(X)$ may vary.

Let $p(X)$ denote the probability density function of X.

Assumption 5. $p(x) > 0$ *for all* $x \in \mathbb{R}^d$, $p(\cdot)$ *is twice-continuously differentiable.*

Proof of Proposition 1

See Theorem 1 in Gozalo and Linton (2000). □

Proof of Proposition 2

Using the standard large sample asymptotics argument (see for example Newey and Mc-Fadden (1994)),

$$\sqrt{n_{x,\widehat{h}}} \left(\widehat{\theta}(x) - \theta(x) \right) \tag{1.19}$$

$$= \left(\frac{1}{n_{x,\widehat{h}}} \sum_{\|x_i - x\| \leq \widehat{h}} F_i F_i^T \right)^{-1} n_{x,\widehat{h}}^{-1/2} \sum_{\|x_i - x\| \leq \widehat{h}} F_i \cdot (\varepsilon_i + P(x_i) - f(x_i; \theta(x))) + O_p \left(n_{x,\widehat{h}}^{-1/2} + \widehat{h}^{2k+2} \right).$$

To simplify notation, $F_i \equiv f_\theta(x_i; \theta(x))$. Recall that $n_{x,\widehat{h}}$ denotes the number of observations less than $\widehat{h}$ away from x. When X is d-dimensional, $n_{x,\widehat{h}} = O_p\left(n\widehat{h}^d\right)$ when $n \to \infty$, $\widehat{h} \to 0$, and $n\widehat{h}^d \to \infty$. The magnitude of the bias

$$E_{0 < \|x_i - x\| \leq h} [P(x_i) - f(x_i; \theta(x))] = O\left(\widehat{h}^{2k+2}\right) \tag{1.20}$$

follows from (1.8) using the standard change-of-variable method in nonparametric estimation (see, for example, page 2303 of Hardle and Linton (1994)). The proposition then follows from (1.19) and (1.20). □

Proof of Proposition 3

The crossvalidation criterion function is

$$CV\left(h\right) = \frac{1}{n}\sum_{i=1}^{n}\left[y_i - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)\right]^2$$

$$= \frac{1}{n}\sum_{i=1}^{n}\left[\varepsilon_i + P\left(x_i\right) - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)\right]^2$$

$$= \frac{1}{n}\sum_{i=1}^{n}\varepsilon_i^2 + \frac{1}{n}\sum_{i=1}^{n}\left[P\left(x_i\right) - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)\right]^2$$

$$+ \frac{2}{n}\sum_{i=1}^{n}\varepsilon_i\left[P\left(x_i\right) - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)\right].$$

By (1.10), (1.9), and the uniform bounds in Assumption 2–4,

$$\frac{1}{n}\sum_{i=1}^{n}\left[P\left(x_i\right) - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)\right]^2 = O_p\left(h^{4k+4} + \left(nh^d\right)^{-1}\right). \tag{1.21}$$

We will later prove the following lemma.

Lemma 1. *Under the conditions of Proposition 3,*

$$\frac{1}{n}\sum_{i=1}^{n}\varepsilon_i\left[P\left(x_i\right) - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)\right] \tag{1.22}$$

$$= o_p\left(\frac{1}{n}\sum_{i=1}^{n}\left[P\left(x_i\right) - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)\right]^2\right).$$

Lemma 1 and (1.21) imply

$$CV\left(h\right) = \frac{1}{n}\sum_{i=1}^{n}\varepsilon_i^2 + O_p\left(h^{4k+4} + \left(nh^d\right)^{-1}\right) \tag{1.23}$$

which is minimized at $\widehat{h} = n^{-1/(4+4k+d)}$. It can then be calculated using (1.10) that

$$P\left(x\right) = f\left(x; \widehat{\theta}\left(x\right)\right) + O\left(n^{-(2+2k)/(4+4k+d)}\right).$$

$\square$

Proof of Lemma 1

ε_i and $P\left(x_i\right) - f\left(x_i; \widehat{\theta}_{-i,h}\left(x_i\right)\right)$ are independent (recall that $\widehat{\theta}_{-i,h}\left(x_i\right)$ does not use observation i hence is independent of ε_i). Assume for now that $\widehat{\theta}_{-i,h}\left(x_i\right)$ is independent of ε_j

and $\widehat{\theta}_{-j,h}(x_j)$ (this is almost correct, and we will make it rigorous later), then (1.22) is the average of n independent variables with zero mean. In this case, the central limit theorem implies

$$\frac{1}{\sqrt{n}} \sum_{i=1}^{n} \varepsilon_i \left[P(x_i) - f\left(x_i; \widehat{\theta}_{-i,h}(x_i)\right) \right] \xrightarrow{d} N(0, V)$$

and, by Assumption 3,

$$V = O_p \left(\frac{1}{n} \sum_{i=1}^{n} \left[P(x_i) - f\left(x_i; \widehat{\theta}_{-i,h}(x_i)\right) \right]^2 \right)$$

$$= O_p \left(h^{4k+4} + \left(nh^d\right)^{-1} \right)$$

by (1.21). Therefore,

$$\frac{1}{n} \sum_{i=1}^{n} \varepsilon_i \left[P(x_i) - f\left(x_i; \widehat{\theta}_{-i,h}(x_i)\right) \right] = O_p \left(n^{-1/2} \left(h^{2k+2} + \left(nh^d\right)^{-1/2} \right) \right)$$

$$= o_p \left(h^{4k+4} + \left(nh^d\right)^{-1} \right).$$

A quick way to see the last step is to note that $n^{-1/2}$ is the parametric rate of convergence which is faster than the rate of convergence of the robust parametric estimator $(h^{2k+2} + \left(nh^d\right)^{-1/2}$, see Proposition 2 and (1.7)). This proves Lemma 1 except that the proof has relied on the assumption that $\widehat{\theta}_{-i,h}(x_i)$ is independent of ε_j and $\widehat{\theta}_{-j,h}(x_j)$. However, because $\widehat{\theta}_{-i,h}(x_i)$ is estimated using only observations less than h away from x_i, $\widehat{\theta}_{-i,h}(x_i)$ is independent of ε_j and $\widehat{\theta}_{-j,h}(x_j)$ if x_i and x_j are more than $2h$ apart. Since $h \to 0$, $\widehat{\theta}_{-i,h}(x_i)$ is independent of a majority of ε_j and $\widehat{\theta}_{-j,h}(x_j)$ hence the proof also goes through. The details of the exact proof provide no additional intuition and contain mere book-keeping of the correlation for those few observations that are not independent. These details are suppressed for brevity and available from the authors upon request. □

Option Pricing Formula

This section collects several existing option pricing formulas that are used in the paper's empirical analysis.

CIR model

Cox et al. (1985) show that, when the short rate follows the CIR model in (1.14), the price of a call option with maturity τ and strike price K on a T-year Treasury zero-coupon bond with par \$1 is

$$C\left(\tau,T,r_0,K\right) = B\left(r_0,T\right)\chi^2\left(2r^*\left[\phi\left(\tau\right)+\psi-B(T-\tau)\right],\frac{4\kappa\theta}{\sigma^2},\frac{2\phi\left(\tau\right)^2 r_0 e^{\gamma\tau}}{\phi\left(\tau\right)+\psi-B(T-\tau)}\right)$$

$$- KB\left(r_0,\tau\right)\chi^2\left(2r^*\left[\phi\left(\tau\right)+\psi\right],\frac{4\kappa\theta}{\sigma^2},\frac{2\phi\left(\tau\right)^2 r_0 e^{\gamma\tau}}{\phi\left(\tau\right)+\psi}\right)$$

where r_0 is the short rate at the time of option pricing and $\chi^2\left(\cdot,n,c\right)$ denotes the cumulative probability distribution function of a non-central Chi-square distribution with degree of freedom n and non-centrality parameter c. The other terms used in the option pricing formula are

$$B\left(r_0,T\right) = A\left(T\right)\exp\left(B\left(T\right)r_0\right)$$

$$A\left(T\right) = \left(\frac{2\gamma\exp\left(\frac{1}{2}\left(k+\gamma\right)T\right)}{\left(k+\gamma\right)\left(\exp\left(\gamma T\right)-1\right)+2\gamma}\right)^{\frac{2k\theta}{\sigma^2}}, B\left(T\right) = -\frac{2\left(\exp\left(\gamma T\right)-1\right)}{\left(k+\gamma\right)\left(\exp\left(\gamma T\right)-1\right)+2\gamma}$$

$$\gamma \equiv \sqrt{k^2+2\sigma^2}, r^* = -\frac{1}{B\left(T-\tau\right)}\log\left[\frac{A\left(T-\tau\right)}{K}\right], \phi\left(\tau\right) = \frac{2\gamma}{\sigma^2\left(e^{\gamma\tau}-1\right)}, \psi = \frac{\kappa+\gamma}{\sigma^2}.$$

Vasicek model

Jamshidian (1989) shows that, when the short rate process follows (1.15), the price of a call option with maturity τ and strike price K on a T-year Treasury zero-coupon bond with par \$1 is

$$C\left(\tau,T,r_0,K\right) = B\left(r_0,T\right)\Phi(z_1) - KB\left(r_0,\tau\right)\Phi(z_2)$$

where r_0 is the short rate at the time of option pricing and $\Phi(\cdot)$ denotes the cumulative probability distribution function of a standard normal random variable. The other terms

used in the option pricing formula are

$$B\left(r_0, T\right) = \exp\left[A\left(T\right) + B\left(T\right) r_0\right]$$

$$A\left(T\right) = -\frac{\sigma^2}{4k}B\left(T\right)^2 - \left(T + B\left(T\right)\right)\left(\theta - \frac{\sigma^2}{2k^2}\right), B\left(T\right) = -\frac{1}{k}\left(1 - e^{-kT}\right)$$

$$z_1 = \frac{1}{\sigma_p}\log\left[\frac{B\left(r_0, T\right)}{B\left(r_0, \tau\right)K}\right] + \frac{\sigma_p}{2}, z_2 = \frac{1}{\sigma_p}\log\left[\frac{B\left(r_0, T\right)}{B\left(r_0, \tau\right)K}\right] - \frac{\sigma_p}{2}$$

$$\sigma_p = \sigma\sqrt{\frac{\left(1 - e^{-2\kappa\tau}\right)\left(1 - e^{-\kappa(T-\tau)}\right)^2}{2\kappa^3}}.$$

Chen (1992) shows that the price of a Treasury future that delivers a T-year zero coupon bond in τ years is

$$F\left(\tau, T, r_0\right) = \exp\left[C\left(\tau, T\right) + D\left(\tau, T\right) r_0\right]$$

where

$$C\left(\tau, T\right) = A\left(T\right) + \frac{1}{4k}B\left(T\right)e^{-2k\tau}\left(e^{k\tau} - 1\right)\left(B\left(T\right)\sigma^2 + e^{k\tau}\left(B\left(T\right)\sigma^2 + 4k\theta\right)\right)$$

$$D\left(\tau, T\right) = e^{-k\tau}B\left(T\right).$$

Table 1.1: Simulation

This table reports the Treasury option pricing simulation results. It compares four estimation methods: the parametric estimator using the correct model (Cox et al. (1985) process), the parametric estimator using a misspecified model (Vasicek (1977) model), the proposed robust parametric estimator which uses the misspecified Vasicek (1977) model but explicitly adjusts for misspecification, and the nonparametric estimator. The simulation is iterated 100 times and each simulation sample path corresponds to five years of weekly observations. Panel 1 shows the average root integrated mean squared error ($RIMSE$) defined as $RIMSE \equiv \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\widehat{C}_i - C_i \right)^2}$ where $\widehat{C}$ and C are, respectively, the estimated and the true Treasury option prices. Panel 2 shows the average regions of fit (h in (1.12)) in the robust parametric method. Panel 3 shows the estimation $RIMSE$ for parametric estimation using the correct CIR model where the closed-form option price C is perturbed to $C \cdot (1 + \varepsilon)$. ε is uniformly distributed over $[-\omega, \omega]$ to capture potential noise when numerical integration instead of the closed-form formula is used to compute the option prices. In Panel 4, the parametric estimation uses the true CIR model but uses numerical integration to obtain option prices.

1. Performance of the option price estimators

	$RIMSE$
Parametric	$0.00022
Parametric (using misspecified)	$0.041
Nonparametric	$0.013
Proposed (using misspecified)	$0.0015

2. Robust parametric estimator: region of fit (h) along various dimensions

	Interest rate	Option maturity	Bond maturity
h	0.026	0.01	0

3. Simulate numerical error

ω	0.01%	0.1%	0.2%	0.3%	0.5%	1%
$RIMSE$	$0.00023	$0.00061	$0.0012	$0.0017	$0.0028	$0.0056

4. Performance of parametric estimation using correct model and numerical integration

	$RIMSE$
Parametric (Numerical)	$0.0063

Table 1.2: CBOT Treasury option pricing

This table reports the Treasury option pricing result using CBOT Treasury option data from May 1990 to December 2006. Three pricing methods are compared: the parametric estimator, the robust parametric estimator, and the nonparametric estimator. Both the parametric and the robust parametric estimators use the possibly misspecified option pricing formula (1.18) which assumes that the short rate follows the Vasicek (1977) process. Panel 1 shows the average root integrated mean squared error ($RIMSE$) defined as $RIMSE \equiv \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{C}_i - C_i\right)^2}$ where $\widehat{C}$ and C are, respectively, the estimated and the observed Treasury option prices. Also shown in panel 1 is the R-square in the regression of observed call option price on predicted option price. The estimation in Panel 1 uses observations in the entire sample period. Panel 2 shows the out-of-sample $RIMSE$ and R-square comparisons of the three estimation methods. The out-of-sample estimation uses five years' observations to obtain parameter estimates and then measures the $RIMSE$ and R-square in the subsequent year using the estimated parameters. The first year of out-of-sample comparison is 1996.

1. In-sample pricing performance

	Parametric	Nonparametric	Proposed
$RIMSE$	0.476	0.383	0.212
R^2	0.498	0.744	0.902

2. Out-of-sample pricing performance

	$RIMSE$			R^2		
	Parametric	Nonparametric	Proposed	Parametric	Nonparametric	Proposed
1996	0.468	0.379	0.164	0.523	0.788	0.941
1997	0.485	0.375	0.221	0.476	0.727	0.947
1998	0.543	0.495	0.324	0.487	0.623	0.834
1999	0.430	0.347	0.149	0.578	0.794	0.955
2000	0.395	0.292	0.148	0.482	0.798	0.930
2001	0.418	0.325	0.199	0.559	0.804	0.933
2002	0.540	0.444	0.247	0.582	0.793	0.912
2003	0.632	0.481	0.296	0.485	0.761	0.922
2004	0.549	0.385	0.322	0.596	0.817	0.932
2005	0.538	0.432	0.414	0.532	0.804	0.971
2006	0.401	0.405	0.399	0.527	0.654	0.907
Average	0.491	0.396	0.262	0.530	0.760	0.926

Figure 1.1: **Compare option prices along the dimension of option maturity**

This figure compares the option prices of CIR model (true model in simulation) and Vasicek model along the option maturity dimension. Prices from Vasicek model are shown in neighborhoods around option maturity of 1 month, 3 months, 6 months, and 1 year. The parameter for CIR process is set to that in (1.17). The parameters for Vasicek process are set to those estimated in section 1.3, which differ across the four Vasicek price curves shown. The underlying bond maturity is set to 10 years and the short rate is set to 7% (approximately the mean interest rate) in the simulation.
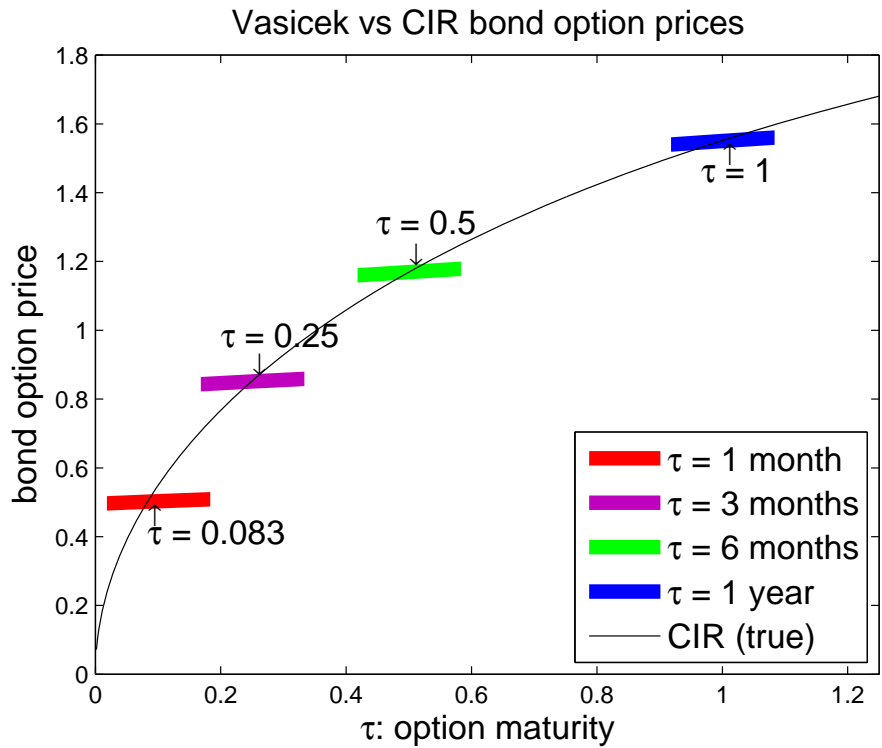
Figure 1.2: **Compare option prices along the dimension of bond maturity**

This figure compares the option prices of CIR model (true model in simulation) and Vasicek model along the bond maturity dimension. Prices from Vasicek model are shown in neighborhoods around bond maturity of 2, 5, 10, and 30 years. The parameter for CIR process is set to that in (1.17). The parameters for Vasicek process are set to those estimated in section 1.3, which differ across the four Vasicek price curves shown. The option maturity is set to 3 months and the short rate is set to 7% (approximately the mean interest rate) in the simulation.
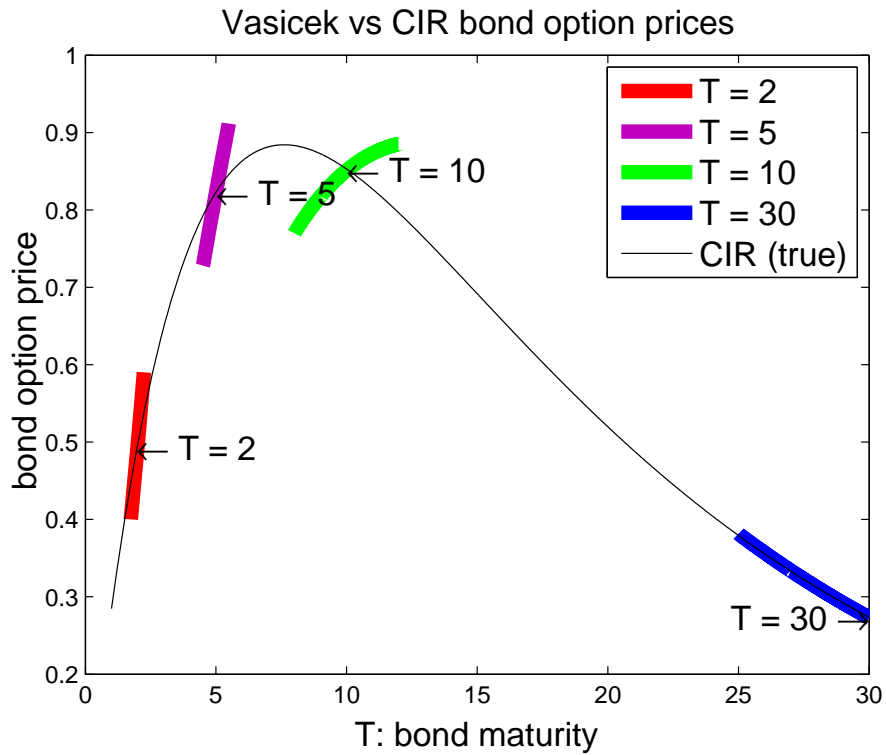
Figure 1.3: **Compare option prices along the dimension of short rate**

This figure compares the option prices of CIR model (true model in simulation) and Vasicek model along the short rate dimension. Prices from Vasicek model are shown in neighborhoods around short rate of 0.04, 0.07, and 0.1, which are approximately the mean and mean plus/minus one standard deviation of the short rate. The parameter for CIR process is set to that in (1.17). The parameters for Vasicek process are set to those estimated in section 1.3, which differ across the three Vasicek price curves shown. The option maturity is set to 3 months and the bond maturity is set to 10 years.
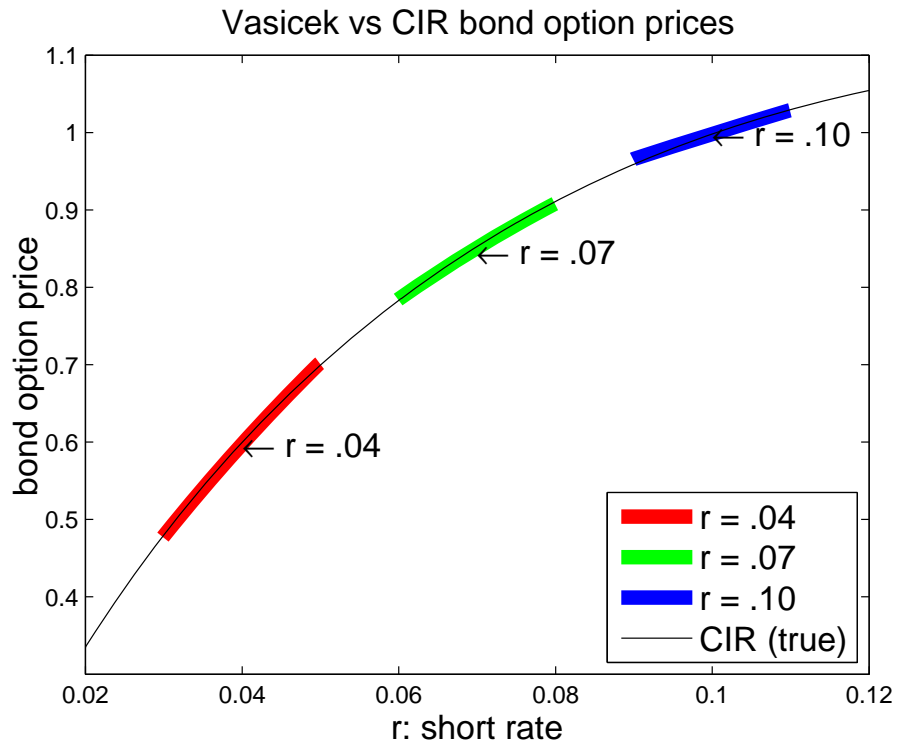
Figure 1.4: **Scatter plots of observed and estimated Treasury option prices**
This figure shows the scatter plots of observed Treasury option prices against option prices estimated, respectively, using parametric methods, nonparametrics, and the robust parametric method (labeled "robust prices" in the plot). The sample period is May 1990 – December 2006.
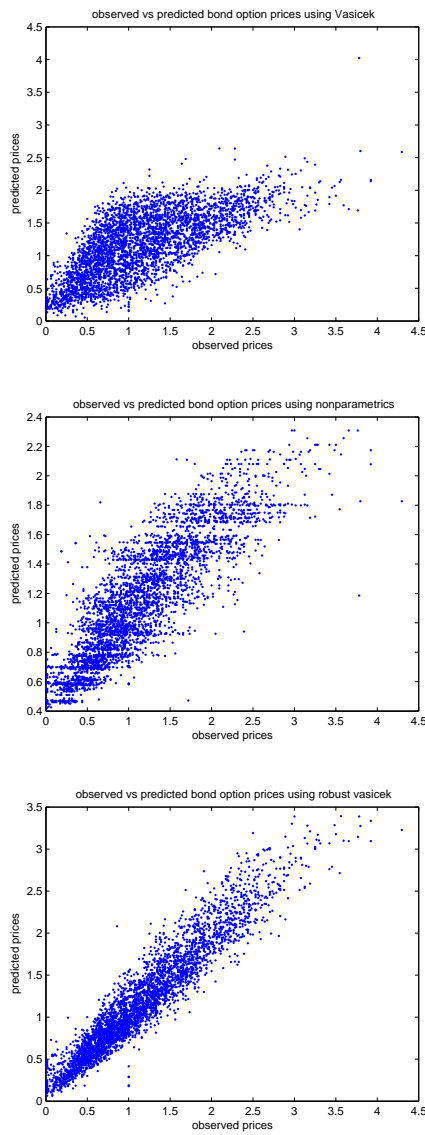
Figure 1.5: **RIMSE and regions of fit** This figure shows the root integrated mean squared error (RIMSE) in CBOT Treasury option pricing for various regions of fit along the dimensions of option maturity, bond maturity, and short rate. The robust parametric method selects a region of fit separately for each dimension to minimize the RIMSE. In the plot for bond maturity, the horizontal axis refers to the number of nearest bond maturities. I.e., 1 means using the 1 nearest bond maturity (e.g., bond with 5-, 10-, and 30-year maturities are included in 10-year Treasury option pricing). The sample period is May 1990 – Dec 2006.
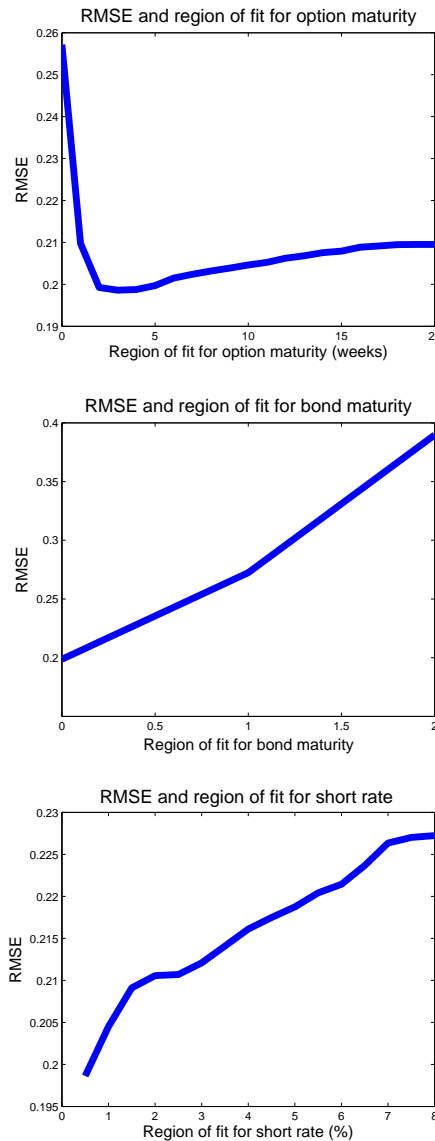
Chapter 2

The Information in Credit Default Swap Volume

2.1 Introduction

Since the first credit default swaps (CDS) were traded by JPMorgan in 1995, the CDS market has blossomed to become a major asset class in the capital markets. This is illustrated in Figure 2.1 from the Bank for International Settlements (BIS) which shows the semiannual total amounts of CDS from 2004 to 2010[1]. The main reason for this drastic growth and continuing vitality of the CDS market is that CDS can be used in both capital allocation and speculation. By providing protections, CDS make it easier for credit risks to be held by those who are in the best position to take them and allow financial institutions to make loans that they would not otherwise be able to make. CDS also enable speculators to take huge negative side bets without holding any underlying debts. No matter what they are used for, CDS could reveal useful and unambiguous information about credit risks because CDS are purely about the likelihood of default. Also, since most of the major players are insiders in the CDS market, the existence of asymmetric information and insider trading is highly likely (see Acharya and Johnson (2007)). Thus, one might expect that at least some

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[1]Though the total amount of CDS halved after the financial crisis, CDS trading activity has not decreased because most of the reduction comes from trade compression (see Duffie et al. (2010) and Vause (2010)).

new information on credit risk would be reflected in the CDS market first.

This paper examines the informational content of CDS trading for future asset prices of the reference entities. Specifically, I focus on the informational role of CDS net notional outstanding, which is the sum of net CDS bought by all net buyers (or equivalently the sum of net CDS sold by all net sellers). The net notional amounts generally represent the maximum possible net funds transfers between net sellers and net buyers of protection[2], and hence mean the actual amounts of insurance offered by CDS. Especially when compared to the total amount of existing debt, CDS net notional outstanding directly shows how much of the debt is insured with CDS, and is considered a natural measure of investors' view on the likelihood of the credit event of the reference entity. This indicates that CDS-to-debt, the ratio of CDS net notional to the total amount of existing debt, increases as credit quality is deteriorated, and vice versa.

CDS net notional could contain more relevant information on credit risk than CDS prices. According to the data from the Depository Trust & Clearing Corporation (DTCC), more than 80% of CDS trades are made between dealers. The Office of the Comptroller of the Currency (OCC) also reports that a small number of dealers account for more than 95% of market share. These suggest that a considerable portion of CDS trades occurs between the largest dealers and as a result, the corresponding CDS prices might not reveal valuable information on credit risk changes because they could make trades to rebalance their portfolios by adding redundant CDS positions, rather than respond to the changes.

Given this motivation, I perform an empirical study on whether the information in CDS net notional can predict future CDS and stock prices. I use the most comprehensive and disaggregated data on the weekly CDS positions from the Depository Trust & Clearing Corporation (DTCC) over the period November 2008 through June 2011. The data include both the gross and net amount of notional contracts outstanding. Combining the DTCC data with the debt records from Compustat, I form CDS-to-debt ratio in order to test the predictability of CDS net notional for future CDS and stock price movements.

The results of my examination are two fold. First, I find cross-sectional evidence that a rise in current CDS-to-debt ratios predicts an increase in CDS prices and a decrease in

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[2]Actual net funds transfers are dependent on the recovery rate for the underlying debt instruments.

stock prices within the next 3 weeks. This suggests that it takes time for the information expressed in the CDS net notional to get incorporated into asset prices. Second, I show that the predictability is greater for the subsamples where we expect a priori more investor interest, e.g. entities that are in good credit condition such as firms with investment grade credit ratings or low CDS-to-debt ratios. This implies that the firms regarded as junk or already considerably insured with CDS are not a concern for investors. Additional predictability test on a daily basis confirms that information gradually flows from the CDS market to the stock market in a persistent way. All these results suggest that investors pay limited attention to information contained in CDS net notional because CDS net notional is not observable in real time and could have lower priority to other information sets such as earnings, sales, and macro information.

This paper contributes to furthering our understanding of how information in a derivative market gets incorporated into asset prices. Since Black (1975) pointed out that informed investors might choose to trade derivatives due to the higher leverage, a number of studies have explored these cross-market information flows. Their informational sources can largely be divided into two categories: security volume and prices.

Regarding the latter, Acharya and Johnson (2007) examine the effects of insider trading in the credit market. They find evidence that information flows from the CDS market to the equity market for firms that are more likely to experience credit event in the future. Chakravarty et al. (2004) investigate the behavior of investors with private information who can choose to trade in the stock market or in the options market. They provide evidence that stock option trading contributes to price discovery in the underlying stock market. Ni and Pan (2010) examine the interaction between price discovery in stocks and the trading of options and CDS during the short sale ban in 2008. They confirm the theory prediction of Diamond and Verrecchia (1987) in which prohibiting short-sales slows the speed of adjustment to private information in the derivatives market. Longstaff et al. (2005) study the lead-lag relations among CDS, bond, and stock prices in a VAR framework and find that both stock and CDS markets lead the bond market. However, there is no clear lead of the CDS prices with respect to stock prices, and vice versa.

Regarding the former, Easley et al. (1998) provide a theoretical model of asymmetric

information in which option order flows contain information about the future direction of the underlying stock price. Pan and Poteshman (2006) empirically test their information model by constructing put-call ratios from option volume initiated by buyers to open new positions and find a strong predictability for future stock prices. Like these papers, I contribute a measure of credit risk from CDS volume and directly test for its effects on future asset prices.

To the best of my knowledge, this paper is the first work to explore the informational role of CDS volume. On a related plain, the determinants of CDS net notional in DTCC are investigated by Oehmke and Zawadowski (2012). They find that firms which recently experienced credit rating demotion from investment to speculative grades have more CDS outstanding and suggest that investors exposed to these firms use the CDS market to hedge.

The remainder of the paper is organized as follows. Section 2.2 describes credit default swaps and explains what information is in their net notional amounts. Section 2.3 details the data employed. Section 2.4 examines the informational content in CDS notional for CDS and stock prices of the reference firms empirically, and section 2.5 concludes.

2.2   Credit default swap volume

2.2.1   Credit default swap

A credit default swap is a bilateral agreement between two counterparties, in which one party (the writer) offers the other party (the buyer) protection against a credit event by a third party (the reference entity) for a specified period of time, in return for premium payment. Counterparties are often banks, insurance companies, or hedge funds. The reference entity may be a corporate or a sovereign. CDS documentation must specify what constitutes a credit event that triggers the capital payoff on the CDS. The key credit events are failure to pay, bankruptcy, and restructuring.

A CDS is economically similar to an insurance contract on debt issued by the reference entity. The buyer pays a premium regularly and the writer pays par in return for 100 nominal of debt if the reference entity suffers a credit event before the maturity of the deal.

However there exist a number of significant differences between a CDS and an insurance policy. First, a CDS does not require the buyer to hold the insured risk at the time that a claim is made whereas an insurance contract owner typically has to have a direct economic exposure to obtain insurance. For example, an investor can buy a CDS written on IBM without holding bonds, but cannot buy a car insurance without having a car. Because of this feature, CDS can be used by investors not only for hedging but also for speculation. Investors who hold bonds issued by the reference entity may use CDS to eliminate or reduce the risk of default. CDS in which the buyer owns the underlying debt is referred to as covered credit default swaps. Meanwhile, CDS buyers can take huge speculative side bet on the reference entity by buying CDS without holding the underlying debt, hoping for deterioration in its credit quality. Especially speculators prefer CDS market because buying protection in the CDS market is easier in terms of liquidity than taking an equivalent position by shorting bonds. CDS in which the buyer does not hold the underlying security is called naked credit default swaps.

Second, in contrast to insurance contracts, CDS contracts are traded. Rather than being traded on an exchange, they are negotiated over the counter (OTC) in which counterparties in different locations privately communicate and make deals by phone and through electronic messages. It is therefore difficult to know how much insurance exists on each borrower, or who has insured whom and for how much. Third, insurance companies, the writers of insurance policies, are regulated by an insurance regulator, while CDS writers do not have to be regulated entities. Although CDS contracts are typically written under the International Swaps and Derivatives Association (ISDA) documentation, it is considerably different from insurance documentation, which raises the concern that systemically important counterparties may suffer devastating losses on large unhedged CDS positions.

The privacy of the OTC market and unregulated environment press the dealers to use the central clearing counterparty. After two counterparties agree on the terms of a credit default swap, they can clear the CDS by having the clearinghouse stand between them, acting as the buyer of protection for one counterparty and the seller of protection to the other. The clearinghouse can reduce both systemic and counterparty risks. Once the swap is cleared, the original counterparties are insulated from direct exposure to each other's default

so that systemic risk is lowered. In addition, the clearinghouse reduces counterparty risk by using stringent membership access, robust margining regime, and clear default management procedures.

2.2.2 Credit default swap volume

It is not unusual for the total notional amount of credit default swaps written on the reference entity to exceed the total amount of debt issued by that reference entity because active market participants, typically derivatives dealers, have large but nearly offsetting positions since they intermediate between buyers and sellers. According to data from DTCC, more than 80% of total number of CDS trades on single names occurred between dealers by June 2011, while about 0.1% of trades were between non-dealers. In addition, vast credit default swap positions were held by big bank credit derivatives dealers. Figure 2.2 from the Office of the Comptroller of the Currency (OCC) exhibits historical CDS market share of the largest dealers and their recent positions in detail. It presents that JPMorgan Chase, the largest dealer, has for more than 40% of CDS gross notional outstanding held by dealers all the time. The fact that top 3 dealer firms account for more than 80% of all CDS contracts outstanding and top 5 for more than 95% confirms that there is a high degree of concentration among CDS dealers. It also reports that JPMorgan Chase bought protection coverage on $2.95 trillion of debt principal, and sold protection on $2.97 trillion by the 2nd quarter of year 2011. Since most of dealers' positions are redundant, gross notional amounts of outstanding CDS in the market tends to be overstated and is therefore not a good measure of the effective amount of insurance offered by CDS. From the definition of gross notional that is the sum of all existing contracts, its changes could indicate the turnover. However gross notional is notably biased. Because DTCC releases the data weekly, creating and canceling the contracts partially or fully in a unit period cannot be captured in changes in gross notional. Therefore, it would be a devalued measure. On the other hand, turnover could be overstated when a clearinghouse executes trade compression which reduces gross notional considerably without any trades initiated by dealers.

What is relevant is the actual size of the potential claims which are transferred from one pocket to others in case of the credit event. It is calculated as sum of *net* CDS bought by

all net buyers (or equivalently as sum of net CDS sold by all net sellers). Economically this net notional amount represents the maximum possible net fund transfers between net sellers of protection and net buyers of protection that could be required upon the occurrence of a credit event relating to particular reference entity. Figure 2.3 plots the empirical density of the ratio of net notional and gross notional amounts of outstanding CDS. It demonstrates that roughly 10% of gross notional amounts of outstanding CDS would be paid if the reference entity defaults. When dealers trade with other dealers not due to any credit risk change but for rebalancing their credit portfolios, any changes in CDS premium are not representative of the true demand by real end users, typically non-dealers. This means that the net notional which is little changed by portfolio rebalancing could give more accurate information on demand for CDS.

The net notional amount of outstanding CDS provides the key information on market's perception regarding the credit status of the reference entity especially when combined with the total amount of existing debt. Since CDS-to-debt, the ratio of CDS net notional outstanding to the total amount of existing debt, directly indicates how much of the debt is insured with CDS, it is a natural measure of investors' view on the likelihood of the credit event of the reference. One can expect a high level of CDS-to-debt ratio when investors anticipate that credit condition of the reference is worsened. When investors believe that a credit event for the reference is very unlikely, the level of CDS-to-debt ratio is low.

Regardless of whether CDS positions are covered or naked, the ratio is informative. Clearly the size of CDS relative to the debt used in speculation presents the market's concern on the credit quality of the reference. Since payoff to CDS is discrete, either 0 or expected loss, the investors who take speculative side bets using CDS have the most pessimistic view. The naked CDS holders strongly believe that the credit quality of reference will be deteriorated and in deep trouble. The amount of covered CDS positions indicates the market's perception as well. Assuming that there is no arbitrage opportunity, investors have no incentive to buy the underlying debt together with CDS, because it is identical to buying risk-free assets if counterparty risk is ignored. They initially invest money in the underlying, realize changes in credit risk later, and then hedge their exposure using CDS. Moreover, when the primary debt holders insure their lending using CDS, they are

no longer concerned about monitoring the firm's management which might incur the poor performance of the firm and eventually the credit event. It means that the amount of covered CDS contracts also reveals market's view on credit risk of the reference entity. Especially for the reference entities whose bonds are illiquid, investors use CDS markets to speculate or hedge exposures (Oehmke and Zawadowski, 2012).

The respective portion of the net notional amounts used for hedging and speculation is difficult to gauge. However, if a ratio is greater than 1, the debt is over-insured using CDS and it can be considered that at least the excess amount of CDS was used in speculation.

2.3   Data

I focus on 208 US companies over the period of November 2008 through June 2011 that satisfy the following conditions: (1) The firms are enlisted in NYSE and NASDAQ. (2) The firms are neither in financial nor in utility sectors. (3) CDS net notional and premium quotes are available. (4) The amounts of debt issued by the firms are available from Compustat.

2.3.1   The credit default swap volume

The CDS contracts data are obtained from the Depository Trust & Clearing Corporation's (DTCC) Trade Information Warehouse (TIW).[3] The data record weekly aggregate gross and net notional positions written against single name reference entities. TIW collects the information on CDS positions from Monday to Friday and usually releases it next Tuesday after the stock market is closed though no official announcement time is scheduled. DTCC reports that TIW covers around 95% of globally traded CDS, and hence, provides the most accurate and comprehensive data on CDS positions. Notional represents the par amount of credit protection bought (or sold), equivalent to debt or bond amounts, and is used to derive the coupon payment calculations for each payment period and the recovery amounts in the credit event. Gross notional outstanding is the sum of CDS contracts bought (or equivalently sold) for all contracts in aggregate for single reference entities. Net notional outstanding is

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[3]As transparency in OTC (credit derivatives) market was requested after Lehman's default, DTCC began publishing the CDS information on Nov. 7, 2008.

the sum of the net protection bought by buyers (or equivalently net protection sold by net sellers). The aggregate net notional is the sum of net protection bought (or equivalently sold) across all counterparty families which will typically include all of the accounts of a particular asset manager or corporate affiliates rolled up to the holding company level.

Figure 2.4 illustrates gross and net notional calculation and trade compression in detail as an example of CDS positions over the counter. Counterparty A, B, and C are very active in trading CDS and they hold simultaneously long and short CDS positions referencing the same underlying borrower. Assume that A buys $5 million of CDS from B initially and all the other CDS contracts are made later. The net notional amount of CDS is equal to the gross notional amount of CDS, $5 million, at initial trade. However, the net notional amount of CDS is different from the gross amount of CDS after all trades are done. The gross notional amount, the sum of all outstanding CDS bought (or equivalently sold) is $15 million while the net notional amount, the sum of all the net positive positions is only $2 million. Consequently, it is $2 million, not $15 million transfer that occurs among counterparties in case of credit event on the reference entity. This process that eliminates redundant positions held by counterparties and creates replacement trades is called trade compression or portfolio compression. Therefore, the gross notional amount is equal to the net notional amount after all possible trade compressions are executed. This example also demonstrates that an increase in gross notional amount doesn't necessarily mean a rise in net notional amount. While the gross notional increases from $5 million to $15 million, the net notional decreases from $5 million to $2 million. Market participants who don't have a negative view on the reference entity could buy CDS to reduce their existing positions by netting.

2.3.2 Credit default swap premium

The daily credit default swap premium data are obtained from Bloomberg. Credit default swaps all written on senior debt and with maturity of 5 years are gathered because they are typical and most liquid. DTCC CDS position data and Bloomberg CDS premium data are merged using the reference entity name as an identifier. When matching two datasets, corresponding stock identifiers such as ticker and cusip are simultaneously collected from

Bloomberg.

2.3.3 The debt

The amounts of total outstanding debt data are obtained from Compustat. Total outstanding debt is measured by the sum of long-term debt (#9) and debt in current liabilities (#34).

2.3.4 S&P credit ratings

Credit ratings issued by Standard & Poor's (S&P) are used. Historical credit ratings data are obtained via Bloomberg.

2.3.5 Stock prices

The daily stock price data are obtained from CRSP. To test the informational content of CDS trading for the idiosyncratic component of future stock returns, I construct the risk-adjusted returns using a four-factor model of market, size, value, and momentum. In terms of the construction, I run the rolling regression with 25-day window to estimate coefficients with a reasonable degree of precision and pin down conditional coefficients in an environment with time-varying factor loadings.

2.4 Empirical results

The main focus of this article is to test the informational content of CDS-to-debt ratio for other security prices. Therefore, my empirical specifications are designed to address the fundamental question of how information gets incorporated into security prices. The ratio of CDS notional to total debt is employed as an explanatory variable for both contemporaneous and predictive regressions to measure the impact of information.

2.4.1 CDS-to-debt ratio

Before the regression analysis, it is worth taking a look at descriptive statistics of CDS-to-debt ratios to confirm that CDS-to-debt ratios using net notional is a good measure of

market's perception on the credit risk of the reference entity. Tables 2.1 and 2.2 present sample distributions of the ratios of net and gross notional amounts outstanding to the total debt issued by the reference firms over credit rating respectively. In Table 2.1, CDS-to-debt ratio increases monotonically across the credit rating, which is consistent with conventional wisdom. All the firms with AAA or AA rating have the ratios within 30%. More than 70% of investment grade firms have CDS net notional less than 30% of the debt whereas only 40% of the firms with speculative grade have CDS to-debt ratio within 30%. Furthermore only 3.6% of the investment grade firms have more net notional than the total debt, and 21.7% of the speculative grade firms are over-insured with CDS. It confirms that CDS-to-debt ratio using net notional is a natural and good measure of investors' concerns on the credit quality of the reference.

On the other hand, gross notional is not so informative as net notional in terms of the level of insurance. In Table 2.2, About two thirds of investment grade firms have more CDS gross notional than the total debt, and even some AAA or AA rated firms could be interpreted as over-insured if gross notional is used in ratio construction. These numbers can hardly make sense because 65% of over-insurance level is too high for investment grade entities which have less than 5% of probability of default historically. It is therefore hard to gauge the investors' concerns on the firms whose gross CDS-to-debt ratio is higher than 100% by a certain level, and it should be net notional, not gross notional that is used to the ratio. In the following empirical analysis, both CDS-to-debt ratios using net and gross notional are employed as explanatory variables and it is confirmed that net notional is the natural and good measure.

2.4.2 CDS premium

In this section, the informational content of CDS-to-debt ratio on CDS premium movements is examined in both contemporaneous and predictive regressions of the following forms:

$$\Delta \text{CDS Premium}_t^i = \alpha + \beta X_t^i + \epsilon_t^i \tag{2.1}$$

$$\Delta \text{CDS Premium}_{t+1}^i = \alpha + \beta X_t^i + \epsilon_{t+1}^i \tag{2.2}$$

where time indices t and $t+1$ denote contemporaneous and predictive regressions respectively in weekly frequency. Both net and gross notional are used in ratio construction and regression results are shown in Tables 2.3 and 2.4. The regressions establish a number of basic results and stylized facts about CDS volume. First, I find that CDS premium increases as net CDS-to-debt ratio increases and this is consistent with the economic theory that demand and price move together in the same direction. The β coefficient of net CDS-to-debt in contemporaneous regression (2.1) is positive and statistically significant. Using the entire data sample, net CDS-to-debt ratio has a slope coefficient of 9.91 basis points with a t-statistic of 2.85. This result implies that changes in net CDS-to-debt ratio can be a good proxy for demand of the credit risk.

Analysis with subsamples across credit ratings and the level of the CDS-to-debt ratios provides better understanding of the relationship between the CDS notional and premium. For the firms with investment grade or low level of the CDS-to-debt ratio, the contemporaneous relationship between changes in premium and the ratio is stronger in magnitude and statistical significance. One would expect that investors pay little attention to the firms whose credit is already deteriorated so that they are recognized as junk or considerably insured with CDS. Moreover, since they have a high level of insurance, a small change in insurance level can hardly tell whether their credit condition really gets better or worse. In contrast, the firms in good health of credit get more attention from market participants. Because demoting from investment to speculative grade is of great interest to credit market investors, they will use CDS to hedge if credit risk increases. This is in accordance with Oehmke and Zawadowski (2012)'s finding that firms which lose investment grade status have more CDS net notional outstanding.

The changes in net notional also have predictive power for future premium changes. The β coefficient of net CDS-to-debt in predictive regression (2.1) is positive and significant. Its estimate is 8.84 basis points with a t-statistic of 3.17 using all the data sample. This suggests that changes in insurance level contain the information on forecast in credit risk and there is a delay to reflect the information into security prices. The net notional is not observable on real-time basis because it is a calculated number after doing some mathematics of netting redundant contracts out. Therefore, there could be delayed reactions to the changes in

demand pressure. Similarly to contemporaneous analysis, predictability is greater for firms in good credit status.

Though the changes in gross CDS-to-debt explain the concurrent movement in premium, it has no predictive power for future CDS premium as expected. A slope coefficient for the changes in gross CDS-to-debt ratio is also positive and significant for contemporaneous regression but both magnitude and statistical significance is smaller. To see whether gross CDS-to-debt ratio has the same information as in net CDS-to-debt ratio for CDS premium, I run the regressions with the changes in both ratios as independent variables. Table 2.4 confirms that both changes explain the current changes in CDS premium but only changes in net CDS-to-debt ratio predict the future changes. This means that the gross notional has different information from net notional on CDS premium and is not useful to get an idea about future dynamics.

To explore further how information in CDS net notional gets incorporated into CDS prices, the horizon of predictability is extended up to 5 weeks. The slope coefficients and their t-statistics are reported in Table 2.5. The predictability persists up to 3rd week and the magnitude is the largest at 2nd week. Also subsample analysis shows that most of predictability comes from the firms in good credit status. Moreover, there is no reversal over longer horizons, which indicates that the predictability is truly information based rather than the result of mechanical price pressure.

2.4.3   Stock prices

Having identified a measure of information flow in the CDS volume to the credit default swaps premium, I next apply this directly to weekly stock returns in following regression specifications:

$$R_t^i = \alpha + \beta X_t^i + \epsilon_t^i \tag{2.3}$$

$$R_{t+1}^i = \alpha + \beta X_t^i + \epsilon_{t+1}^i \tag{2.4}$$

where R_{t+1}^i and R_t^i denote four-factor risk-adjusted return of the firm i in next and current weeks respectively. The economic motivation for using the risk-adjusted returns is to test the information content of CDS volume for the idiosyncratic component of future stock returns

that are not explained by common factors—market, size, value, and momentum. If the risk-adjusted returns have the component determined by credit risk, one would expect that it responds in opposite direction to the changes in net CDS-to-debt ratio. The magnitude of response would be dependent on how large the credit component is in the risk-adjusted returns and how closely it is connected to the CDS volume change. Again, both net and gross notional are used in ratio construction and regression results are summarized in Table 2.6.

In contemporaneous analysis, it is shown that the risk-adjusted return decreases as net CDS-to-debt ratio increases and this satisfies the conventional expectation that stock price performs poorly as credit quality is deteriorated. The β coefficient of net CDS-to-debt using all the data sample is -2.38 basis points with a t-statistic of -1.94. The relationship is stronger for the firms with good quality of credit as for CDS premium. Investment grade firms have a slope coefficient of -3.52 basis points with a t-statistic of -2.76 and firms with low level of insurance have -12.12 basis points with a t-statistic of -4.34. Intuitively, one would expect investors to have more care about the credit risk of the healthy firms and therefore see stronger predictability from the risk-adjusted returns as confirmed in CDS premium. On the contrary, all the coefficients of CDS-to-debt ratio using gross notional are exceedingly small and not statistically significant regardless of firms' credit condition. Thus gross CDS-to-debt ratio does not have information on credit risk of the reference.

I test the hypothesis that information contained in CDS trading activity is valuable in predicting next week stock returns. The null hypothesis is that the market is in a separating equilibrium and information in CDS contracts has no predictive power. The second column of Table 2.6 confirms that there is a cross-sectional predictability and the null hypothesis is rejected. The magnitude and statistical significance of the coefficients are even stronger than those in contemporaneous analysis except for the firms with low levels of insurance. This implies that information on credit risk contained in CDS net notional flows gradually into stock market.

I also extend the horizon of predictability up to 5 week to investigate the information flow from CDS net notional to stock prices. The slope coefficients and their t-statistics are reported in Table 2.5. As for CDS prices, the predictability persists up to 3rd week and

the magnitude is the largest at 2nd week.[4] For good credit companies, changes in CDS net notional can predict 4th week stock returns. The absence of reversal over longer horizons suggests that the predictability is information based.

I take a closer look at the predictability of the net CDS-to-debt ratio for future stock return by running 1-day regressions to investigate how information flow occurs. Regression specification is given by

$$R^i_{t+\omega+1,t+\omega} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)^i_{t,t-5} + \epsilon^i_{t+\omega+1} \tag{2.5}$$

where $R^i_{t+\omega+1,t+\omega}$ is the next day four-factor risk-adjusted return of the firm i from time $t+\omega$. Since weekly net CDS positions are collected Friday after market is closed, calculated over weekend, and typically released next Tuesday after market is closed, t is always Friday and ω represents the delay from Friday in regression (2.5). For example, if ω is 3, $R^i_{t+\omega+1,t+\omega}$ is 1-day return from Wednesday to Thursday in next week. Here, an independent variable is CDS-to-debt ratio using only net notional. The results are summarized in Table 2.9. Since the information about CDS notional is released typically on Tuesday, if investors care much about CDS net notional the coefficients on Monday and Tuesday would be negatively significant and those after Tuesday would be insignificant. For all weekdays, however, there is predictability of CDS-to-debt ratio for 1-day risk-adjusted returns for all weekdays and there is no surprise from the announcement. As shown in previous regressions, predictability is greater for firms in good credit condition.

All of these results suggest that the predictability of CDS volume mainly comes from gradual information flow and limited attention. Since CDS net notional data are not observable in real time and could have lower priority to other information sets such as earnings, sales, and macro information to stock investors, cognitively-overloaded investors pay attention to only a subset of publicly available information which can be easily accessed. Especially when the information in CDS contracts could not be captured by market, size, value, and momentum, it would be incorporated into stock prices slowly.

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[4]Except for the firms with low level of the CDS-to-debt ratio, the predictability with a standard deviation change in CDS-to-debt ratio, 2%, can hardly beat the bid-ask spread of stock prices. For instance, the average bid-ask spread is about 10 basis points for IBM which is one of the most actively traded firms, and it is larger than 2 times of the predictability for most entries in Table 2.8.

2.5 Conclusion

This paper investigates the informational content of credit default swap volume for other security prices of the reference entities. Combined with the total debt in the market, CDS net notional outstanding directly indicates how much of the debt are insured with CDS and therefore its change could be a natural and good measure of market participants' demand for CDS used for hedging or speculation against the credit event of the reference entity. As consistent with economic theory of demand and price, CDS net notional explains the concurrent movements of CDS premium and stock prices. Furthermore I find cross-sectional evidence that the current increase in CDS-to-debt ratio can predict a decrease in stock prices and a rise in CDS premium of the reference firms in the next week. Greater predictability for firms with credit rating of investment grade or low CDS-to-debt ratio suggests that investors pay more attention to firms in good credit conditions than those regarded as junk or already insured considerably with CDS. Daily analysis confirms that the information in CDS net notional flows gradually into stock prices. Because CDS volume information is neither real-time observable nor above other financial information to investors, the predictability could come from gradual information flow and investors' limited attention.

Figure 2.1: **Credit Default Swaps Notional Outstanding**

This figure exhibits semiannual CDS notional amounts outstanding from the Bank for International Settlements (BIS) from the 2nd half of 2004 to the 1st half of 2011. Blue bars represent notional amounts of CDS written on single name instruments while sum of blue and green bars do CDS on all instruments. The total notional amount of the CDS market was $6 trillion in 2004, $57 trillion by June 2008, and $32 trillion in 2011. Most of recent reduction from a peak to a current level in outstanding notional has occurred through trade compression as demanded by the regulators which reduces the total notional amount of outstanding CDS positions after eliminating redundant positions and allowing for additional trading in the interim (Duffie et al., 2010).
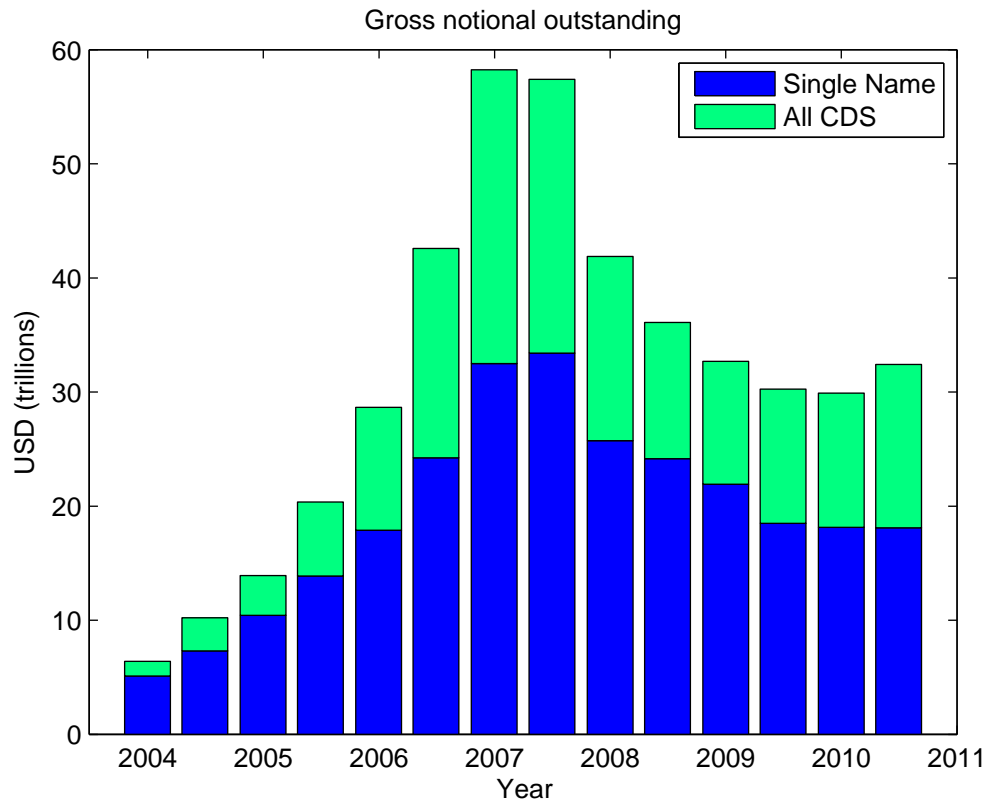
Figure 2.2: **CDS Dealers Market Share and Position**

This figure illustrates the distribution of CDS contracts held by top 5 largest dealers. Historical market share is shown in (a). Top 5 largest dealers account for more than 95% of all dealers' gross positions all the time. Each dealer's position by the 3rd quarter of year 2011 is split into the amounts bought and sold in (b). It is confirmed that the largest dealers account for most of total contracts outstanding and they have nearly offsetting positions.

(a) Historical Market share
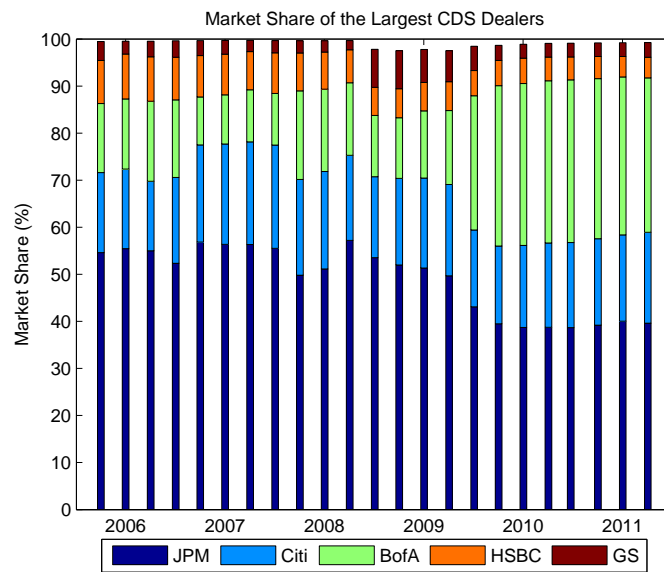
(b) Positions in detail
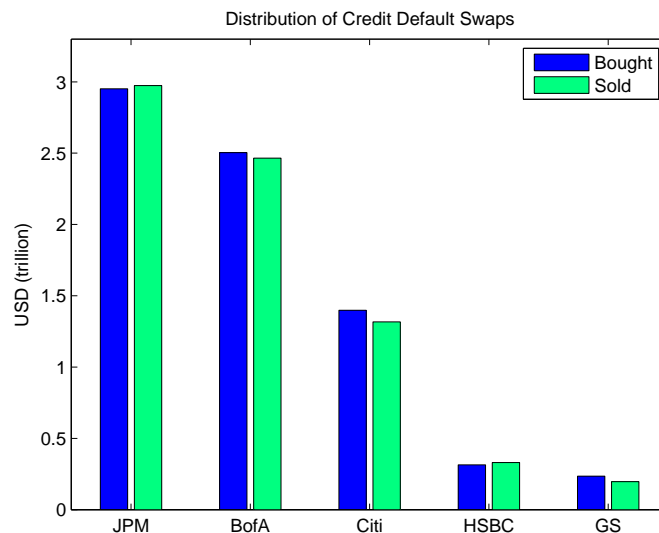
Figure 2.3: **Gross vs. Net Notional**

This figure demonstrates the empirical density of the ratio of net notional and gross notional amounts outstanding of CDS. Average, median, and standard deviation ratio of net notional to gross notional amounts are 9.6%, 9.0%, and 3.2% respectively. More than 90% of samples have the ratio of net notional to gross notional amounts between 5% and 15%.
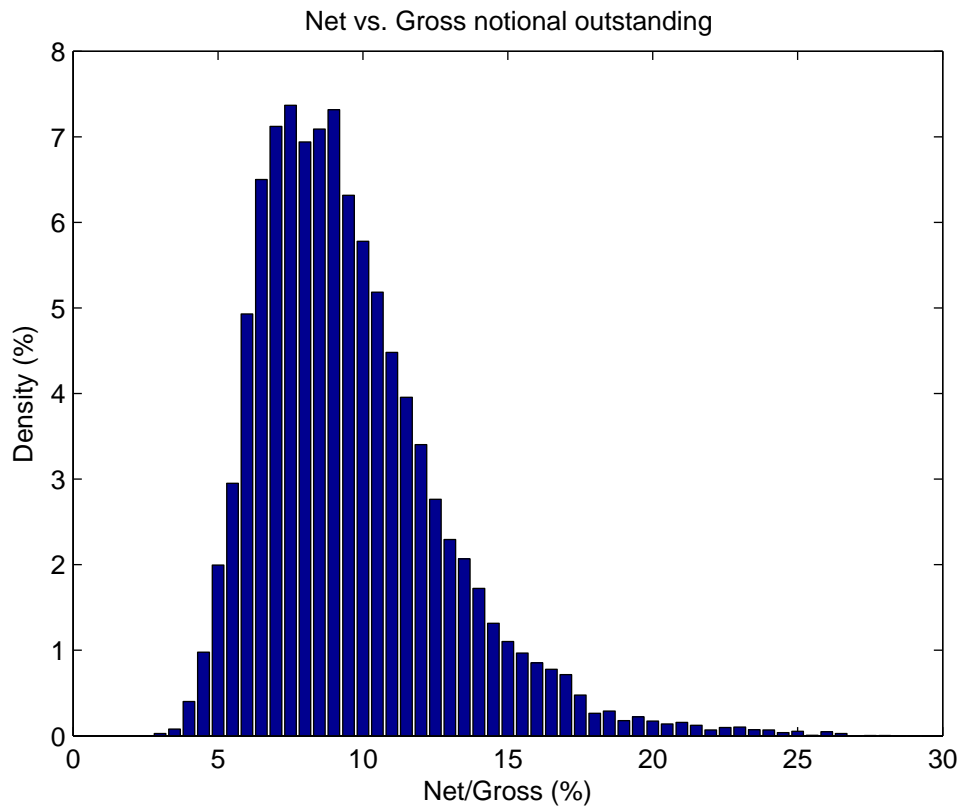
Figure 2.4: **CDS trade over the counter market and trade compression**

Figure 2.4 illustrates an example of credit default swaps positions over the counter and how trade compression works. In (a), counterparty A sold CDS on $5M$ of debt principal and bought $6M$ in total. Likewise, B and C sold $5M$ and $5M$, and bought $6M$ and $3M$ in total respectively. By subtracting amounts sold from amounts bought, net positions of A, B, and C are calculated in (c), $1M$, $1M$, -$2M$ respectively. Gross notional, the sum of CDS bought (or equivalently sold) for all contracts, is $15M$ while net notional, the sum of net CDS bought (or equivalently sold), is $2M$. This means that it is not $15M$ but only $2M$ that would change pockets in case of the credit event. Trade compression is the process from the (a) to (b) that eliminates redundant contracts and creates replacement contracts to improve market transparency and reduce the associated counterparty risk.

(a) before trade compression

(b) after trade compression
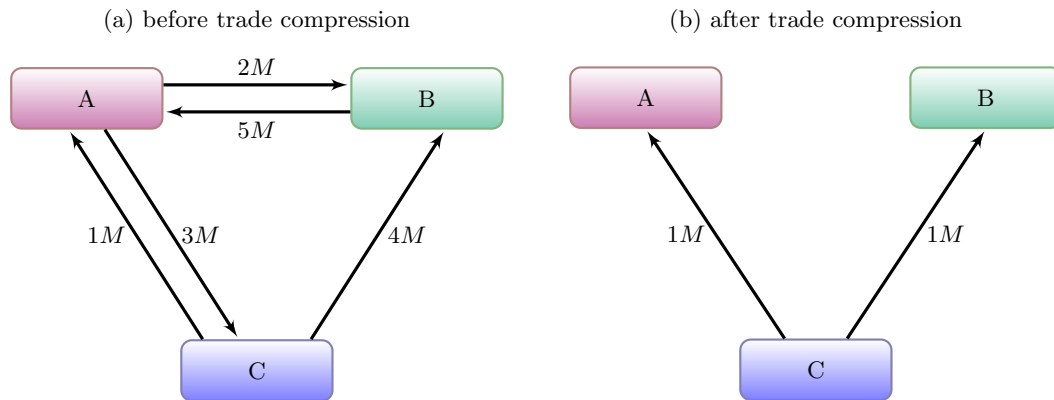
(c) **Example of aggregate net notional calculation**

	sold CDS to			bought from			Total gross		Net notional
	A	B	C	A	B	C	sold	bought	positions
Counterparty A		-2M	-3M		5M	1M	-5M	6M	1M
Counterparty B	-5M		0M	2M		4M	-5M	6M	1M
Counterparty C	-1M	-4M		3M	0M		-5M	3M	-2M
				Gross Notional		-15M	15M		
				Net Notional					2M

Table 2.1: **Net CDS-to-Debt distribution over credit rating**

This table presents sample distribution of the ratio of net notional amounts outstanding to total debt issued by the reference firms over credit rating. The ratio increases monotonically across the credit rating. More than 70% of firms with investment grade have CDS net notional less than 30% of the debt whereas only 40% of the firms with speculative grade have such. Furthermore only 3.6% of the firms with investment grade have more CDS net notional than the total debt. 21.7% of the firms with speculative grade, however, are over-insured with CDS.

	CDS Net Notional/Total Debt (%)				
	0 - 10%	10 - 30%	30 - 50%	50 - 100%	100% -
AAA or AA	74.0	26.0			
A	42.7	40.6	9.4	4.3	3.0
BBB	23.3	40.8	13.5	18.1	4.3
BB	11.7	31.6	14.8	22.5	19.4
B or lower	13.9	20.4	22.0	18.0	25.7
Investment	32.9	39.9	11.3	12.3	3.6
Speculative	12.5	27.5	17.5	20.8	21.7

Table 2.2: **Gross CDS-to-Debt distribution over credit rating**

This table presents sample distribution of the ratio of gross notional amounts outstanding to total debt issued by the reference firms over credit rating. Using gross notional isn't as informative as net notional. Since 65% of investment grade firms have more CDS gross notional than the total debt, it is hard to gauge the investors' concern on the firms whose CDS-to-debt ratio is at certain level higher than 100%. Even some AAA or AA rated firms could be interpreted as over-insured if gross notional is used in ratio construction.

	CDS Gross Notional/Total Debt (%)				
	0 - 50%	50 - 100%	100 - 500%	500 - 1000%	1000% -
AAA or AA	49.4	44.4	6.2		
A	25.6	17.4	47.8	6.0	3.2
BBB	7.6	16.8	50.1	17.7	7.8
BB	3.3	8.4	37.0	23.0	28.3
B or lower	7.2	2.1	28.1	29.9	32.7
Investment	16.2	18.6	46.9	12.6	5.7
Speculative	4.7	6.1	33.7	25.6	29.9

Table 2.3: **Predictability of CDS-to-debt ratio for weekly CDS premium change**
This table reports the results of cross-sectional univariate regressions of weekly changes in CDS premium on changes in CDS-to-debt ratio from Nov. 2008 through Jun. 2011. The independent variables are constructed from both net and gross notional amounts of CDS and total debt. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$\Delta\text{CDS Premium}_{t+1 \text{ or } t}^{i} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)_{t}^{i} + \epsilon_{t+1 \text{ or } t}^{i}$$

	Net CDS-to-debt				Gross CDS-to-debt			
	Current week		Next week		Current week		Next week	
	α	β	α	β	α	β	α	β
All	-4.56	9.91	-4.62	8.84	-6.24	1.81	-6.59	-0.15
Firms	(-0.09)	(2.85)	(-0.10)	(3.17)	(-0.13)	(2.34)	(-0.14)	(-0.21)
Investment	-4.40	16.16	-5.65	14.77	-6.35	3.23	-8.75	0.56
Grade	(-0.09)	(2.69)	(-0.12)	(3.21)	(-0.13)	(2.65)	(-0.18)	(0.58)
Speculative	-6.22	4.25	-0.50	8.80	-8.03	0.64	-6.05	0.18
Grade	(-0.11)	(0.93)	(-0.01)	(2.55)	(-0.15)	(1.04)	(-0.11)	(0.25)
CDS/Debt	-8.90	40.60	-7.72	33.99	-9.38	4.01	-9.08	0.08
< 50%	(-0.18)	(4.09)	(-0.16)	(4.01)	(-0.20)	(1.40)	(-0.19)	(0.04)
CDS/Debt	6.09	4.45	7.29	5.93	0.10	1.60	-0.05	0.40
> 50%	(0.12)	(1.15)	(0.15)	(1.94)	(0.00)	(2.49)	(-0.00)	(0.62)

Table 2.4: **Predictability of both net and gross CDS-to-debt ratio for weekly CDS premium**

This table reports the results of cross-sectional regressions of weekly changes in CDS premium on changes in CDS-to-debt ratio from Nov. 2008 through Jun. 2011. The independent variables are constructed from both net and gross notional amounts of CDS and total debt. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$\Delta \text{CDS Premium}_{t+1 \text{ or } t}^i = \alpha + \beta \Delta \left(\frac{\text{Net CDS}}{\text{Debt}} \right)_t^i + \gamma \Delta \left(\frac{\text{Gross CDS}}{\text{Debt}} \right)_t^i + \epsilon_{t+1 \text{ or } t}^i$$

	Current week			Next week		
	α	β	γ	α	β	γ
All	-6.92	8.36	2.08	-6.95	9.02	0.28
Firms	(-0.14)	(2.28)	(2.29)	(-0.15)	(3.10)	(-0.43)
Investment	-7.29	13.19	3.16	-9.39	14.0	0.56
Grade	(-0.15)	(2.12)	(2.36)	(-0.20)	(2.97)	(0.56)
Speculative	-9.09	3.00	0.81	-4.81	9.54	0.32
Grade	(-0.17)	(0.68)	(1.20)	(-0.09)	(2.67)	(0.50)
CDS/Debt	-10.61	36.77	4.13	-8.90	32.82	-0.56
< 50%	(-0.23)	(3.50)	(1.29)	(-0.19)	(3.65)	(-0.29)
CDS/Debt	-0.84	3.09	2.05	-0.54	0.57	0.52
> 50%	(-0.02)	(0.78)	(2.58)	(-0.01)	(1.81)	(0.92)

Table 2.5: **Predictability of net CDS-to-debt ratio for weekly CDS premium in long horizon**

This table reports the results of cross-sectional univariate regressions of weekly changes in CDS premium on changes in CDS-to-debt ratio up to 5 weeks from Nov. 2008 through Jun. 2011. CDS Premium$_{t+\tau}^i$ denotes τth week CDS premium change of firm i. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$\Delta \text{CDS Premium}_{t+\tau}^i = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)_t^i + \epsilon_{t+\tau}^i$$

	1st		2nd		3rd		4th		5th	
	α	β	α	β	α	β	α	β	α	β
All	-4.62	8.84	-10.34	13.48	-10.08	5.90	-10.44	0.58	-10.61	1.39
Firms	(-0.10)	(3.17)	(-0.21)	(3.87)	(-0.21)	(2.28)	(-0.21)	(0.22)	(-0.22)	(0.53)
Investment	-5.65	14.77	-8.66	19.32	-9.41	11.47	-9.50	5.15	-9.84	0.52
Grade	(-0.12)	(3.21)	(-0.18)	(4.16)	(-0.19)	(3.46)	(-0.19)	(1.38)	(-0.20)	(0.14)
Speculative	-0.50	8.80	-12.68	13.93	-12.64	-0.35	-13.52	-1.29	-16.73	2.00
Grade	(0.01)	(2.55)	(-0.23)	(1.98)	(-0.22)	(-0.09)	(-0.24)	(-0.27)	(-0.30)	(0.55)
CDS/Debt	-7.72	33.99	-13.13	30.85	-12.56	-0.24	-11.57	11.22	-13.36	1.89
< 50%	(-0.16)	(4.01)	(-0.27)	(3.55)	(-0.26)	(-0.04)	(-0.24)	(1.35)	(-0.27)	(0.26)
CDS/Debt	7.29	5.93	-1.60	10.79	-1.67	7.27	-3.99	-1.75	-3.60	2.01
> 50%	(0.15)	(1.94)	(-0.03)	(4.03)	(-0.03)	(2.54)	(-0.08)	(-0.66)	(-0.07)	(0.73)

Table 2.6: **Predictability of CDS-to-debt ratio for weekly stock returns**

This table reports the results of cross-sectional regressions of weekly 4-factor adjusted stock returns on changes in CDS-to-debt ratio from Nov. 2008 through Jun. 2011. The independent variables are constructed from both net and gross notional amounts of CDS and total debt. R_{t+1} is weekly adjusted return from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$R_{t+1 \text{ or } t}^{i} = \alpha + \beta \Delta \left(\frac{\text{CDS}}{\text{Debt}} \right)_{t}^{i} + \epsilon_{t+1 \text{ or } t}^{i}$$

| | Net CDS-to-debt | | | | Gross CDS-to-debt | | | |
| | Current week | | Next week | | Current week | | Next week | |
	α	β	α	β	α	β	α	β
All	-2.42	-2.38	2.95	-3.59	2.13	-0.05	2.08	0.15
Firms	(0.42)	(-1.94)	(0.51)	(-2.89)	(0.37)	(-0.32)	(0.37)	(1.18)
Investment	2.47	-3.52	2.65	-4.84	2.63	-0.06	2.65	0.20
Grade	(0.49)	(-2.76)	(0.52)	(-3.42)	(0.50)	(-0.31)	(0.50)	(0.87)
Speculative	1.19	-3.44	3.34	-4.85	-2.17	0.00	-2.02	0.26
Grade	(0.10)	(-1.62)	(0.28)	(-1.84)	(-0.18)	(0.00)	(-0.18)	(0.84)
CDS/Debt	3.90	-12.12	3.71	-11.87	4.35	-0.26	3.64	0.37
< 50%	(0.69)	(-4.34)	(0.65)	(-3.49)	(0.78)	(-0.49)	(0.66)	(0.60)
CDS/Debt	-2.11	-0.66	-0.04	-2.31	-3.44	0.01	-1.38	0.07
> 50%	(-0.19)	(-0.48)	(-0.00)	(-1.67)	(-0.31)	(0.09)	(-0.13)	(0.56)

Table 2.7: **Predictability of both net and gross CDS-to-debt ratio for weekly stock returns**

This table reports the results of cross-sectional regressions of weekly 4-factor adjusted stock returns on changes in both net and gross CDS-to-debt ratio from Nov. 2008 through Jun. 2011. The independent variables are constructed from both net and gross notional amounts of CDS and total debt. R_{t+1} is weekly risk-adjusted return from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$R^i_{t+1 \text{ or } t} = \alpha + \beta\Delta \left(\frac{\text{Net CDS}}{\text{Debt}} \right)^i_t + \gamma\Delta \left(\frac{\text{Gross CDS}}{\text{Debt}} \right)^i_t + \epsilon^i_{t+1 \text{ or } t}$$

	Current week			Next week		
	α	β	γ	α	β	γ
All	2.23	-2.87	0.03	2.14	-3.62	0.23
Firms	(0.40)	(-2.22)	(0.21)	(0.39)	(-2.88)	(1.77)
Investment	2.65	-3.38	-0.04	2.61	-4.75	0.22
Grade	(0.52)	(-2.47)	(-0.21)	(0.50)	(-3.38)	(0.98)
Speculative	-0.40	-5.17	-0.13	-0.25	-6.00	0.19
Grade	(-0.03)	(-2.17)	(-0.42)	(-0.02)	(-2.17)	(0.57)
CDS/Debt	4.02	-11.45	-0.19	3.35	-11.76	0.52
< 50%	(0.71)	(-4.19)	(-0.38)	(0.60)	(-3.61)	(0.86)
CDS/Debt	-2.94	-1.28	0.08	-1.03	-2.51	0.17
> 50%	(-0.27)	(-0.87)	(0.54)	(-0.10)	(-1.82)	(1.23)

Table 2.8: **Predictability of net CDS-to-debt ratio for weekly stock returns in long horizon**

This table reports the results of cross-sectional regressions of weekly stock returns on changes in CDS-to-debt ratio up to 5 weeks from Nov. 2008 through Jun. 2011. $R_{t+\tau}^i$ denotes τth week stock return of firm i. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$R_{t+\tau}^i = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)_t^i + \epsilon_{t+\tau}^i$$

	1st		2nd		3rd		4th		5th	
	α	β	α	β	α	β	α	β	α	β
All	2.95	-3.59	3.23	-3.83	3.64	-3.30	3.34	-1.62	3.56	-0.40
Firms	(0.51)	(-2.89)	(0.56)	(-3.22)	(0.62)	(-3.21)	(0.57)	(-1.85)	(0.60)	(-0.46)
Investment	2.65	-4.84	2.67	-4.76	6.52	-6.15	2.41	-2.91	2.07	-1.08
Grade	(0.52)	(-3.42)	(0.51)	(-3.40)	(0.50)	(-3.00)	(0.45)	(-2.23)	(0.38)	(-0.96)
Speculative	3.34	-4.85	4.60	-6.48	2.67	-4.53	5.79	-3.68	7.16	-1.08
Grade	(0.28)	(-1.84)	(0.41)	(-1.92)	(0.56)	(-2.61)	(0.51)	(-1.99)	(0.63)	(-0.71)
CDS/Debt	3.71	-11.87	2.88	-10.20	2.38	-8.46	1.34	-7.33	1.31	-3.84
< 50%	(0.65)	(-3.49)	(0.51)	(-3.56)	(0.42)	(-2.44)	(0.24)	(-2.18)	(0.23)	(-1.54)
CDS/Debt	-0.04	-2.31	2.34	-3.08	3.73	-2.49	4.81	-0.80	6.05	0.03
> 50%	(-0.00)	(-1.67)	(0.23)	(-2.55)	(3.73)	(-2.52)	(0.47)	(-0.90)	(0.59)	(0.03)

Table 2.9: **Predictability of net CDS-to-debt ratio for daily stock returns**

This table reports the results of cross-sectional regressions of daily 4-factor adjusted stock returns on changes in CDS-to-debt ratio from Nov. 2008 through Jun. 2011. The independent variables are constructed from both net and gross notional amounts of CDS and total debt. $R_{t+\omega+1,t+\omega}$ is 1 day return from time $t + \omega$ where ω denotes weekday or delay. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$R_{t+\omega+1,t+\omega}^{i} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)_{t}^{i} + \epsilon_{t+\omega+1}^{i}$$

	Mon		Tue		Wed		Thu		Fri	
	α	β	α	β	α	β	α	β	α	β
All	0.09	-0.59	0.37	-0.74	0.24	-0.61	0.36	-0.69	0.12	-0.77
Firms	(0.07)	(-2.09)	(0.33)	(-2.93)	(0.20)	(-2.36)	(0.29)	(-2.78)	(0.09)	(-3.24)
Investment	0.30	-0.94	0.33	-0.96	0.30	-0.93	0.35	-0.95	0.13	-0.88
Grade	(0.27)	(-3.15)	(0.33)	(-3.47)	(0.29)	(-3.30)	(0.33)	(-3.32)	(0.12)	(-2.99)
Speculative	-0.75	-0.80	0.42	-0.98	-0.06	-0.78	0.27	-0.88	-0.05	-1.34
Grade	(-0.32)	(-1.66)	(0.17)	(-1.83)	(-0.03)	(-1.52)	(0.11)	(-1.69)	(-0.02)	(-2.00)
CDS/Debt	0.43	-2.26	0.57	-2.44	0.44	-2.17	0.49	-2.54	0.25	-2.61
< 50%	(0.37)	(-3.74)	(0.52)	(-3.46)	(0.37)	(-3.29)	(0.40)	(-3.36)	(0.19)	(-3.43)
CDS/Debt	-0.92	-0.29	-0.31	-0.42	-0.46	-0.38	-0.14	-0.46	-0.36	-0.54
> 50%	(-0.43)	(-0.94)	(-0.14)	(-1.66)	(-0.22)	(-1.32)	(-0.07)	(-1.66)	(-0.17)	(-1.96)

Chapter 3

The Relationship between Credit Default Swap Volume and Put Option Prices

3.1 Introduction

Credit default swaps (CDS) and put options are similar in that both provide protection against downside risk at a low cost to their holders. A CDS is a bilateral contract between two counterparties in which the writer offers the buyer protection against a credit event by the reference entity for a specified period of time. The buyer pays premium regularly, quarterly in usual, and receives payoff if a credit event such as failure to pay, bankruptcy, and restructuring, occurs to the reference entity before the maturity date. Since the CDS buyer is not required to hold the insured risk at the time that a claim is made, CDS have been used by investors not only for hedging a credit event but also for speculation with anticipation that the reference entity is highly likely to suffer a credit event. Regardless of what they are used for, CDS could contain useful information about credit risks because CDS are designed for likelihood of the default. The exponential growth of CDS market during the last decade can suggest that a number of investors who have lots of concern on credit risks have been trading CDS such that new information about credit risk would be

reflected in the CDS market first.[1]

Equity put option is a contract between two parties in which the buyer has the right, but not an obligation, to sell the underlying equity at the strike price by maturity, while the seller, has the obligation to buy the asset at the strike price if the buyer exercises the option. A put option is used in similar purpose to a credit default swap. The most obvious use of a put option is as a type of insurance. In the protective put option strategy, the investor buys enough put options to cover their holdings of the equity so that if a drastic downward movement of the underlying equity's price occurs, they have the option to sell the holdings at the strike price. Another use is for speculation: an investor can take a short position in the underlying equity without trading in it directly.

Since both CDS and put options are used in hedging and negative side bets for the reference (underlying) firms, one might expect that there could exist the close relationship between CDS and put options. In response, recent literature has explored the role of volatility in determination of CDS spreads. Pan and Singleton (2008) extract the credit risk premium from sovereign CDS spreads and find that it co-varies with several economic measures of the financial market volatility including VIX. Zhang et al. (2009) suggest that the volatility risk alone predicts considerable portion of variation in CDS spreads from high-frequency data. Wang et al. (2010) analyzed the predictability of variance risk premium for credit spreads at firm level.

However the relationship between CDS *volume* and put option has not been done. A novelty of the paper is in its examination of this relationship. CDS net notional outstanding is the actual size of the potential claims which are transferred from one pocket to others in case of the credit event. Especially when it is combined with the total amount of outstanding debt, it directly shows how much of the debt is insured with CDS. The ratio of CDS net notional outstanding to the total amount of debt is a natural measure of investors' concern on the credit risk of the reference entity.[2] Therefore, it is worth investigating whether CDS net notional contain has the informational content for future put option returns and changes in implied volatilities. This study could enlarge our understanding on the information in

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[1]See chapter 2 on detail explanation.

[2]See chapter 2 on detail explanation.

CDS volume for future asset prices.[3]

To address the informational relationship, I first perform the weekly contemporaneous analysis between CDS-to-debt ratios and both returns and changes in implied volatilities of put options. Regression analysis suggests that movements in put options cannot be accompanied by CDS-to-debt ratios for all put options with time-to-maturities of 1, 3, and 6 months. This implies that the common risk components in determination of CDS volume and put option prices cannot be found. Secondly I look into the predictability of CDS-to-debt ratios for future movements in prices and implied volatilities of put options in daily basis. The regression results show that CDS-to-debt ratios have no forecasting power in predicting put options prices and their implied volatilities for all time-to-maturities. All of these results suggest that there exists no close relationship in credit default swaps volume and put option prices. The regression estimates are not statistically significant and display specific patterns in neither magnitude nor sign. This is not incompatible with the findings in the chapter 2: credit default swaps volume have informational content not on raw stock returns but on adjusted stock returns. Stock prices are driven by a number of factors such as market, size, value, and momentum. If these factors have greater influence on stock returns than credit risk have, the informational content in CDS net notional for stock prices might be captured in not raw returns but adjusted returns. Since options are mostly contingent on stock prices, if option returns are not controlled by major risk factors, it is hard to observe the relationship between CDS volume and put option prices.

This paper focuses on on the relationship between put option and credit default swap volume. In the context of the relationship between put option and credit risks other than credit default swap volume, Cremers et al. (2008) investigate whether implied volatilities contain useful information for credit spreads. They show that both the level of individual implied volatilities and the implied-volatility skew are determinants of credit spreads. Cao et al. (2010) find that put option implied volatilities dominate historical volatilities in explaining the time-series variation in CDS spreads. The disconnection between CDS volume and put option prices could be attributed to the difference in their underlying assets and

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[3]Chapter 2 finds cross-sectional predictability of credit default swap volume for future CDS and stock prices.

time-to-maturities, which would be investigated in advance.

The rest of the paper proceeds as follows. Section 3.2 describes the data. Section 3.3 examines the relationship between credit default swaps volume and put options and discusses the findings. Section 3.4 concludes.

3.2 Data

The list of firms that are included in this study is the same that is employed in chapter 2. It consists of 208 US companies enlisted in NYSE and NASDAQ from November 2008 to December 2011. They are neither in financial nor utility sectors. For all firms, the options trading data and the amounts of debt issued are available in OptionMetrics and Compustat respectively. CDS net notional and premium quotes are also available. To investigate the relationship between credit default swaps volume and put options, I obtain these data sets from the following sources.

3.2.1 The credit default swap volume

I obtain the CDS contract data from the Depository Trust & Clearing Corporation's (DTCC) Trade Information Warehouse (TIW). The data include weekly CDS aggregate gross and net notional positions written against single name reference entities.[4]

3.2.2 The debt

I obtain the total amounts of debt outstanding issued by the firms from Compustat to form CDS-to-debt ratios. Total outstanding debt is measured by the sum of long-term debt (#9) and debt in current liabilities (#34).

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[4]Section 2.3.1 explains gross and net notional outstanding in detail. Figure 2.4 illustrates an example of CDS positions over the counter which describes gross and net notional calculation and trade compression in detail.

3.2.3 Put option

I obtain daily put options information from the OptionMetrics which provides daily trading information such as closing prices, implied volatility, open interest, and trading volume on exchange-listed equity options in the US. I choose non-zero open interest at-the-money (ATM) put options of which the information content are currently in use by market participants. I compute daily returns and changes in implied volatility of put options for maturity of 1, 3, and 6 months, and test the relationship between these put options and CDS-to-debt ratios.

3.2.4 S&P credit ratings

I obtain credit ratings from Standard & Poor's (S&P) through Bloomberg system.

3.3 Empirical results

This study primarily investigates the relationship between CDS-to-debt ratios and returns and changes in implied volatility of put options. I construct CDS-to-debt ratios from net notional, that is, the sum of net positive positions of all market participants, and total outstanding debt issued by the reference entity.[5] The ratio of CDS notional to total debt is used as an explanatory variable for predictive regressions to test the relationship.

3.3.1 Put option return

In this section, I examine the relationship between CDS-to-debt ratios and put option prices. First, contemporaneous analysis is performed using following regression:

$$R_{t+1,t}^i = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)_t^i + \epsilon_{t+1}^i \tag{3.1}$$

where $R_{t+1,t}^i$ denotes the weekly option returns. Regression results are shown in Table 3.1. I find no evidence that CDS-to-debt ratios co-move with put option prices for all time-to-maturities of 1, 3, and 6 months in any direction. All of estimates are not significant and

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[5]Sample distribution of CDS-to-debt ratios is reported in Tables 2.1 and 2.2.

both magnitude and sign does not show any specific pattern. The result implies that credit
default swaps volume and put option prices are not associated simultaneously.

Next, I explore the informational content in CDS-to-debt ratios for the future put option
prices. Predictive analysis is executed using following regression:

$$R^i_{t+\tau,t} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)^i_t + \epsilon^i_{t+\tau} \tag{3.2}$$

where $R^i_{t+\tau,t}$ represents the τ-day put option returns. The results are demonstrated in
Tables 3.3, 3.4, and 3.5. Similarly to contemporaneous regression, there is no predictability
of CDS-to-debt ratios for the future put option price movements for all time-to-maturities
of 1, 3, and 6 months except. This suggests that CDS-to-debt ratios have no informational
content, which is not contrary to the findings in chapter 2. CDS net notional has the
informational content for stock returns adjusted by market, size, value, momentum factors,
and doesn't forecast the raw stock returns. A number of risk factors including credit risk are
playing roles in determination of stock prices and the component of stock returns which are
not explained by major risk factors are captured in CDS volume. Put options are derivative
contracts dependent on stock prices and if option returns are not controlled by those factors,
there might exist no close relationship between CDS net notional and put option prices.

3.3.2   Changes in implied volatility

In this section, I investigate the relationship between CDS-to-debt ratios and implied volatil-
ities. First, contemporaneous analysis is performed using following regression:

$$IV^i_{t+1,t} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)^i_t + \epsilon^i_{t+1} \tag{3.3}$$

where $IV^i_{t+1,t}$ denotes the weekly changes in implied volatilities respectively. Regression
results are shown in Table 3.2. It indicates that implied volatilities seems to have no
connection with CDS-to-debt ratio concurrently for all kinds of option except the options
with 1 month time-to-maturity and their underlying firms are less than 50% insured by
CDS. For those firms, put option implied volatility increases around 3% while CDS-to-debt
ratio rises 1%. However, it is marginally significant – t-stat is 2.1 – it might not imply that
there exists close relationship between those two.

I also test whether CDS-to-debt ratios can predict movements of implied volatilities of
put options. I perform the predictive analysis using following regressions:

$$IV_{t+\tau,t}^i = \alpha + \beta \Delta \left(\frac{\text{CDS}}{\text{Debt}} \right)_t^i + \epsilon_{t+\tau}^i \tag{3.4}$$

where $IV_{t+\tau,t}^i$ represents the τ-day changes in put option implied volatilities. Tables 3.6, 3.7,
and 3.8 show the result for options with time-to-maturities of 1, 3, and 6 months respectively.
The results present that CDS-to-debt ratios has no forecasting power in predicting the future
changes in put option implied volatilities for all time-to-maturities of 1, 3, and 6 months.

All regression analysis suggest that there exists no close relationship between credit
default swaps volume and put option prices. This disconnection could come from the
difference in their features in underlying and maturity. Credit default swaps are contingent
claim on the debt issued by the reference firms while equity put options depends on the
underlying stocks. Most actively traded CDS are of 5-year maturity and CDS quotes are
derived based on this time-to-maturity. On the other hand, the longest time-to-maturity
for liquid put options is only 6 months. Therefore when stock prices moves, put option
prices correspond no matter whether it is related with the credit risk. For instance, if
stocks fluctuates notably by the risk such as noise trader risk which is independent to the
credit risk, there will be considerable change in put option prices but there might not be
significant variation in demand for credit default swaps. Since large portion of CDS traders
are insiders and dealers, they could be in better position to distinguish whether the risk
that moves stock prices is connected to the likelihood of the credit event. Especially stock
prices are exposed to lots of risks and noises. When the risks and noises are short-lived
and have no component from credit risk, credit default swaps volume and put option prices
could not be linked. This disparity needs to be scrutinized in advance.

3.4 Conclusion

This paper studies the relationship between the credit default swaps net notional and put
option prices. From the similarity between CDS and put option in terms of payoff structure,
one can expect the close connection which is found in neither contemporaneous nor predic-
tive analysis. CDS-to-debt ratio, a natural indicator of investors' view on credit event, is

not associated with put option prices concurrently. Neither has the ratio forecasting power

in predicting future put option price movement for all time-to-maturities.

Table 3.1: **Contemporaneous analysis of net CDS-to-debt ratio for weekly put
option returns**

This table reports the results of cross-sectional regressions of weekly put option returns with
maturity of 1, 3, and 6 months on changes in CDS-to-debt ratio from Nov. 2008 through
Dec. 2011. The independent variables are constructed from net notional amounts of CDS
and total debt. $R_{t+1,t}$ is a week return from time t. Since information on CDS notional is
collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses.
The time-series correlation is controlled by using Newey and West (1987) with five-week
lags.

$$R^i_{t+1,t} = \alpha + \beta \Delta \left(\frac{\text{CDS}}{\text{Debt}} \right)^i_t + \epsilon^i_{t+1}$$

	1M		3M		6M	
	α	β	α	β	α	β
All	-5.41	-0.11	-2.9	-0.01	-1.97	-0.1
Firms	(-1.94)	(-0.44)	(-1.59)	(-0.03)	(-1.55)	(-0.48)
Investment	-5.61	-0.04	-3.17	-0.08	-2.07	0.16
Grade	(-1.99)	(-0.12)	(-1.67)	(-0.13)	(-1.57)	(0.44)
Speculative	-4.48	0.23	-2.84	0.86	-1.96	-0.63
Grade	(-1.57)	(0.46)	(-1.62)	(0.92)	(-1.56)	(-0.56)
CDS/Debt	-5.29	-0.85	-3.14	0.19	-2.19	-0.36
< 50%	(-1.87)	(-1.16)	(-1.71)	(0.31)	(-1.72)	(-0.58)
CDS/Debt	-5.86	-0.09	-2.13	0.59	-1.32	-0.16
> 50%	(-2.13)	(-0.39)	(-1.08)	(1.09)	(-0.92)	(-0.43)

Table 3.2: **Contemporaneous analysis of net CDS-to-debt ratio for weekly change in put option implied volatilities**

This table reports the results of cross-sectional regressions of weekly put option implied volatilities with maturity of 1, 3, and 6 months on changes in CDS-to-debt ratio from Nov. 2008 through Dec. 2011. The independent variables are constructed from net notional amounts of CDS and total debt. $IV_{t+1,t}$ is a week change in implied volatility from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$IV_{t+1,t}^i = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)_t^i + \epsilon_{t+1}^i$$

	1M		3M		6M	
	α	β	α	β	α	β
All	0.25	0.05	-0.10	0.08	-0.03	0.01
Firms	(0.44)	(0.82)	(-0.24)	(0.77)	(-0.08)	(0.1)
Investment	0.26	-0.03	-0.14	0.18	-0.01	0.06
Grade	(0.43)	(-0.33)	(-0.30)	(1.12)	(-0.03)	(0.57)
Speculative	0.20	-0.06	0.20	-0.14	-0.08	-0.08
Grade	(0.39)	(-0.57)	(0.42)	(-0.75)	(-0.22)	(-0.29)
CDS/Debt	0.27	0.29	-0.08	0.05	-0.10	0.14
< 50%	(0.44)	(2.10)	(-0.18)	(0.32)	(-0.27)	(0.85)
CDS/Debt	0.16	-0.01	-0.01	0.11	0.09	-0.11
> 50%	(0.31)	(-0.20)	(-0.02)	(0.71)	(0.24)	(-0.77)

Table 3.3: **Predictability of net CDS-to-debt ratio for daily option returns: 1 month**

This table reports the results of cross-sectional regressions of daily put option returns with maturity of 1 month on changes in CDS-to-debt ratio from Nov. 2008 through Dec. 2011. The independent variables are constructed from net notional amounts of CDS and total debt. $R_{t+\tau,t}$ is τ-day return from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$R^i_{t+\tau,t} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)^i_t + \epsilon^i_{t+\tau}$$

	1		2		3		4		5	
	α	β	α	β	α	β	α	β	α	β
All	-1.86	-0.10	-2.87	-0.08	-3.33	0.00	-2.63	0.02	-5.11	-0.10
Firms	(-1.25)	(-1.26)	(-1.69)	(-0.72)	(-1.51)	(-0.03)	(-0.93)	(0.11)	(-1.83)	(-0.39)
Investment	-1.90	0.07	-2.90	-0.07	-3.50	0.21	-2.80	0.22	-5.32	0.05
Grade	(-1.27)	(0.58)	(-1.69)	(-0.44)	(-1.59)	(1.07)	(-0.98)	(0.89)	(-1.90)	(0.09)
Speculative	-1.73	-0.02	-2.63	-0.02	-2.80	-0.10	-1.81	-0.04	-4.09	-0.31
Grade	(-1.18)	(-0.17)	(-1.52)	(-0.07)	(-1.22)	(-0.50)	(-0.63)	(-0.16)	(-1.43)	(-0.94)
CDS/Debt	-1.91	0.29	-2.91	0.04	-3.23	0.26	-2.49	0.35	-4.96	0.37
< 50%	(-1.26)	(1.28)	(-1.70)	(0.14)	(-1.46)	(0.67)	(-0.87)	(0.72)	(-1.77)	(0.51)
CDS/Debt	-1.75	-0.14	-2.77	-0.12	-3.53	0.03	-2.94	0.08	-5.57	0.04
> 50%	(-1.23)	(-1.59)	(-1.62)	(-0.90)	(-1.59)	(0.17)	(-1.05)	(0.40)	(-1.99)	(0.16)

Table 3.4: **Predictability of net CDS-to-debt ratio for daily option returns: 3 months**

This table reports the results of cross-sectional regressions of daily put option returns with maturity of 3 months on changes in CDS-to-debt ratio from Nov. 2008 through Dec. 2011. The independent variables are constructed from net notional amounts of CDS and total debt. $R_{t+\tau,t}$ is τ-day return from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$R^i_{t+\tau,t} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)^i_t + \epsilon^i_{t+\tau}$$

	1		2		3		4		5	
	α	β	α	β	α	β	α	β	α	β
All	-1.20	-0.10	-1.85	-0.20	-2.30	-0.02	-1.46	0.11	-2.67	0.10
Firms	(-1.25)	(-0.97)	(-1.67)	(-1.59)	(-1.60)	(-0.10)	(-0.79)	(0.55)	(-1.46)	(0.38)
Investment	-1.36	-0.02	-1.99	-0.08	-2.49	0.15	-1.69	0.06	-2.82	-0.67
Grade	(-1.43)	(-0.12)	(-1.78)	(-0.35)	(-1.74)	(0.59)	(-0.89)	(0.20)	(-1.49)	(-1.26)
Speculative	-0.70	-0.45	-1.90	-0.48	-2.04	0.05	-1.47	0.27	-2.47	1.38
Grade	(-0.70)	(-1.41)	(-1.58)	(-1.58)	(-1.30)	(0.15)	(-0.79)	(0.60)	(-1.39)	(1.48)
CDS/Debt	-1.27	0.00	-2.01	-0.49	-2.42	-0.72	-1.48	-1.09	-2.69	-1.46
< 50%	(-1.30)	(-0.02)	(-1.78)	(-1.26)	(-1.66)	(-1.39)	(-0.79)	(-1.67)	(-1.44)	(-1.72)
CDS/Debt	-1.08	-0.23	-1.30	-0.08	-1.81	0.21	-1.32	0.40	-2.23	0.64
> 50%	(-1.12)	(-1.65)	(-1.11)	(-0.27)	(-1.25)	(0.74)	(-0.70)	(1.27)	(-1.17)	(1.16)

Table 3.5: **Predictability of net CDS-to-debt ratio for daily option returns: 6 months**

This table reports the results of cross-sectional regressions of daily put option returns with maturity of 6 months on changes in CDS-to-debt ratio from Nov. 2008 through Dec. 2011. The independent variables are constructed from net notional amounts of CDS and total debt. $R_{t+\tau,t}$ is τ-day return from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$R^i_{t+\tau,t} = \alpha + \beta \Delta \left(\frac{\text{CDS}}{\text{Debt}} \right)^i_t + \epsilon^i_{t+\tau}$$

	1		2		3		4		5	
	α	β	α	β	α	β	α	β	α	β
All	-0.61	-0.16	-1.23	-0.10	-1.47	-0.03	-0.98	0.01	-1.72	0.08
Firms	(-0.86)	(-2.01)	(-1.59)	(-1.03)	(-1.47)	(-0.20)	(-0.75)	(0.09)	(-1.33)	(0.45)
Investment	-0.64	-0.01	-1.27	0.23	-1.51	0.29	-1.00	0.2	-1.84	-0.24
Grade	(-0.89)	(-0.05)	(-1.63)	(0.96)	(-1.49)	(0.98)	(-0.74)	(0.89)	(-1.39)	(-0.77)
Speculative	-0.36	-0.27	-1.17	-0.38	-1.29	0.09	-0.79	0.33	-1.53	1.39
Grade	(-0.53)	(-1.28)	(-1.45)	(-1.70)	(-1.22)	(0.29)	(-0.62)	(0.87)	(-1.21)	(1.62)
CDS/Debt	-0.63	-0.08	-1.37	-0.22	-1.51	-0.03	-0.98	-0.23	-1.92	0.12
< 50%	(-0.88)	(-0.45)	(-1.76)	(-0.88)	(-1.51)	(-0.07)	(-0.75)	(-0.60)	(-1.52)	(0.26)
CDS/Debt	-0.58	-0.17	-0.86	-0.11	-1.29	-0.02	-1.00	-0.05	-1.04	0.02
> 50%	(-0.83)	(-1.80)	(-1.04)	(-0.77)	(-1.27)	(-0.11)	(-0.73)	(-0.28)	(-0.70)	(0.07)

Table 3.6: **Predictability of net CDS-to-debt ratio for daily change in put option implied volatilities: 1 month**

This table reports the results of cross-sectional regressions of daily put option implied volatilities with maturity of 1 month on changes in CDS-to-debt ratio from Nov. 2008 through Dec. 2011. The independent variables are constructed from net notional amounts of CDS and total debt. $IV_{t+\tau,t}$ is τ-day return from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$IV^i_{t+\tau,t} = \alpha + \beta \Delta \left(\frac{\text{CDS}}{\text{Debt}} \right)^i_t + \epsilon^i_{t+\tau}$$

	1		2		3		4		5	
	α	β	α	β	α	β	α	β	α	β
All	0.96	-0.02	0.74	-0.04	0.45	0	0.95	0.03	0.32	-0.04
Firms	(3.85)	(-0.64)	(2.45)	(-0.87)	(1.21)	(-0.07)	(1.98)	(0.45)	(0.56)	(-0.79)
Investment	0.97	-0.05	0.76	-0.08	0.42	-0.01	0.94	-0.03	0.30	-0.02
Grade	(3.73)	(-0.83)	(2.44)	(-0.72)	(1.06)	(-0.06)	(1.91)	(-0.27)	(0.50)	(-0.29)
Speculative	0.88	-0.02	0.60	0.00	0.46	0.01	0.87	0.10	0.27	0.05
Grade	(3.68)	(-0.22)	(1.98)	(-0.07)	(1.43)	(0.08)	(1.93)	(0.99)	(0.52)	(0.50)
CDS/Debt	0.96	0.10	0.72	-0.22	0.41	-0.03	0.93	-0.27	0.35	-0.17
< 50%	(3.65)	(1.16)	(2.35)	(-1.69)	(1.03)	(-0.28)	(1.90)	(-1.60)	(0.58)	(-1.27)
CDS/Debt	0.95	-0.06	0.77	-0.02	0.52	0.02	0.93	0.10	0.19	-0.11
> 50%	(3.96)	(-1.18)	(2.49)	(-0.37)	(1.53)	(0.24)	(1.96)	(1.65)	(0.37)	(-1.29)

Table 3.7: **Predictability of net CDS-to-debt ratio for change in put option implied volatilities: 3 months**

This table reports the results of cross-sectional regressions of daily put option implied volatilities with maturity of 3 months on changes in CDS-to-debt ratio from Nov. 2008 through Dec. 2011. The independent variables are constructed from net notional amounts of CDS and total debt. $IV_{t+\tau,t}$ is τ-day return from time t. Since information on CDS notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in parentheses. The time-series correlation is controlled by using Newey and West (1987) with five-week lags.

$$IV^i_{t+\tau,t} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)^i_t + \epsilon^i_{t+\tau}$$

	1		2		3		4		5	
	α	β	α	β	α	β	α	β	α	β
All	0.04	0.01	-0.25	-0.04	-0.36	0.02	0.19	-0.03	-0.05	0.03
Firms	(0.24)	(0.21)	(-1.16)	(-0.63)	(-1.29)	(0.45)	(0.51)	(-0.47)	(-0.12)	(0.46)
Investment	0.03	-0.06	-0.28	-0.08	-0.40	0.11	0.15	-0.06	-0.11	0.16
Grade	(0.18)	(-0.76)	(-1.26)	(-0.81)	(-1.38)	(1.49)	(0.39)	(-0.47)	(-0.23)	(1.23)
Speculative	0.04	-0.10	-0.24	-0.18	-0.30	-0.04	0.14	-0.13	-0.21	-0.51
Grade	(0.17)	(-0.79)	(-0.88)	(-1.41)	(-0.99)	(-0.36)	(0.32)	(-0.70)	(-0.46)	(-2.61)
CDS/Debt	0.07	0.08	-0.27	0.02	-0.36	0.05	0.20	-0.12	-0.09	-0.07
< 50%	(0.36)	(0.83)	(-1.25)	(0.18)	(-1.23)	(0.42)	(0.53)	(-0.73)	(-0.19)	(-0.40)
CDS/Debt	0.08	-0.01	-0.13	0.09	-0.20	0.11	0.31	0.11	0.06	0.07
> 50%	(0.37)	(-0.17)	(-0.46)	(0.89)	(-0.72)	(1.15)	(0.82)	(0.93)	(0.14)	(0.58)

Table 3.8: **Predictability of net CDS-to-debt ratio for daily change in put option
implied volatilities: 6 months**

This table reports the results of cross-sectional regressions of daily put option implied
volatilities with maturity of 6 months on changes in CDS-to-debt ratio from Nov. 2008
through Dec. 2011. The independent variables are constructed from net notional amounts
of CDS and total debt. $IV_{t+\tau,t}$ is τ-day return from time t. Since information on CDS
notional is collected on Fridays, t is always Friday. Fama-MacBeth t-stats are reported in
parentheses. The time-series correlation is controlled by using Newey and West (1987) with
five-week lags.

$$IV^i_{t+\tau,t} = \alpha + \beta\Delta\left(\frac{\text{CDS}}{\text{Debt}}\right)^i_t + \epsilon^i_{t+\tau}$$

	1		2		3		4		5	
	α	β	α	β	α	β	α	β	α	β
All	-0.07	0.03	-0.29	0.04	-0.33	-0.01	0.03	-0.02	-0.01	-0.09
Firms	(-0.52)	(0.56)	(-1.73)	(0.85)	(-1.47)	(-0.19)	(0.09)	(-0.40)	(-0.03)	(-1.27)
Investment	-0.10	-0.07	-0.31	-0.08	-0.35	-0.09	-0.02	-0.13	0.01	-0.20
Grade	(-0.69)	(-0.49)	(-1.78)	(-0.58)	(-1.51)	(-1.13)	(-0.05)	(-1.24)	(0.02)	(-1.34)
Speculative	0.14	0.07	-0.20	0.02	-0.28	0.04	0.24	0.01	-0.14	0.01
Grade	(0.76)	(0.68)	(-0.99)	(0.23)	(-1.10)	(0.40)	(0.79)	(0.08)	(-0.40)	(0.04)
CDS/Debt	-0.12	0.09	-0.39	0.05	-0.37	0.01	-0.01	-0.09	-0.04	-0.12
< 50%	(-0.83)	(0.92)	(-2.29)	(0.56)	(-1.60)	(0.09)	(-0.03)	(-0.93)	(-0.10)	(-0.82)
CDS/Debt	0.00	-0.01	-0.03	0.03	-0.19	0.00	0.10	0.00	0.07	-0.08
< 50%	(-0.01)	(-0.12)	(-0.11)	(0.47)	(-0.82)	(-0.01)	(0.32)	(-0.02)	(0.19)	(-0.97)

Bibliography

Acharya, V. and Johnson, T. (2007). Insider trading in credit derivatives. *Journal of Financial Economics*, 84(1):110–141.

Aït-Sahalia, Y. (1999). Transition densities for interest rate and other nonlinear diffusions. *The journal of finance*, 54(4):1361–1395.

Aït-Sahalia, Y. and Duarte, J. (2003). Nonparametric option pricing under shape restrictions. *Journal of Econometrics*, 116(1):9–47.

Aït-Sahalia, Y. and Lo, A. (1998). Nonparametric estimation of state-price densities implicit in financial asset prices. *The Journal of Finance*, 53(2):499–547.

Amihud, Y., Mendelson, H., and Pedersen, L. (2005). Liquidity and asset prices. *Foundation and Trends in Finance*, 1(4):1–96.

Black, F. (1975). Fact and fantasy in the use of options. *Financial Analysts Journal*, 31:36–72.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *The journal of political economy*, pages 637–654.

Blanco, R., Brennan, S., and Marsh, I. (2005). An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. *The Journal of Finance*, 60(5):2255–2281.

Campbell, J., Lo, A., and MacKinlay, A. (1997). *The econometrics of financial markets*. Princeton University Press Princeton, NJ.

Cao, C., Yu, F., and Zhong, Z. (2010). The information content of option-implied volatility for credit default swap valuation. *Journal of Financial Markets*, 13(3):321–343.

Carr, P. and Madan, D. (1999). Option valuation using the fast fourier transform. *Journal of Computational Finance*, 2(4):61–73.

Chakravarty, S., Gulen, H., and Mayhew, S. (2004). Informed trading in stock and option markets. *The Journal of Finance*, 59(3):1235–1258.

Chaplin, G. (2005). *Credit derivatives: risk management, trading & investing*. Wiley.

Che, Y. and Sethi, R. (2011). Credit derivatives and the cost of capital. *Working Paper*.

Chen, R. (1992). Exact solutions for futures and european futures options on pure discount bonds. *Journal of Financial and Quantitative Analysis*, 27(01):97–107.

Connor, G. and Linton, O. (2007). Semiparametric estimation of a characteristic-based factor model of common stock returns. *Journal of Empirical Finance*, 14(5):694–717.

Cox, J., Ingersoll Jr, J., and Ross, S. (1985). A theory of the term structure of interest rates. *Econometrica*, pages 385–407.

Cremers, M., Driessen, J., Maenhout, P., and Weinbaum, D. (2008). Individual stock-option prices and credit spreads. *Journal of Banking & Finance*, 32(12):2706–2715.

Diamond, D. and Verrecchia, R. (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics*, 18(2):277–311.

Duffie, D., Li, A., and Lubke, T. (2010). Policy perspectives on OTC derivatives market infrastructure. *Federal Reserve Bank of New York Staff Reports*, (424).

Duffie, D., Pan, J., and Singleton, K. (2000). Transform analysis and asset pricing for affine jump-diffusions. *Econometrica*, 68(6):1343–1376.

Duffie, D. and Singleton, K. (1997). An econometric model of the term structure of interest-rate swap yields. *Journal of finance*, pages 1287–1321.

Easley, D., O'hara, M., and Srinivas, P. (1998). Option volume and stock prices: Evidence on where informed traders trade. *The Journal of Finance*, 53(2):431–465.

Ericsson, J., Jacobs, K., and Oviedo, R. (2009). The determinants of credit default swap premia. *Journal of Financial and Quantitative Analysis*, 44(01):109–132.

Fama, E. and MacBeth, J. (1973). Risk, return and equilibrium: some empirical tests. *Journal of Political Economy*, 81:607–636.

Fan, J. (1992). Design-adaptive nonparametric regression. *Journal of the American statistical Association*, pages 998–1004.

Fan, J. and Gijbels, I. (1996). *Local polynomial modelling and its applications*. Chapman Hall.

Fiske, S. and Taylor, S. (1991). *Social cognition*. Mcgraw-Hill Book Company.

Gourieroux, C., Monfort, A., and Tenreiro, C. (2000). Panel data econometrics: Future directions. chap. kernel m-estimators.

Gozalo, P. and Linton, O. (2000). Local nonlinear least squares: Using parametric information in nonparametric regression. *Journal of econometrics*, 99(1):63–106.

Greene, W. (1997). *Econometric analysis*. Prentice Hall, 3rd edition.

Hamilton, J. (1994). *Time series analysis*. Princeton University Press, 2nd edition.

Hansen, L. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, pages 1029–1054.

Hansen, L. and Jagannathan, R. (1991). Implications of security market data for models of dynamic economies. *Journal of Political Economy*, 99(2):225–262.

Hansen, L. and Jagannathan, R. (1997). Assessing specification errors in stochastic discount factor models. *Journal of Finance*, 52(2):557–590.

Hardle, W., Hall, P., and Marron, J. (1988). How far are automatically chosen regression smoothing parameters from their optimum? *Journal of the American Statistical Association*, pages 86–95.

Hardle, W. and Linton, O. (1994). Applied nonparametric methods. *Handbook of econometrics*, 4:2295–2339.

Hardle, W. and Marron, J. (1985). Optimal bandwidth selection in nonparametric regression function estimation. *The Annals of Statistics*, 13(4):1465–1481.

Hausman, J. (1978). Specification tests in econometrics. *Econometrica*, pages 1251–1271.

Hong, H.and Stein, J. (2007). Disagreement and the stock market. *Journal of Economic Perspectives*, 21(2):109–128.

Hotchkiss, E. and Ronen, T. (2002). The informational efficiency of the corporate bond market: An intraday analysis. *Review of Financial Studies*, 15(5):1325–1354.

Jamshidian, F. (1989). An exact bond option formula. *Journal of Finance*, pages 205–209.

Jarrow, R. (2011). The economics of credit default swaps. *Annual Review of Financial Economics*, 3:2.1–2.23.

Jordan, B. and Kuipers, D. (1997). Negative option values are possible: The impact of treasury bond futures on the cash us treasury market. *Journal of Financial Economics*, 46(1):67–102.

Kane, A. and Marcus, A. (1984). Conversion factor risk and hedging in the treasury-bond futures market. *Journal of futures markets*, 4(1):55–64.

Livingston, M. (1987). The effect of coupon level on treasury bond futures delivery. *Journal of futures markets*, 7(3):303–309.

Longstaff, F., Mithal, S., and Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *The Journal of Finance*, 60(5):2213–2253.

Marin, J. and Rahi, R. (2000). Information revelation and market incompleteness. *Review of Economic Studies*, 67(3):563–579.

Matzkin, R. (1994). Restrictions of economic theory in nonparametric methods. *Handbook of econometrics*, 4:2523–2558.

Merton, R. (1973). Theory of rational option pricing. *The Bell Journal of Economics and Management Science*, pages 141–183.

Newey, W. and McFadden, D. (1994). Large sample estimation and hypothesis testing. *Handbook of econometrics*, 4:2111–2245.

Newey, W. and West, K. (1987). A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 29:229–256.

Ni, S. and Pan, J. (2010). Trading puts and CDS on stocks with short sale ban. *Working Paper*.

Norden, L. and Weber, M. (2009). The co-movement of credit default swap, bond and stock markets: an empirical analysis. *European Financial Management*, 15(3):529–562.

Oehmke, M. and Zawadowski, A. (2012). The anatomy of the cds market. *Working Paper*.

Pan, J. and Poteshman, A. (2006). The information in option volume for future stock prices. *Review of Financial Studies*, 19(3):871–908.

Pan, J. and Singleton, K. (2008). Default and recovery implicit in the term structure of sovereign cds spreads. *The Journal of Finance*, 63(5):2345–2384.

Ploberger, W. and Phillips, P. (2003). Empirical limits for time series econometric models. *Econometrica*, 71(2):627–673.

Powell, J. (1994). Estimation of semiparametric models. *Handbook of econometrics*, 4:2443–2521.

Rubinstein, M. (1994). Implied binomial trees. *Journal of finance*, pages 771–818.

Squam Lake Working Group on Financial Regulation (2009). *Credit Default Swaps, Clearinghouses, and Exchanges*. Council on Foreign Relations Press.

Stulz, R. (2010). Credit default swaps and the credit crisis. *Journal of Economic Perspectives*, 24(1):73–92.

Tibshirani, R. and Hastie, T. (1987). Local likelihood estimation. *Journal of the American Statistical Association*, pages 559–567.

Vasicek, O. (1977). An equilibrium characterization of the term structure. *Journal of financial economics*, 5(2):177–188.

Vause, N. (2010). Counterparty risk and contract volumes in the credit default swap market. *Bank for International Settlements Quarterly Review*, page 59.

Wang, H., Zhou, H., and Zhou, Y. (2010). Credit default swap spreads and variance risk premia. *Working Paper*.

White, H. (1982). Maximum likelihood estimation of misspecified models. *Econometrica*, pages 1–25.

Zhang, B., Zhou, H., and Zhu, H. (2009). Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. *Review of Financial Studies*, 22(12):5099–5131.