The complete picture of Credit Default Swap spreads - a Quantile Regression approach *

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Abstract

We study the determinants of Credit Default Swap (CDS) spreads through quantile regressions. In addition to traditional variables, the results indicate that CDS spreads are also determined by illiquidity costs. However, contrary to stocks or bonds, we show that CDS transaction costs should be measured by absolute, rather than relative, bid-ask spreads. Quantile regressions indicate that both the slopes and the goodness-of-fit of the model increase with CDS premiums, which is consistent with the credit spread puzzle. Furthermore, our results imply that the empirical models of CDS spreads based on classical mean regressions presented in most previous studies are only successful for the subset of high-risk firms.

JEL Classification: G12, G13, C14, C23

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1 Introduction

The existing theoretical models show that credit spreads depend on the probability of firms defaulting and on the fraction of the promised payments that bondholders are able to recover.[1] However, both of these variables are unobservable and hard to estimate. This has created the need for empirical research on good, easy-to-measure proxies for those fundamental variables. Even credit ratings, which have been widely used as credit risk proxies, are becoming subject to ever stronger criticisms. The reliability of credit rating agencies has been recurrently questioned with their failure to forewarn investors of the defaults of Enron, WorldCom, Parmalat, the bankruptcies following the collapse of the equity market bubble of the late 1990s, and the subprime crisis of 2007. Hence, good empirical models relating credit spreads to easily observable market variables are of crucial importance both to academics and market practitioners.

This paper examines the empirical determinants of Credit Default Swap (CDS) spreads. Following the existing literature, we study the explanatory power of the option-implied volatility, put skew, historical stock return, macroeconomic factors, and credit ratings. Additionally, we introduce CDS liquidity, measured by CDS bid-ask spreads, as an explanatory variable of CDS premiums. However, we argue that the appropriate measure to compare transaction costs across different CDS names is the *absolute*, rather than the relative, bid-ask spread. While this is an intuitive result from the way CDS prices are quoted in the market, it is contrary to the correct use of relative spreads in the stock and bond markets. Therefore, we provide a detailed discussion to support the use of the absolute spread.

We study the determinants of CDS spreads using quantile regressions (QR). While the classical linear regression only describes the conditional mean, the quantile regression describes the entire conditional distribution of the dependent variable. The QR has thus the potential to uncover differences in the response of the dependent variable across its different quantiles. The QR has been usefully applied in several areas of economics and finance to describe relations where the conditional distribution of the dependent variable

[1] There are two main approaches to credit risk modelling: the structural approach of Merton (1974), Black and Cox (1976), and many subsequent papers; and the reduced-form approach of Jarrow and Turnbull (1995), Duffie and Singleton (1999), and others. For recent attempts to reconcile the two approaches see, e.g., Duffie and Lando (2001).

changes significantly with the regressors (see the survey in Koenker and Hallock (2001)). In our particular application to CDS spreads, the QR allows the impact of a change in a given regressor to be different between firms with conditionally high or low credit risk. Hence, our approach is able to produce a robust and complete picture of the determinants of CDS spreads.

Using a panel data of monthly CDS spreads across 260 firms from the European and US markets, from Aug/2002 to Feb/2007, we find the following main results.

First, we find that CDS premiums are strongly correlated with the equity implied volatility, put skew, equity historical returns, and absolute CDS bid-ask spreads. While the first variables have been used in other papers, the results on bid-ask spreads are an important contribution of this paper. More precisely, we find that CDS premiums significantly increase with absolute bid-ask spreads across all conditional quantiles of the CDS distribution. Since the scarce theoretical literature on CDS liquidity is ambiguous as to whether liquidity should have a positive or negative effect on CDS spreads, our robust empirical evidence favors models where the liquidity premium is earned by the protection seller. Furthermore, our results show that the choice between relative and absolute bid-ask spreads is of first-order importance. While CDS premiums increase with CDS absolute bid-ask spreads, they decrease with relative bid-ask spreads. This may help to reconcile the apparently conflicting results of Tang and Yan (2007) and Acharya and Johnson (2007), who describe a negative relation between CDS premiums and relative bid-ask spreads, and the contemporaneous work of Bongaerts, Jong, and Driessen (2010), who find a positive relation with absolute bid-ask spreads (like we do).

Second, we find that the sensitivity of CDS spreads to the explanatory variables is much stronger for firms with high CDS spreads (i.e., firms in high conditional quantiles) than for firms with low CDS spreads (i.e., low conditional quantiles). For example, a given increase in implied volatility has a stronger effect in the CDS premium when the firm already has a high CDS premium relative to other firms with the same implied volatility, i.e., when the firm is in a high conditional quantile. Furthermore, the goodness of fit is also an increasing function of the conditional quantile of the CDS distribution, going from a rather poor fit for low-risk firms to a very strong fit for high-risk firms.

This relation is intuitive. When the firm's CDS spread is high, meaning that default is more likely, bad news about the firm, e.g., unanticipated operational losses, would generate correlated movements in the firm's put options, stock price, and CDS. Long positions in put options and long positions in CDS contracts can both be regarded as insurance protection against bankruptcy and tend therefore to move together as the firm approaches the default state. On the contrary, for a low risk firm far away from the default threshold, the same bad news might just cause a drop in the stock price without any significant effect on the CDS premium.

Interestingly, we find that the results from a standard linear regression are similar to the results in the higher quantiles (where the goodness-of-fit and estimated slopes are higher), but quite different from the results for the median CDS. This suggests that we should read with caution the results from standard linear regressions presented in several previous empirical studies (e.g., Campbell and Taksler (2003), Cremers, Driessen, Maenhout and Weinbaum (2008), Ericsson, Jacobs, and Oviedo (2009), and Zhang, Zhou and Zhu (2009)). While one typically assumes that a standard conditional mean regression describes the “center” of the distribution, our analysis shows that the OLS results are dominated by extreme outlier values, thus describing the right tail, rather than the center, of the CDS distribution. The empirical determinants of CDS spreads found through classical regressions are therefore only successful for the subset of conditionally high-risk firms. In other words, the standard approach fails to account for the heterogeneity of the CDS data and the quantile regression, a more robust econometric methodology, is necessary to get proper inference.

The result that the fit of the model increases with the conditional quantile of CDS spreads is consistent with the credit spread puzzle, that is, with the fact that structural models strongly underestimate credit spreads for low-risk names, while not underestimating so severely the spreads for high-risk names (see, e.g., Huang and Huang (2003)). Our results confirm that the variables motivated by structural models have a strong explanatory power for high-risk firms, but that other variables may be necessary to fully explain the spreads of low-risk firms. In particular, our finding that CDS liquidity is significant across all quantiles is consistent with the standard notion that the puzzle is partly explained by liquidity, that is, with the idea that illiquidity drives most of the spread of low risk firms. From an applied trading perspective, a stronger link between equity options and credit spreads for riskier entities implies that typical hedging or arbitrage strategies, such as capital structure arbitrage, are expected to be more effective when applied to firms with conditionally high CDS spreads.[2]

The empirical work on CDS determinants is recent and scarce. Collin-Dufresne, Goldstein and Martin (2001) were the first to study directly bond credit spreads, instead of yields. However, they find that market volatility and jump probability have a rather limited explanatory power. More encouragingly, Campbell and Taksler (2003) find that firms' equity idiosyncratic volatility can explain as much cross-sectional variation in corporate yield spreads as credit ratings.[3] Ericsson, Jacobs, and Oviedo (2009) show that firm volatility and leverage are important determinants of CDS spreads. Cremers, Driessen, Maenhout and Weinbaum (2008) show that forward-looking information embedded in equity options, such as the at-the-money implied volatility and put skew, are able to explain one third of the total variation in credit spreads of corporate bonds. Zhang, Zhou and Zhu (2009) use high frequency data and argue that CDS spreads can be largely explained by intra-day refined measures of historical volatility and jump probability.

The rest of the paper is organized as follows. Section 2 discusses the measurement of liquidity in the CDS market. Section 3 describes the data and section 4 motivates and describes the quantile regression approach. The main empirical results are presented in section 5 and their robustness is verified in section 6. In section 7, we illustrate the applicability of QR to risk management. Specifically, we introduce a model for conditional credit value-at-risk and estimate the credit value-at-risk for some CDS in the sample. The last section concludes.

2 CDS liquidity

We start by reviewing the literature on CDS liquidity. The literature is mixed and therefore it is an empirical question whether CDS liquidity has a positive or negative effect on CDS premiums. However, the results are very sensitive to how CDS liquidity is

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[2] For a description of capital structure arbitrage see, e.g., Yu (2006) and Lardy (2006).

[3] In the opposite direction, Norden and Weber (2004) show that the CDS market anticipates credit rating announcements.

measured. Hence, we also discuss in detail the liquidity measure used in this paper: the absolute bid-ask spread.

2.1 Arguments for a liquidity effect in CDS spreads

Since Amihud and Mendelson (1986) there has been an extensive research on liquidity effects in asset pricing. It is by now well established that expected stock and bond returns increase with the illiquidity of the asset. However, the effect of liquidity in the CDS market is much less straightforward and the literature has not yet reached a consensus neither on the effects nor on the measure of liquidity in the CDS market.

While some authors, such as Longstaff, Mithal, and Neis (2005), have argued that liquidity frictions in the CDS market are negligible, more recent papers have found different results. Tang and Yan (2007) find that CDS premiums are related to several measures of trading frictions, including the relative CDS bid-ask spread. Acharya and Johnson (2007) also regress CDS levels on relative bid-ask spreads, but find a surprising weak negative relation.

Several papers model CDS illiquidity as an additional intensity in reduced-form models. For example, Chen, Cheng, and Wu (2005) find that CDS premiums decrease with illiquidity. In the model of Chen, Fabozzi, and Sverdlove (2008), illiquidity only reduces the value of the default leg and thus mechanically reduces the CDS premium, i.e., the liquidity premium is always earned by the protection buyer. They measure liquidity through relative bid-ask spreads and find supportive results. On the contrary, Buhler and Trapp (2008) model liquidity as a discount on the premium leg of the CDS. However, they separately model bid and ask quotes and also allow for interactions with liquidity in the bond market. They find mixed results on the relation between CDS premiums and liquidity.[4]

More recently, the contemporaneous work of Bongaerts, Jong, and Driessen (2010) proposes an equilibrium model where expected returns on credit derivatives depend on transaction costs. In general, the sign of liquidity effects depends on investors' non-traded risk exposure, risk aversion, horizon, and wealth. For the particular case of CDS, they find empirical evidence for a liquidity premium earned by the protection seller, i.e., for

[4] See Brigo, Predescu, and Capponi (2010) for a survey.

CDS spreads that increase with expected CDS illiquidity. Importantly, they depart from the previous papers and measure CDS liquidity through the absolute, rather than the relative, bid-ask spread (as we do in this paper).[5]

Alternatively, we can also regard the CDS as the insurance contract that it really is. The insurance literature shows that information asymmetry causes the insurance premium to increase in equilibrium (see Acharya and Johnson (2007) or Chiappori (2000)). Assuming that the CDS bid-ask spread (a typical measure of liquidity) is a good proxy for the amount of information asymmetry in the market, a higher bid-ask spread should be associated with a higher CDS level.

2.2 Measuring liquidity in the CDS market

The CDS market has grown explosively in recent years. According to ISDA data, the notional amount outstanding grew from less than 1 trillion dollars in 2001 to more than 62 trillion dollars in 2007. The amount outstanding in CDS contracts has become larger than the notional amount of the underlying securities, which means that CDS are being used not only to hedge but also to speculate on credit risk. The market has become more fluid with the standardization of trading procedures lead by the ISDA. The creation of the DJ CDX and iTraxx indexes in 2003/04 marked the maturity of the market. These facts are consistent with a market that is becoming more active and fluid, i.e., more “liquid”. Any candidate for a liquidity proxy should therefore display a pattern consistent with an increase in liquidity over recent years.

Measuring liquidity in the CDS market is not as straightforward as in the stock or bond markets. While in these markets the cost of an instantaneous roundtrip transaction can be precisely computed from the observed bid-ask spread, the cost for a similar roundtrip transaction in a CDS can only be *estimated* from market data because there will be a stream of payments until the unknown time of default or maturity of the CDS, whichever happens first.

[5] Also, Pan and Singleton (2008) estimate default intensities for sovereign CDS under the assumption that pricing errors are proportional to absolute bid-ask spreads.

Using the market standard reduced-form pricing model for marking CDS positions to market (see O'Kane and Turnbull (2003)), the Expected Transaction Cost (ETC) of an instantaneous roundtrip transaction for a CDS maturing in *N* periods is

$$ETC = BAS \sum_{i=1}^{N} \Delta\mathrm{t_i} \cdot \mathrm{d(t_i)} \cdot \mathrm{PS(t_i)} + BAS \sum_{i=1}^{N} \frac{\Delta\mathrm{t_i}}{2} \cdot \mathrm{d(t_i)} \cdot (\mathrm{PS(t_{i-1})} - \mathrm{PS(t_i)})$$

where *BAS* is the bid-ask spread (the ask minus the bid quote), $\Delta\mathrm{t_i} = \mathrm{t_i} - \mathrm{t_{i-1}}$ is the number of years between payment dates, $\mathrm{d(t_i)}$ is the risk-free discount factor for time $\mathrm{t_i}$, and $\mathrm{PS(t_i)}$ is the market-implied probability of survival until $\mathrm{t_i}$.The first term represents the present value of the premium differences and the second term accounts for premium accrued from the previous payment date to the time of the credit event. The ETC thus measures the cost, as a percentage of the nominal value, for an investor that buys and immediately sells a CDS contract.

However, the ETC is not directly observable because it depends on the unobservable survival probabilities. The ETC will thus be influenced by the particular model used to estimate survival probabilities. Hence, it is sometimes convenient to proxy for CDS transaction costs through directly observable measures, such as the bid-ask spread, as done in the recent literature. However, it is not immediately obvious whether one should use relative or absolute bid-ask spreads. Therefore, we must first compare the properties of these two proxy candidates.

To estimate the Expected Transaction Costs (ETC), we adopt the standard reduced-form mark-to-market model to extract default probabilities from market CDS prices (see O'Kane and Turnbull (2003)). We assume a constant default intensity λ, obtaining $\mathrm{PS(t_i)} = \mathrm{e}^{-\lambda \mathrm{t_i}}$. We further assume a constant recovery rate of 40% for every CDS and a constant risk-free rate of 5%. We estimate ETC for all CDS contracts in our monthly sample and then compute cross sectional averages at each month.

Figure 1 shows the evolution of the average ETC and also the observed absolute and relative bid-ask spread. Consistent with the facts described above, the ETC shows a strong decline throughout the sample period. Similarly, the absolute bid-ask spread also decreases throughout the period. Contrary to these two measures, the relative spread shows an erratic behavior that seems inconsistent with the facts described above. Hence, we conclude that the ETC and the *absolute* bid-ask spreads are the only measures consistent with the evolution of liquidity in the market.

Furthermore, ETC and *absolute* bid-ask spreads display a very similar pattern. In fact, the absolute BAS captures almost all of the variation in ETC: a regression of ETC on absolute BAS has an R-squared of 0.97. Hence, the absolute bid-ask spread by itself seems to be a very good measure of liquidity in the CDS market.

2.3 Intuition for absolute rather than relative bid-ask spreads

Given that the standard measure of liquidity for stocks and bonds is the relative bid-ask spread, the use of absolute bid-ask spreads for CDS contracts may seem surprising at first. However, the intuition is simple. Contrary to stock prices, CDS premiums are already expressed in a comparable way, i.e., in basis points per annum of the notional amount of the contract. Further dividing the CDS bid-ask spread by the CDS mid quote can bias the comparison of liquidity between different names. We now provide some simple examples to illustrate this point.

Consider first a simple example from the stock market. Suppose stock A is trading at \$9.95-\$10.05 (bid of \$9.95, ask of \$10.05). The absolute spread is thus \$0.1, the mid price \$10.00, and the relative spread is 1%. If an investor buys \$1,000 of shares and immediately sells then back to the market maker, he suffers a transaction cost of \$1000*(9.95-10.05)/10.05, which is approximately equal to 1% of the initial \$1,000. Compare now with stock B, trading at \$19.90-\$20.10, thus with a larger absolute spread of \$0.2, but the same relative spread of 1%. The same roundtrip transaction would again incur a cost of roughly 1% of \$1,000. These two stocks have the same liquidity costs and this is captured by their identical relative bid-ask spreads. A comparison through the absolute spreads would be misleading. It is in this sense that it is appropriate to use the relative bid-ask spread in the stock market.

In the CDS market, the argument is reversed. Suppose that a CDS on firm A is trading at 95bp-105bp, i.e., the absolute bid-ask spread is 10bp and the relative spread is 10%. A roundtrip transaction for \$1,000 notional would result in a cost of $\$1{,}000 \times (105bp - 95bp) = \$1{,}000 \times 10bp$. For simplicity, we can assume this is paid annually until default or the end of the contract. Compare now with a CDS on firm B, trading at

190bp-210bp, i.e., with a larger absolute spread of 20bp, but the same relative spread of 10%. The same roundtrip transaction would result in a larger annual cost of $\$1{,}000 \times (210bps - 190bps) = \$1{,}000 \times 20bps$. Note that in both cases the cost is captured by the absolute spread. While these two CDS have different transaction costs, their relative bid-ask spreads are misleadingly identical. Hence, the proper measure of liquidity in the CDS market is the *absolute* bid-ask spread.

This example can be modified to highlight a further potential problem when CDS spreads are regressed on *relative* bid-ask spreads. Suppose that the CDS on firm B is instead trading at 390bp-410bp, that is, with the same absolute spread of 20bp, but a smaller relative spread of 5%. While CDS spreads in this market increase with absolute bid-ask spreads, a regression of CDS spreads on relative bid-ask spreads would give a misleading negative slope. More generally, if the absolute bid-ask spread does not increase faster than the CDS level (mid quote), a regression of the CDS level on the relative spread will be biased towards finding a negative slope. This negative relation is misleading since the CDS level would still show a positive relation with the absolute spread and thus with the true ETC (since these two measures are very strongly correlated, as discussed above). We conjecture that some of the negative relations found in Acharya and Jonhson (2007) and Tang and Yan (2007) may be in part due to this problem.

3 Data

This section describes the sample of CDS quotes and their explanatory variables and presents some preliminary data analysis.

3.1 Variables

3.1.1 CDS quotes

We obtain CDS data from Bloomberg Financial Services. The sample consists of monthly observations of US and European corporate CDS names. All quotes refer to 5-year CDS contracts with modified restructuring clauses and to reference credit obligations ranking at the senior level of the debt structure. Monthly bid and offer quotes are captured on the last business day of each month. Whenever possible, major quote providers (brokers) are used instead of Bloomberg composite quotes. Our dependent variable, denoted as CDS_{it}, is the midpoint between the bid and ask quotes for firm i in month t.

The sample period is from August 2002 to February 2007. The CDS market is relatively young and the amount of available data is increasing over time. The sample excludes earlier periods of more sparse and unreliable quotes. Moreover, the sample is restricted to entities with at least 60% of quotes available for the 55 months considered. Overall, the sample consists of a set of 260 firms, amounting to 13,470 CDS spread quotes.

3.1.2 Implied volatility

The equity-options implied volatility is a forward-looking measure of volatility, thus providing timely warnings of credit deterioration.[6] Higher firm-specific equity volatility suggests a higher probability that the firm's value will cross the threshold of default, hence increasing CDS quotes. Equity volatility is therefore a typical determinant of CDS premiums. We use the at-the-money (ATM) put implied volatility available in Bloomberg.

3.1.3 Put skew

The put skew is the difference between the implied volatilities of deep-out-of-the-money (DOTM) and ATM put options. Buying DOTM puts on the firm's equity provides protection against very large losses, especially in case of a default where the equity price may approach zero. Hence, both DOTM puts and CDS can be used to trade credit risk and their price must thus be closely related. The higher the put skew, the more protection is being sought in the options market, thus indicating a higher probability of a downside jump in the firm's value and hence a higher CDS spread.

We collect options data from the Bloomberg implied volatility surface database. In order to build a consistent volatility smile measure across all stocks, we select the 50-delta and the 25-delta put options expiring on the month following the near contract expiration date.[7] The implied volatility for a 50-delta option is approximately the implied volatility of an at-the-money option, whereas a 25-delta option corresponds to an out-of-

[6] See, e.g., Malz (2000), Stamicar and Finger (2005), and Cao, Yu and Zhong (2005).
[7] Even though 10-delta implied volatilities are available, we chose 25-delta volatilities for liquidity concerns.

the-money option. The put skew is computed as the difference between the 25 and 50-delta volatilities.

3.1.4 Stock return

In the structural model of Merton (1974), the probability of default largely depends on the firm’s asset process and asset growth rate. A higher drift in the firm’s value process increases the probability of the market value of the firm staying far from the default threshold, hence decreasing CDS spreads. Given the well-known momentum pattern in stock returns, we conjecture that past equity performance may predict future expected asset growth. The equity return can also be interpreted as reflecting the firm’s health, or alternatively, as being a high-frequency proxy for leverage (see Cremers, Driessen, Maenhout and Weinbaum, 2008). Therefore, we include the firm's past stock return over a 6-month rolling window.

3.1.5 Credit rating

Traders and market participants routinely use credit ratings as an important source of information regarding the credit worthiness of a firm and therefore it is important to show that our variables add new information relative to ratings. We include a dummy for each credit rating class and define the base omitted category to be A-rated firms, so that the coefficients on the other dummies can be interpreted as differences to this rating. The credit rating history for each entity is collected from the S&P Long Term Issuer Credit Rating. Whenever the rating history is not available from S&P, we use the Moody’s Senior Unsecured Debt Rating.

3.1.6 Macroeconomic variables

In addition to the firm specific variables described above, we also control for common factors that have the same effect for all firms at a given point in time. We do this through two alternative specifications. First, we simply include time dummies to absorb the time-series variation left unexplained by the firm-specific variables. Second, we directly test the importance of macroeconomic factors by including the following variables:

- *risk-free interest rate,* defined as the 10-year treasury rate. A higher risk-free rate may lead to lower credit spreads. For example, Longstaff and Schwartz (1995) suggest that a higher risk-free rate increases the risk-neutral drift of the firm value process, thus reducing the probability of default.

– *slope of the treasury yield curve*, defined as the 10-year minus 2-year rate. In Longstaff and Schwartz (1995) a rising slope lowers credit spreads. Furthermore, the term structure slope is a well-known leading indicator of the business cycle, with a positively sloped structure usually signaling "good times".
– *5-year swap spread*, defined as the difference between the 5-year interest rate swap and the treasury rate. This spread is commonly seen as a credit spread reflecting overall credit conditions, even though it may also largely reflect a convenience yield to holding treasuries (see Feldhutter and Lando (2008)).
– *market implied volatility*, defined as the implied volatility of at-the-money put options on the respective market main index (S&P 500, FTSE 100, or Eurostoxx 50). Collin-Dufresne, Goldstein and Martin (2001) show that credit spreads are related to overall market volatility.

All macroeconomic data is collected from Bloomberg. Table I provides a brief summary of the determinants of CDS spreads.

3.2 Preliminary data analysis

Table II presents some descriptive statistics. The sample is well balance by market and industry (see Panel A and Panel B). The five major industry groups (financial, utilities, industrial, tech and consumer) are significantly represented in the sample. The financial sector has the lowest sample average CDS spread (32 bps), while the tech sector has the highest (84 bps).

The sample average CDS spread has a decreasing pattern through time, showing the biggest declines in 2003 and 2004. The same pattern is observed across all industry groups. The sample average CDS spread shows an impressive reduction from 130 bps in 2002 to 63 bps in 2007. Figure 2 plots the time-series evolution of the average CDS spread, implied volatility, put skew, and CDS bid-ask spread. These variables show a steep decline during the sample period, suggesting a possible reduction in risk-aversion and in transactions costs in the CDS market.

Regarding credit ratings (see Panel C), A and BBB rated firms clearly dominate the sample, together representing roughly three fourths of the sample. The AA and BB rated firms are, approximately, 20% of the sample. The AAA and B firms are only 3% of the sample. The evolution of the sample average CDS spread by credit rating also shows a decreasing pattern.

Panel D shows aggregate summary statistics and Fisher-ADF panel unit root tests. The Fisher-ADF panel unit root test strongly rejects the null of non-stationarity in the panel, thus dismissing any spurious regression issues.[8] Additionally, Panel E reports the correlation matrix of the key determinants of CDS spreads split by firm-specific and macroeconomic factors. Interestingly, the sample correlation of CDS spreads and implied volatility (0.62) is much larger than with the firm's stock return (-0.20), suggesting that equity options embed more valuable information to explain credit spreads than past stock returns. Naturally, firm-specific factors have a much larger sample correlation with CDS spreads than macroeconomic factors.

Finally, Figure 3 displays a boxplot of CDS spreads as a function of implied volatility. As expected, CDS spreads rise with the level of implied volatility. Also, there is a clear tendency for dispersion, measured by the interquantile range of CDS spreads, to increase with implied volatility. The tails of the distributions show an even stronger increase in dispersion. Figure 4 shows an histogram of all CDS spreads. The distribution clearly has a heavy right tail and strong skewness. These results indicate that the standard linear conditional mean regression, though appropriate to model CDS averages, would be rather incomplete to describe the full distributional relationship between the CDS spreads and its covariates. Hence, we use the conditional quantile regression approach to provide a more complete picture of CDS spreads. We provide an outline of this empirical methodology in the following section.

4 Empirical methodology

We start by motivating the need for Quantile Regressions (QR) in credit spreads through the theoretical structural model of Merton (1974) and highlighting the main

[8] See Baltagi (2001) for a survey on unit root tests in a panel data context.

advantages of QR with references to interesting applications in other areas. Then, we detail the QR procedure and specify our benchmark model.

4.1 Motivating the usage of Quantile Regression

4.1.1 Intuition from a structural model

We use the well-known model of Merton (1974) to study the relation between fundamental variables and credit spreads. Even though the model is not able to accurately describe the credit spreads observed in the market, it is a very useful framework to gain intuition on the effect of some determinants of credit spreads. In Merton (1974), zero-coupon debt matures in T years with a face value of F. The riskless rate is r. The value of the firm's assets is currently V and follows a geometric Brownian motion with volatility σ. The credit spread, defined as the difference between the yield on the firm's risky debt and the risk-free rate, is given by $s = -(1/T)\ln((Fe^{-rT} - p)/F) - r$, where $p = Fe^{-rT}N(-d_2) - VN(-d_1)$ is the value of a put option on the assets, N(.) is the Normal cdf, $d_1 = \left(\ln\frac{V}{F} + \left(r + \frac{\sigma^2}{2}\right)T\right)/\left(\sigma\sqrt{T}\right)$, and $d_2 = d_1 - \sigma\sqrt{T}$. We can thus compute the derivative of the spread with respect to volatility:

$$\frac{\partial s}{\partial \sigma} = \frac{1}{T\,(\,Fe^{-rT} - \,p\,)}\,\vartheta$$

where $= V \sqrt{T}\, exp\left(-\frac{d_1{}^2}{2}\right)/\sqrt{2\pi}$.

Figure 5 illustrates this relation for a firm with debt maturing in 5 years with a face value of 100, current assets value of 155, and a 5% risk-free rate, which implies a leverage ratio of 0.5. The top panel shows that the credit spread s increases at an increasing rate (i.e., nonlinearly) with the volatility σ. The bottom panel shows the same information, but in a way more directly related to our empirical framework. More precisely, the bottom panel shows that the derivative of s with respect to σ (the beta coefficient in a regression of spreads on volatility) is not constant; it increases with level of the spread.

Given this intuition, we should consider the possibility that the sensitivities to other empirical determinants of credit spreads may also vary according to the level of CDS spread itself. Together with the preliminary data analysis in the previous section, these results suggest that a simple conditional mean regression is not appropriate to completely describe credit spreads and that a more flexible framework, like the quantile regression, is required.

4.1.2 Applications of Quantile Regression

The standard linear regression specifies the conditional mean of a response variable as a function of a set of covariates, $E(y|x)$. However, by focusing exclusively on the conditional mean, the traditional approach fails to acknowledge that the covariates shape the whole conditional distribution of the dependent variable and it may thus produce a rather incomplete analysis.[9] The quantile regression (QR), introduced by Koenker and Basset (1978), is an extension of the conditional mean to a collection of models for different conditional quantile functions. The QR detects changes in the shape of the distribution of y across the predictor variables and can thus be used to explain the heteroskedasticity present in the data.[10]

There is a growing empirical literature employing quantile regressions. One strand of this literature focus on value at risk and tails of distributions - see, for example, Taylor (1999), Chernozhukov and Umantsev (2001) and Engle and Manganelli (2004). Other applications in finance include Bassett and Chen (2001), who use quantile regression index models to characterize mutual fund investment styles. Also, Barnes and Hughes (2002) apply quantile regressions to study the cross section of stock market returns. Other applications of quantile regression can be found in economics, hydrology and ecology. In particular, quantile regression is now regarded as a standard analysis tool for wage and income studies in labour economics (see, e.g., Buchinsky, 1994, and Koenker and Hallock, 2001).

[9] Mosteller and Tukey (1977, p. 266) state that: "what the regression curve does is give a grand summary for the averages of the distributions (…). We could go further and compute several different regression curves (…) and thus get a more complete picture of the set. Ordinarily this is not done, and so regression often gives a rather incomplete picture. Just as the mean gives an incomplete picture of a single distribution, so the regression curve gives a corresponding incomplete picture for a set of distributions".

[10] As Buchinsky (1998, p. 89) asserts "….potentially different solutions at distinct quantiles may be interpreted as differences in the response of the dependent variable to changes in the regressors at various points in the conditional distribution of the dependent variable..." implying that it is possible to interpret changing coefficients across the distribution as the result of systematic differences in firm behavior. See also Cade and Noon (2003).

In our case, a panel of credit spreads with heterogeneous variances implies that there is not a single moment that fully characterizes changes in the probability distributions. Instead of focusing exclusively on changes in the means, the QR describes changes in multiple points of the distributions.

4.2 Quantile Regression methodology

The general univariate linear quantile regression model can be written as

$$y_i = x'_i\beta_\theta + u_{\theta i}, \qquad i = 1, \dots, n \tag{1}$$

where n is the sample size, β_θ is an unknown $k \times 1$ vector of regression parameters associated with the θth percentile, x_i is a vector of independent variables, y_i is the dependent variable of interest and $u_{\theta i}$ is an unknown error term. The θth conditional quantile of y_i given x_i is

$$Q_\theta(y_i|x_i) = x'_i\beta_\theta \tag{2}$$

which follows from the necessary assumption concerning the error term, $u_{\theta i}$, $Q_\theta(u_{\theta i}|x_i) = 0$, i.e., the conditional θth quantile of the error term is equal to zero. The quantile regression method allows the marginal effects to change at different points in the conditional distribution by estimating the partial derivatives of the conditional quantile function with respect to the set of explanatory variables,

$$\frac{\partial Q_\theta(y_i|x_i)}{\partial x} = \beta_\theta \tag{3}$$

using different values for θ, this way allowing for parameter heterogeneity. For a sample of size n and for any θ in the interval $(0, 1)$, the parameter vector β_θ, can be estimated by

$$\hat{\beta}_\theta = \underset{\beta}{\operatorname{argmin}} \frac{1}{n}\sum_{i=1}^{n} \rho_\theta(y_i - x'_i\beta) \tag{4}$$

where the *check function* $\rho_\theta(.)$ is defined as,

$$\rho_\theta(u_{\theta i}) = \begin{cases} \theta u_{\theta i}, & u_{\theta i} \geq 0 \\ (\theta - 1)u_{\theta i}, & u_{\theta i} < 0 \end{cases} \tag{5}$$

The estimator does not have an explicit formula and is found through linear programming techniques (Koenker and Basset, 1978). The weights in (5) are symmetric for the least absolute deviation (LAD) estimator (the median regression, $= 0.5$) and asymmetric otherwise. Additionally, all data observations are used to construct each quantile regression estimate thus avoiding a sample selection bias.[11]

The quantile regression can alleviate some typical empirical problems, such as the presence of outliers, heterogeneity and non-normal errors. While the optimal properties of standard regression estimators are not robust to modest departures from normality, the quantile regression results are robust to heavy tailed distributions. Furthermore, while the least squares method is highly sensitive to outliers, the quantile regression solution is invariant to outliers of the dependent variable that tend to $\pm\infty$ (Coad and Rao, 2006). In the context of this study, high-yield firms are of interest in their own right and should not be dismissed as outliers. Finally, a quantile regression approach avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. Relaxing this assumption allows one to acknowledge firm heterogeneity and consider the possibility that estimated slope parameters vary at different quantiles of the conditional distribution of CDS spreads.

In the same spirit of the least squares R-Squared goodness of fit measure, Koenker and Machado (1999) developed a fit measure for quantile regressions, the Pseudo R-Squared, defined as

$$R^2(\theta) = 1 - \frac{\sum_{i=1}^{n} \left| y_i - x'_i \hat{\beta}_\theta \right|}{\sum_{i=1}^{n} \left| y_i - Q_\theta(y) \right|} \in (0,1) \tag{6}$$

where $\sum_{i=1}^{n} \left| y_i - x_i' \hat{\beta}_\theta \right|$ is the sum of the absolute residuals of y_i about the estimated conditional quantile and $\sum_{i=1}^{n} \left| y_i - Q_\theta(y) \right|$ is the sum of the absolute difference of y_i about the unconditional quantile of y, for a given θ, $Q_\theta(y)$.

4.3 Cluster bootstrap standard errors

The bootstrap method, introduced by Efron (1979), is the most commonly used approach for the estimation of the covariance matrix of the quantile regression parameter vector. The bootstrap is a resampling procedure designed to mimic repeated random

[11] Koenker and Hallock (2001) put it in the following way: “We have occasionally encounter the faulty notion that something like quantile regression could be achieved by segmenting the response variable into subsets according to its unconditional distribution and then doing least squares fitting on these subsets. Clearly, this form of “truncation on the dependent variable” would yield disastrous results in the present example. In general, such strategies are doomed to failure for all the reasons so carefully laid out in Heckman’s (1979) work on sample selection.”

sampling from the underlying population, simulating the probability distribution of the desired statistics without making unreasonable assumptions. The basic idea behind bootstrapping is to generate new samples by sampling with replacement from the original data.[12]

Our sample is a typical panel data set containing observations on multiple firms across multiple months. In this context, a suitable resampling method is the pairs cluster bootstrap (also known as cluster bootstrap or non-overlapping block bootstrap), which assumes independence across clusters but preserves within cluster correlation.[13] This method involves obtaining the bootstrap samples $\{(y_{1j}^{bs}, x_{1j}^{bs}), \dots, (y_{Gj}^{bs}, x_{Gj}^{bs})\}$, $j = 1, \dots, B$, by sampling with replacement G clusters (firms) from the original sample $\{(y_1, x_1), \dots, (y_G, x_G)\}$, until B bootstrap samples are obtained. Each firm observed over T periods of time is sampled, with replacement, with an equal probability of $\frac{1}{G}$. The bootstrap estimates of $\hat{\beta}_{\theta j}$ are used to construct the estimate of the standard error,

$$se_{\hat{\beta}_\theta} = \sqrt{\frac{1}{B-1}\sum_{j=1}^{B}\left(\hat{\beta}_{\theta j}^{bs} - \hat{\beta}_\theta^{*}\right)^2} \tag{7}$$

where $\hat{\beta}_{\theta j}^{bs}$ is the quantile regression estimator based on the j^{th} bootstrap sample and $\hat{\beta}_\theta^{*} = \frac{1}{B}\sum_{j=1}^{B}\hat{\beta}_{\theta j}^{bs}$ is the sample average of all the bootstrap replications.[14] The confidence intervals and *t*-tests are asymptotically normal and can be computed as usual, but using the cluster robust estimate of the standard error $se_{\hat{\beta}_\theta}$.

4.4 Benchmark empirical model

Our benchmark panel quantile regression is

$$\begin{aligned} Q_\theta(CDS_{it}|x_{it}) = \alpha_\theta + \beta_{\theta v}\cdot ivol_{it} + \beta_{\theta s}\cdot skew_{it} \\ + \beta_{\theta r}\cdot ret_{it} + \beta_{\theta b}\cdot bas_{it} + \delta'_\theta \cdot t\_dum_t \end{aligned} \tag{8}$$

[12] See Efron and Tibshirani (1993) for a detailed analysis of the bootstrap theory.
[13] See Cameron, Gelbach and Miller (2008) for an analysis of bootstrap based cluster standard errors; Wooldridge (2003) for an extended analysis of cluster methods in applied econometrics; and, Petersen (2007) for a discussion of robust cluster standard errors in empirical finance applications.
[14] We use 250 replications to estimate the cluster bootstrap standard error (see Efron and Tibshirani, 1993).

where $i = 1, \dots, G$ are the cross-sections (firms) that are observed over $t = 1, \dots, T$ months, CDS_{it} is the CDS spread, $ivol_{it}$ is the implied volatility, $skew_{it}$ is the put skew, ret_{it} is the stock return, bas_{it} is the CDS absolute bid-ask spread, and t_dum_t are time-dummies. The slopes of the regressors are estimated at seven different quantiles θ - the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles - using the same set of explanatory factors for each quantile. Standard errors are estimated using the pairs cluster bootstrap method. The quantile regression procedure yields a series of quantile coefficients, one for each sample quantile. We may thus test whether CDS spreads respond differently to changes in the regressors depending on whether the firm is in the left tail of the distribution (low risk firm) or in the right tail of the distribution (high risk firm).

5 Regression results

We start by presenting the empirical results for a smaller model containing only the traditional explanatory variables; then, we present the main results for the full model with liquidity. Finally, we assess the standard OLS results

5.1 The link between credit default swaps and equity options

Table III presents the first set of benchmark results. Panel A follows the benchmark in the previous literature and considers only the implied volatility and put skew. The results confirm the importance of individual equity options as key determinants of CDS spreads, consistent with the previous empirical and theoretical literature. The coefficients of the at-the-money put implied volatility and put skew are always positive and statistically significant across all quantiles.

Panel B adds the firm's past stock return and quarterly time-dummies. The main findings are as follows. First, the magnitude of the slopes of the regressors varies widely across the conditional distribution of CDS spreads. The coefficients on the firm's implied volatility and put skew are much larger at higher quantiles. While the lower (5th quantile) estimated response rates for implied volatility and put skew are, respectively, 0.72 and 0.57, the largest (95th quantile) estimated response rates are 11.21 and 10.46, respectively. Both set of results are extremely different from the ones obtained in the median, where the estimated slopes for implied volatility and put skew are 2.26 and 2.72, respectively. Overall, the results show that the response of CDS spreads to a change in the firm's implied volatility or put skew increases in a convex way with the quantile θ.

Second, the quality of the regressions' fit, measured by the Pseudo R-Squared, is an increasing function of the conditional quantile. The R^2 increases from 0.09 at the 5th quantile to 0.50 at the 95th quantile. This indicates that CDS spreads are better explained by changes in implied volatility and put skew as one moves along the distribution of credit risk into the upper tail which is populated by high-risk firms.

Third, the firm's stock return is statistically significant in the upper conditional quantiles of the distribution. While for low credit risk firms CDS spreads are insensitive to changes in stock returns, for high credit risk firms, *ceteris paribus*, a 1% increase in the firm stock return decreases CDS spreads by 0.10 bps, 0.19 bps, 0.44 bps and 0.59 bps in the 50th, the 75th, the 90th, and the 95th quantiles, respectively. However, the firm's stock return only adds a very small amount to the regression Pseudo R-Squared.

Finally, the results show that time-dummies, which proxy for common macroeconomic factors, contribute only to a marginal increase in the explanatory power to the model. Moreover, all key individual determinants in the model remain robust to the inclusion of time-dummies.

To sum up, the empirical results show the usefulness of the implied volatility surface measures. However, the at-the-money implied volatility and put skew possess a tiny explanatory power as determinants of credit spreads for less risky firms. Importantly, the credit and options markets converge to a stronger pricing relationship when the credit worthiness of the firm deteriorates.

5.2 The importance of liquidity in the CDS market

Table IV shows that the addition of the absolute CDS bid-ask spread to the basic model increases significantly the Pseudo R-Squared across all quantiles. For example, the Pseudo R-Squared increases from 0.10 to 0.19 in the first decile, from 0.16 to 0.33 in the median, and from 0.42 to 0.56 in the ninth decile. The coefficient on the bid-ask spread increases monotonically from low to high quantiles. Furthermore, despite the addition of this new regressor, the coefficients on implied volatility and put skew remain strongly significant in most quantiles, which suggests that CDS bid-ask spreads capture new independent information. These results are therefore consistent with the existence of a high liquidity premium in the CDS market and thus suggest that liquidity should be included in credit default swap pricing models.

These results are the first to reveal that a large component of the variation of CDS spreads is due to illiquidity costs. Our results come in clear contrast with the weaker results found in other recent papers, which we attribute mostly to the fact that they use the relative CDS bid-ask spread. To better gauge how misleading the relative bid-ask spread can be as a measure of liquidity, we re-estimated our model with the relative spread and found that it has a negative sign in our sample (results available upon request). This negative sign likely results from the bias described in section 2.

5.3 Quantile versus conditional mean regressions

Our preliminary analysis of the distribution of CDS spreads in section 3 already indicates that a Quantile Regression (QR) should provide a better description of the data than a standard conditional mean regression. We now provide direct evidence that this is indeed the case.

We start by showing that the QR estimates are significantly different across quantiles, which proves the necessity of using a technique like QR to analyze an heterogeneous panel of CDS data like ours. Table V shows *t*-tests for the null hypothesis of equal slopes across quantiles. The overwhelming rejection of the null implies that the explanatory variables exert a different effect on CDS spreads at the different points of the distribution. Figure 6 plots several quantile estimates, clearly illustrating that the slopes in the higher quantiles are significantly different from the slopes in the lower quantiles. The different effects of the independent variables at the different quantiles of the distribution confirm a large amount of heterogeneity in the panel and reject the poolability of ordinary least squares.

Nevertheless, in order to compare the QR results with a standard regression, as used in other recent empirical studies, Tables III and IV also present the results of pooled OLS regressions. Based on OLS results, one would conclude that all the covariates strongly affect CDS spreads, with steep and highly significant slopes. However, the quantile regressions give a rather different picture. For example, while the pooled OLS regression indicates a single slope of 3.69 for implied volatility (see Table IV), the quantile regressions show that the slopes vary widely across firms, increasing from 0.65 for a firm lying in the 10th conditional quantile to 3.76 for a firm in the 90th conditional quantile. While the median coefficient is 1.43, the OLS coefficient estimate lies near the ninth decile. The OLS coefficients on the other variables, put skew and stock return, are also close to the coefficients on the 90th quantile. Furthermore, the range between the lower quartile and the median is much smaller than the range between the median and the upper quartile. These features are evidence of a highly skewed conditional distribution and a heavy upper tail. The conditional mean approach is also misleading in terms of goodness of fit: its Adjusted R-squared is much higher than in most quantiles, being close to the Pseudo R-squared attained in the 90th or 95th quantiles.

To further stress that OLS is not appropriate for this panel dataset, Table VI analyzes other classical panel-data methods. In addition to our explanatory variables, we follow the previous literature and include the credit rating of the reference entity in the CDS. The Adjusted R-squared for the pooled OLS regression increases from 0.62 in the benchmark model to 0.72 in the model with credit ratings. However, both the F-test and the Breusch-Pagan LM test show that there are individual effects. More precisely, the Sargan-Hansen test rejects the Random Effects Model in favor of the Fixed Effects Model. Since the fixed effects are extremely significant in this model, the typical pooled OLS regression is biased and inconsistent.

To summarize, our findings show that the explanatory power of the CDS determinants is highly dependent on the level of the CDS premium itself. While for high-risk firms the fit is indeed strong, for low-risk firms the fit is rather poor and the proposed determinants loose significance. Therefore, we argue that the results of some previous empirical studies should be interpreted with caution due to the rather incomplete and misleading picture provided by the traditional conditional mean approach. At best, the results from least squares approaches are only characteristic of the higher conditional quantiles, where the quality of the fit is higher and the significance of the explanatory variables is stronger.

6 Robustness

This section shows that our benchmark results are robust to the inclusion of credit ratings, macroeconomic factors, and to a different measure of liquidity. We also verify that the results do not suffer from simultaneity problems and are not driven by our usage of a panel data set.

6.1 Credit ratings

We start by testing the robustness of our key explanatory variables to the inclusion of credit ratings. Traders and market participants routinely use credit ratings as an important source of information regarding the credit worthiness of a firm and therefore it is important to show that our variables add new information relative to ratings.

We extend the benchmark regression to include a dummy for each credit rating. We define the base omitted category to be A-rated firms, so that the coefficients on the other dummies can be interpreted as differences to this rating. The results in Table VII show that all rating variables are statistically significant and have the expected theoretical sign across the estimated quantiles (except for the AAA dummy which is statistically insignificant). For example, while the 50th percentile of CDS spreads of AA-rated firms is 7.4 bps lower than the 50th percentile of CDS spreads of A-rated firms, the median of BBB-rated firms is 17.6 bps higher. Furthermore, the results show that the inclusion of credit ratings increases the explanatory power of the model: the Pseudo R-Squared increases roughly by 0.14 until the 75th quantile and by 0.10 in the 90th and 95th quantiles.

More important, we find that the coefficients on our key determinants remain strongly statistically significant and all patterns observed in the benchmark regression remain present. To further stress this point, we test directly whether the slopes continue to be different across quantiles. The results in Table VIII show that the slopes do indeed continue to be highly significantly different across quantiles, which justifies the necessity of the Quantile Regression.

Finally, we segment the sample into different groups according to four credit rating classes - AAA/AA, A, BBB, and BB/B - and compare the quantile regression with the pooled least squares regression in each sample segment. The results in Tables IX and X show that even after segmenting the sample into different credit ratings groups, the response of CDS spreads to changes in its key determinants varies widely across quantiles. Hence, credit ratings cannot mimic the pattern captured by quantile regressions. Furthermore, the overoptimistic results attained with pooled OLS regressions are not alleviated by using a subsample for each different rating. That is, even within a single rating class, the OLS results still tend to look like the results for the higher quantiles of that subsample. In addition, segmenting the sample produces less efficient and less robust inference. By contrast, quantile regressions using the entire sample increase the efficiency and robustness of the regression results.

Hence, the results show that our proposed variables contain new information that is independent of credit ratings and that they are important to explain the full conditional distribution of credit spreads.

6.2 Macroeconomic variables

We test the robustness of the benchmark results to using macroeconomic variables instead of time-dummies. The results in Table XI show that the coefficients on firm-specific factors remain very similar to the previous results with time-dummies. Regarding the macro factors, we find that the slope of the treasury yield curve is not statistically significant, while both the index implied volatility and the swap spread have counter-intuitive signs. This suggests that these macroeconomic variables are not robust and that their effects are absorbed by the firm-specific factors included in the regression. Hence, the specification with time-dummies is preferable because they can absorb any time-series variation left unexplained by firm-specific factors and remove the cross-sectional correlation, between firms, in the same time period (see Petersen, 2007).

6.3 Liquidity measure

For our main analysis we adopted the absolute bid-ask spread (BAS) rather than the Expected Transaction Cost (ETC) as our main measure of liquidity because the BAS is directly observable, while the ETC can only be estimated under a model and assumptions. Nevertheless, we now show that our main results are robust to either measure of liquidity.

We estimate the ETC for all CDS in our sample using the method described in section 2. Table XII shows the benchmark quantile regressions with ETC. This table is directly comparable with Table IV where liquidity is measure by BAS. The results are very similar. Namely, the ETC coefficient is strongly significant across all quantiles. The adjusted R^2 increases from 0.15 in the lower quantile to 0.59 in the highest quantile. All other variables maintain their significance in the same quantiles as in Table IV. Hence, we conclude that our results are robust to using either absolute bid-ask spreads or expected transaction costs as measures of liquidity.

6.4 Simultaneity

To check for a possible simultaneity bias effect, all independent variables are lagged one time-period (i.e., one month). The results are reported in Table XIII. All the results remain robust to this specification and show no significant difference. Hence, we conclude that the contemporaneous regression results are not driven nor qualitatively affected by a possible simultaneity bias.

6.5 Time patterns

To assess the evolution of the slopes and R-Squared through the sample period, we estimate a cross-sectional regression at each quarter. The first four panels in Figure 7 show the results for the four key explanatory variables (volatility, put skew, bid-ask spread, and stock return). The estimated slopes are naturally noisy since each point in the figure is estimated using only the information for the cross section at that date. Nevertheless, the results clearly show that throughout the sample period the slopes for implied volatility, put skew, and liquidity at the 90th quantile are very different from the slopes at the 10th quantile. The results for the stock return are less clear, but we still observe a large distance between those quantiles during roughly half of the sample period. Furthermore, the OLS slope tracks the slope of the highest quantile throughout the whole sample for all variables.

The bottom panel in Figure 7 shows the evolution of the cross-sectional R-Squared. The R^2 in the 90th quantile is consistently much higher than in the 10th quantile. Again, the OLS R^2 tracks the 90th quantile very close. Note also that the decline in the R^2

follows the downward evolution of the average CDS spread throughout the period (as shown in Figure 2). This suggests that the credit cycle is an important determinant of the link between equity options and credit spreads. Intuitively, when expected default rates are lower (i.e., credit risk is lower) there is a reduction in the appetite for insurance, and hence the relationship between equity options and credit default swaps becomes weaker.

In summary, these results show that the differences between the highest and lowest quantiles are present at each point in time and therefore are not an artifact of our main estimation on panel data. Furthermore, the OLS problems are persistent throughout the whole sample period. Hence, these results stress the necessity of using Quantile Regressions.

7 Conditional Credit Value-at-Risk

In this section, we provide an application of Quantile Regressions to risk management. We build on the framework of conditional market Value-at-Risk (VaR) introduced by Chernozukhov and Umantsev (2001), and extended in Engle and Manganelli (2004) and Kuester, Mittnik, and Paolella (2006), to develop a model for conditional credit value-at-risk.

7.1 Conditional distributions

To motivate the VaR calculations below, we start by describing the conditional densities of CDS spreads. The conditional quantiles, denoted by $Q_\theta(y|x)$, are the inverse of the conditional cumulative distribution function of the response variable, where $\theta \in (0,1)$ determines the quantile. We can therefore use the fitted quantiles on our benchmark model in (8) to estimate the conditional distribution of CDS spreads.

Figure 8 displays the estimated conditional density functions of CDS spreads for four specific values, namely the 5th, 10th, 90th and 95th percentiles, of implied volatility, CDS bid-ask spread, put skew and stock return. The results show that with an increase in the firm's implied volatility or CDS bid-ask spread, the conditional distribution becomes less peaked around the median, the variance increases significantly and the right tail becomes wider.

These results have implications for risk management. In particular, the Value-at-Risk (VaR) in a CDS position depends critically on the tails of the CDS premium distribution. Hence, our results indicate that a position in a CDS name with high implied volatility or high bid-ask spread should result in a much higher VaR than a position in a name with low volatility or low bid-ask spread.

7.2 Application to Credit Value-at-Risk

Our model estimates the VaR in a CDS position using information from the equity and options markets and from the liquidity of the CDS market itself. This approach has the potential to provide better results than a standard VaR estimation based on historical data whenever the explanatory variables, such as the put skew, contain information about forward-looking market expectations. It may also prove particularly useful for names with a short history in the CDS market.[15]

The Value-at-Risk (VaR) of a given position is the worst loss over a period of time with a given confidence level. A rigorous definition is in McNeil, Frey and Embrechts (2005: 38): "Given some confidence level $\theta \in (0,1)$ the VaR of the portfolio at the confidence level θ is given by the smallest number l such that the probability that the loss L exceeds l is not larger than $(1-\theta)$.

$$VaR_\theta = inf\,\{l: P(L > l) \leq 1-\theta\} = inf\{l: F_L(l) \geq \theta\} \tag{9}$$

In probabilistic terms VaR is a quantile of the loss distribution."

Let X be a vector of model regressors and $F_Y(y|x) = P(Y \leq y|x)$ the conditional distribution function of Y given $X = x$. The conditional θ-quantile of a random variable y with a continuous conditional distribution function is the number $F_Y^{-1}(\theta|x)$ such that

$$P(Y \leq F_Y^{-1}(\theta|x)|X = x) = \theta \tag{10}$$

where $F_Y^{-1}(\theta|x)$ is the θ-quantile regression function. Conditional VaR modelling is cast in terms of the regression quantile function, $F_Y^{-1}(\theta|x)$, the inverse of the conditional distribution function.

Our Conditional single-name Credit VaR analysis seeks to explain the conditional quantiles of an investor's return on a credit default swap, Y, using today's available

[15] Our goal in this section is just to illustrate a potential practical application of QR to risk management. We leave the full assessment of the advantages or disadvantages of this methodology to future work.

information, X. We imagine an investor (e.g., an insurance company) that has sold protection on the CDS (collects the fee) and estimate the loss resulting from a credit deterioration in the underlying entity. Our Credit VaR can thus be interpreted as a "book" loss resulting from the difference between the higher new true cost of providing protection and the lower fee at which the investor sold protection initially. Alternatively, the VaR can be interpreted as a real loss if the investor decides to close the initial position by paying a cash unwind value to the initial counterparty or by taking an offsetting position in a new CDS. Since we are using CDS spreads, the higher conditional CDS quantiles are of interest because they represent the lower conditional quantiles of investor's returns (i.e. credit losses). Our empirical results above show that the fit of the model is particularly strong exactly in the quantiles of interest: for example, in the 95th quantile, our variables explain 60% of the variation in CDS spreads.

In order to transform the distribution of CDS spreads into a distribution of credit losses we use the reduced-form approach described in O'Kane and Turnbull (2003). We assume a flat recovery rate, R, of 40% and a flat interest rate, r, of 5%. For a given spread, the approximate break-even flat hazard rate is computed as

$$\lambda = \frac{CDS}{(1-R)} \tag{11}$$

The mark-to-market on a credit default swap initiated with spread S but with a current market implied hazard rate λ can be modelled as

$$\begin{aligned} MTM(S,\lambda) \equiv S \sum_{i=1}^{N} \Delta \mathrm{t_i} \cdot \mathrm{d}(\mathrm{t_i}) \cdot \mathrm{PS}(\mathrm{t_i}) \\ + S \sum_{i=1}^{N} \tfrac{\Delta \mathrm{t_i}}{2} \cdot \mathrm{d}(\mathrm{t_i}) \cdot \big(\mathrm{PS}(\mathrm{t_{i-1}}) - \mathrm{PS}(\mathrm{t_i})\big) \\ - (1-R) \sum_{i=1}^{N} \mathrm{d}(\mathrm{t_i}) \cdot \big(\mathrm{PS}(\mathrm{t_{i-1}}) - \mathrm{PS}(\mathrm{t_i})\big) \end{aligned} \tag{12}$$

where $\Delta \mathrm{t_i} = \mathrm{t_i} - \mathrm{t_{i-1}}$ is the time between payment dates, $\mathrm{d}(\mathrm{t_i})$ is the risk-free discount factor for date $\mathrm{t_i}$, and $\mathrm{PS}(\mathrm{t_i}) = \mathrm{e}^{-\lambda \mathrm{t_i}}$ is the probability of survival until $\mathrm{t_i}$.

Let $\mathrm{CDS_{it}}$ denote the CDS spread for firm *i* quoted in the market at time t. Let $\lambda^{\theta} \equiv \frac{F^{-1}_{CDS_{it}}(\theta|x_{it})}{(1-R)}$ denote the hazard rate for the fitted CDS at a given quantile θ. We evaluate the entire surface of the credit loss distribution using each fitted CDS spread and compute the Credit Value-at-Risk as

$$VaR_{\theta}(CDS_{it}|X_{it}) = MTM\left(CDS_{it}, \lambda^{\theta}\right) \quad (13)$$

The Value-at-Risk thus represents the change in value of a contract initially negotiated at $\mathrm{CDS_{it}}$ due to a change in the hazard rate to λ^{θ}. This new hazard rate corresponds to a new CDS spread estimated through the θ-quantile regression.

As a practical application of this framework we estimate the conditional credit value-at-risk for two firms in the sample: IBM as an example of a firm with low risk, and Alcoa as an example of a firm that suffered several downgrades and hence with more volatile CDS spreads. We start by estimating the CDS spreads at all quantiles between the 5th and the 95th. Figure 9 shows the resulting surface of CDS spreads for the two firms. Since in this particular application we assume the position of a protection seller, we are interested in the risk of the CDS spread increasing.[16] Hence, Figure 10 isolates the predicted 95th quantile and compares it to the actual CDS premium at which the contract traded in the market. The 95th quantile for IBM shows a strong reduction in the first half of the sample and a relatively stable value in the second half. The reduction in the first half was much stronger than the decline in the actual CDS spread quoted in the market. Alcoa shows a different pattern. Even though the market CDS spread also declines throughout the sample period, the 95th quantile for Alcoa has remained persistently high over most of the sample (excluding the first year where it also decreases).

Finally, we compute the VaR for a CDS written on a \$100 notional with a 5-year maturity. For completeness, Figure 11 displays the entire surface of credit value-at-risk in each firm. The front visible edge of the surface gives the evolution of the 95% VaR over the sample period. As expected, the estimated 95% Credit VaR for IBM strongly decreases since the beginning of the sample, reaching \$2.17 in the last month of the

[16] In general, we can have short or long positions in a CDS, so the whole surface of CDS spreads is useful since it covers both tails.

sample (Feb/2007). In contrast, the 95% VaR for Alcoa remains high throughout the sample, with a value of $4.65 in the last month.

Hence, we conclude that our Credit VaR framework produces intuitive results. While safer firms have lower Values-at-Risk, riskier firms show persistently high Values-at-Risk even when market spreads decrease. This reflects the fact that the fundamental characteristics of the riskier firms make them more sensitive to scenarios of financial distress. In other words, the explanatory variables used in the quantile regression reveal the market assessment that, even in good times (ie, decline in CDS prices), less financially sound firms have a higher probability of reaching high CDS premiums.

8 Conclusion

This paper provides new evidence about the determinants of credit spreads. In addition to variables used in previous studies, such as implied volatility, put skew and stock return, we show that absolute bid-ask spreads are also important determinants of the distribution of CDS spreads. We show that the absolute bid-ask spread is a good measure of the cost of trading a CDS, while the relative bid-ask spread is not. We argue that this distinction can help explain some apparently conflicting results in the literature.

Using quantile regressions, we conclude that the impact and explanatory power of the proposed key determinants of CDS spreads reveal a significant amount of heterogeneity. More precisely, both the estimated slopes and the goodness-of-fit are increasing functions of the conditional quantile of CDS spreads. The classical least squares approach cannot accommodate this heterogeneity and tends to give results similar to those found in the higher quantiles. Hence, we argue that some of the results in previous studies based on the conditional mean approach ought to be complemented with those we found for the entire distribution.

We illustrate the application of the quantile regression framework to credit risk management. The model allows the estimation of Credit VaR directly from the key determinants of CDS spreads, instead of relying only on historical quotes or external credit ratings. Future promising extensions of this framework include incorporating dynamic processes for the explanatory variables (e.g., stochastic volatility) and different forecasting horizons.

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Table I

A. Firm-specific Variable Definitions and Theoretical Predicted Relations with CDS Spreads

Variable	Variable Description	Predicted Sign	Economic Intuition
ivol	Implied Volatility (ATM Put)	+	Higher firm-specific volatility increases the probability that the firm assets' value crosses the default threshold.
skew	Put Skew (OTM Put – ATM Put)	+	Deep-out-of-the-money put options on the firm's equity provide insurance against large negative returns and jumps to default. The higher the Put skew the higher the market probability of a large negative jump in the firm's value.
ret	Stock Return	–	A higher drift in the firm value process reduces the probability of default. Recent performance is a proxy for the firm's financial health. It may also reflect a positive assessment of the firm's expected growth. The equity return can also be interpreted as a high-frequency proxy for leverage.
bas	CDS Bid-Ask Spread	+	The absolute CDS bid-ask spread measures the expected cost of a roundtrip transaction.

B. Macroeconomic Variable Definitions and Theoretical Predicted Relations with CDS Spreads

Variable	Variable Description	Predicted Sign	Economic Intuition
10y treasury rate	Risk-free interest rate (10y treasury)	–	Longstaff and Schwartz (1995) suggest that a higher risk-free rate increases the risk-neutral drift of the firm value process, thus reducing the probability of default.
slope treasury	Slope of the treasury yield curve (10y – 2y)	–	The term structure slope is a well-known leading indicator of the business cycle, with a positively sloped structure usually signaling "good times".
5y swap spread	5y swap spread (5y Swaps – 5y Treasury)	+	This spread is commonly seen as a credit spread reflecting overall credit conditions.
index implied vol	Market implied volatility (ATM Put)	+	Collin-Dufresne, Goldstein and Martin (2001) show that credit spreads are related to overall market volatility.

Table II
Descriptive Statistics

Summary statistics on the key variables included in the regressions. Panel A displays the number of firms included in the sample. Panels B and C display the evolution of sample average CDS spreads by industry and credit rating group, respectively. Panel D displays aggregate descriptive statistics. Panel E shows the correlation matrix of key variables. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly 5-year CDS spreads, from Aug2002 to Feb2007, obtained in Bloomberg.

Panel A. Number of firms by industry and market

Market	Industry					
	Consumer	Financial	Industrial	Utilities	Tech	All
EU	31	25	25	15	17	113
US	33	31	33	26	24	147
All	64	56	58	41	41	260

Panel B. Evolution of sample average CDS spread by industry and year

Year	Industry					
	Consumer	Financial	Industrial	Tech	Utilities	All
2002	106	75	129	216	143	130
2003	77	43	104	103	74	79
2004	65	33	70	72	52	58
2005	69	26	68	62	40	54
2006	66	18	53	63	34	47
2007	48	14	40	52	26	36
Mean	71	32	75	84	54	63
Number of Obs.	3,310	2,914	2,991	2,166	2,089	13,470

Panel C. Evolution of average CDS spread by credit rating and year

Year	Rating Group						
	AAA	AA	A	BBB	BB	B	All
2002	50	54	91	197	759	.	129
2003	32	28	47	98	404	453	79
2004	25	18	32	66	203	360	58
2005	19	16	27	54	230	342	54
2006	13	12	23	43	159	381	47
2007	8	9	18	34	115	260	36
Mean	26	21	35	72	234	363	63
Number of Obs.	197	1,847	5,548	4,855	669	250	13,366

Table II (continued)

Panel D. Aggregate summary statistics on key variables

Variable	Statistic					
	Mean	Median	Std. Dev.	1st pct.	99th pct.	Fisher - ADF test
CDS spread (bps)	63	36	95	7	470	1850.5***
Implied volatility (%)	27	24	11	13	67	1648.3***
Put skew (%)	2.5	1.9	2.7	-1	12	3302.4***
Stock return (%)	7.4	7.5	20	-43	60	1744.3***
Bid-Ask Spread (bps)	7	5	10	2	40	2928.3***
Index implied vol. (%)	16	14	7	9	43	-
10y treasury rate (%)	4.2	4.2	0.4	3.1	5.1	-
Slope treasury (%)	1	0.8	0.9	-0.5	2.5	-
5y swap spread (bps)	35	39	14	10	66	-

Panel E. Correlation matrix

Firm-specific	CDS Spread	Implied volatility	Put skew	Stock return	Bid-Ask Spread
CDS spread	1.00				
Implied volatility	0.62	1.00			
Put skew	0.38	0.44	1.00		
Stock return	-0.20	-0.27	-0.21	1.00	
Bid-Ask Spread	0.69	0.56	0.28	-0.21	1.00

Macroeconomic	CDS Spread	Index implied vol.	10y treasury	Slope treasury	5y swap spread
CDS Spread	1.00				
Index implied vol.	0.19	1.00			
10y treasury	0.04	-0.19	1.00		
Slope treasury	0.10	0.47	-0.40	1.00	
5y swap spread	0.12	-0.20	0.53	-0.08	1.00

Table III
Benchmark Regression

Pooled simultaneous quantile regression of 5-year CDS spreads on firm-specific factors and time-dummies. Explanatory variables include individual implied volatility, put skew, stock return, and CDS bid-ask spread. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007, obtained from Bloomberg. Coefficients and robust *t*-statistics are reported for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The *t*-statistics in brackets, reported below each coefficient, are computed using bootstrapped cluster standard errors which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 250 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

Panel A: Equity Options

	OLS	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Implied volatility	4.79***	0.67***	0.84***	1.24***	2.16***	4.12***	7.96***	10.38***
	(6.49)	(10.09)	(13.12)	(11.64)	(10.25)	(7.82)	(7.62)	(9.63)
Put skew	4.73***	0.91**	1.40***	2.49***	2.91***	5.69***	9.17***	10.53***
	(2.93)	(2.43)	(3.50)	(5.37)	(4.41)	(3.71)	(4.26)	(3.90)
Constant	-78.3***	-4.8***	-6.7***	-11.1***	-20.9***	-49.0***	-104.9***	-132.9***
	(-4.83)	(-3.95)	(-4.90)	(-5.33)	(-4.82)	(-4.81)	(-5.98)	(-7.71)
Adj. R^2 / Pseudo R^2	0.40	0.07	0.08	0.11	0.15	0.25	0.40	0.48

Panel B: Equity Options, Stock Return and Time-dummies

	OLS	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Implied volatility	5.88***	0.72***	0.87***	1.19***	2.26***	4.72***	8.72***	11.21***
	(6.39)	(9.16)	(10.19)	(8.15)	(6.74)	(6.33)	(7.62)	(10.31)
Put skew	5.79***	0.57*	1.00**	1.79***	2.72***	6.79***	9.86***	10.46***
	(3.46)	(1.66)	(2.57)	(3.46)	(3.67)	(3.85)	(4.77)	(3.48)
Stock return	-0.39***	0.01	0.00	-0.04	-0.10**	-0.19*	-0.44**	-0.59***
	(-3.70)	(0.32)	(0.01)	(-1.33)	(-2.10)	(-1.85)	(-2.33)	(-2.79)
Constant	-183.6***	-5.6	-6.2	-6.3	-25.1	-94.3***	-200.4***	-226.8***
	(-4.31)	(-1.34)	(-1.23)	(-0.77)	(-1.58)	(-2.93)	(-4.20)	(-4.53)
Adj. R^2 / Pseudo R^2	0.45	0.09	0.10	0.12	0.16	0.26	0.42	0.50

Table IV
Benchmark Regression Extended with Liquidity

Pooled simultaneous quantile regression of 5-year CDS spreads to firm-specific factors and time-dummies. Explanatory variables include individual implied volatility, put skew, stock return, and CDS bid-ask spread. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007, obtained from Bloomberg. Coefficients and robust *t*-statistics are reported for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The *t*-statistics in brackets, reported below each coefficient, are computed using bootstrapped cluster standard errors which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 250 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	OLS	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Implied volatility	3.69***	0.54***	0.65***	0.84***	1.43***	2.45***	3.76***	5.48***
	(5.93)	(6.83)	(7.92)	(7.08)	(6.52)	(7.83)	(5.29)	(4.36)
Put skew	5.24***	0.19	0.47	1.21***	1.79***	3.64***	6.74***	8.83***
	(3.70)	(0.82)	(1.43)	(3.13)	(3.58)	(3.43)	(4.26)	(3.59)
Stock return	-0.25***	0.01	0.01	-0.01	-0.04	-0.18***	-0.34***	-0.50***
	(-2.77)	(0.41)	(0.29)	(-0.35)	(-1.22)	(-2.89)	(-2.79)	(-2.79)
Bid-Ask spread	4.68***	2.68***	3.13***	4.27***	6.34***	8.79***	10.30***	11.09***
	(8.81)	(8.01)	(15.50)	(10.50)	(12.22)	(12.55)	(10.41)	(7.31)
Constant	-164.7***	-21.6***	-24.5***	-38.7***	-67.1***	-111.7***	-154.3***	-210.3***
	(-5.36)	(-3.41)	(-4.14)	(-4.58)	(-4.83)	(-6.22)	(-5.23)	(-4.27)
Adj. R^2 / Pseudo R^2	0.62	0.17	0.19	0.24	0.33	0.45	0.56	0.60

Table V
Benchmark Regression: Inter-Quantile Differences and Statistical Significance

Inter-quantile differences and statistical significance *t*-tests of the benchmark model reported in Table IV. The *t*-statistics in brackets, reported below each inter-quantile difference coefficient, are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors, for the inter-quantile differences, were obtained using 100 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	Implied Volatility				Put Skew			
	0.25	0.50	0.75	0.90	0.25	0.50	0.75	0.90
0.10	0.20***	0.79***	1.80***	3.11***	0.74***	1.32***	3.17***	6.26***
	(2.60)	(4.15)	(5.93)	(4.40)	(2.66)	(3.12)	(3.20)	(3.83)
0.25		0.59***	1.61***	2.92***		0.57*	2.43***	5.52***
		(4.30)	(5.88)	(4.23)		(1.80)	(2.67)	(3.58)
0.50			1.02***	2.33***			1.86**	4.95***
			(5.31)	(3.65)			(2.59)	(3.57)
0.75				1.31***				3.09***
				(2.68)				(3.17)

	Stock Return				CDS Bid-Ask Spread			
	0.25	0.50	0.75	0.90	0.25	0.50	0.75	0.90
0.10	-0.02	-0.05	-0.19***	-0.35***	1.14***	3.21***	5.66***	7.17***
	(-0.81)	(-1.44)	(-2.90)	(-2.88)	(3.37)	(6.66)	(8.21)	(6.53)
0.25		-0.03	-0.17***	-0.33***		2.07***	4.52***	6.03***
		(-1.36)	(-3.09)	(-2.87)		(5.10)	(7.16)	(5.48)
0.50			-0.14***	-0.30***			2.45***	3.97***
			(-2.98)	(-2.77)			(5.14)	(3.85)
0.75				-0.16*				1.51**
				(-1.95)				(2.06)

Table VI
Classical Approach

Panel least-squares regressions - pooled ordinary least-squares (OLS), fixed effects (FEM) and random effects (REM) - of 5-year CDS spreads on firm-specific variables and time-dummies. Explanatory variables include individual implied volatility, put skew, stock return, CDS bid-ask spread, time-dummies and credit rating group dummies. Rating Group AAA/AA is the base dummy and is omitted in the regression. The sample consists of 13,470 monthly 5-year CDS spreads from Aug2002 to Feb2007. The sample comprises 260 unique firms from the US and the EU. The t-stats in brackets are computed with clustered standard errors which correct for heteroskedasticity and possible correlation within clusters (firms). One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	OLS_1	OLS_2	OLS_3	FEM_1	FEM_2	FEM_3	REM_1	REM_2	REM_3
Implied volatility	5.88***	3.69***	2.30***	4.41***	2.90***	2.84***	4.47***	2.97***	2.83***
	(6.39)	(5.93)	(5.15)	(5.31)	(4.75)	(5.45)	(5.40)	(4.89)	(5.61)
Put skew	5.79***	5.24***	3.52***	3.39***	2.78***	2.66***	3.46***	2.88***	2.69***
	(3.46)	(3.70)	(3.08)	(3.51)	(3.57)	(3.66)	(3.55)	(3.64)	(3.69)
Stock return	-0.39***	-0.25***	-0.41***	-0.39***	-0.26***	-0.29***	-0.39***	-0.26***	-0.30***
	(-3.70)	(-2.77)	(-4.65)	(-4.62)	(-4.71)	(-5.21)	(-4.63)	(-4.69)	(-5.29)
CDS bid-ask spread		4.68***	3.89***		3.38***	3.42***		3.41***	3.44***
		(8.81)	(8.44)		(10.31)	(9.52)		(10.32)	(9.48)
Rating (A)			8.85***			13.65**			13.81***
			(4.54)			(2.32)			(2.82)
Rating (BBB)			32.75***			24.58***			27.11***
			(11.31)			(3.62)			(4.91)
Rating (BB/B)			152.1***			122.5***			127.4***
			(8.66)			(3.70)			(4.27)
Constant	-183.6***	-164.7***	-95.6***	-99.6**	-88.5***	-105.8***	-102.2***	-92.5***	-107.3***
	(-4.31)	(-5.36)	(-4.41)	(-2.43)	(-2.80)	(-3.73)	(-2.65)	(-3.16)	(-4.23)
Adj. R^2	0.45	0.62	0.72	0.41	0.59	0.63	0.44	0.61	0.72
Number of observations	13,470	13,470	13,366	13,470	13,470	13,366	13,470	13,470	13,366

F-test (Fixed Effects)	74***	72***	48***
Breusch-Pagan test (10^3)	110***	94***	75***
Sargan-Hansen test	2751***	964***	396***

Table VII
Extended Regression with Credit Rating Groups

Pooled simultaneous quantile regression of 5-year CDS spreads on firm-specific factors and time-dummies. Explanatory variables include individual implied volatility, put skew, firm stock return, CDS bid-ask spread, time-dummies and credit rating group dummies. Rating Group A is the base dummy and is omitted in the regression. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007. Coefficients and robust *t*-statistics are reported for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The *t*-statistics in brackets, reported below each coefficient, are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Implied volatility	0.28***	0.36***	0.48***	0.71***	1.15***	1.81***	2.54***
	(4.13)	(4.87)	(5.24)	(5.93)	(5.77)	(5.37)	(4.69)
Put skew	0.22	0.35**	0.50**	0.96**	2.09***	3.78***	5.81***
	(1.64)	(2.31)	(2.13)	(2.44)	(2.99)	(3.09)	(3.15)
Stock return	-0.06**	-0.08***	-0.09***	-0.11***	-0.19***	-0.33***	-0.48***
	(-2.37)	(-3.64)	(-4.35)	(-4.73)	(-5.07)	(-4.80)	(-4.28)
Bid-Ask spread	1.78***	2.26***	3.05***	4.06***	5.14***	6.27***	6.60***
	(4.27)	(5.33)	(10.78)	(10.32)	(10.19)	(11.18)	(9.11)
Rating (AAA)	-3.77*	-2.59	-3.04	-3.44	-6.05	-3.51	-5.08
	(-1.78)	(-1.22)	(-1.16)	(-1.06)	(-1.28)	(-0.48)	(-0.30)
Rating (AA)	-7.8***	-8.5***	-8.7***	-7.4***	-7.6***	-8.4***	-9.9***
	(-8.09)	(-9.88)	(-6.92)	(-5.44)	(-5.99)	(-4.94)	(-4.67)
Rating (BBB)	10.2***	11.1***	13.9***	17.6***	22.5***	28.8***	34.5***
	(7.30)	(8.60)	(9.10)	(10.21)	(9.67)	(7.24)	(5.46)
Rating (BB)	51***	58.3***	76.2***	101.5***	145***	175.8***	247.5***
	(7.91)	(7.04)	(8.27)	(5.50)	(6.70)	(3.33)	(2.95)
Rating (B)	111.8***	125.3***	155.4***	219.6***	265.4***	314.3**	514.8***
	(6.75)	(5.85)	(4.42)	(7.05)	(4.62)	(2.12)	(2.68)
Constant	3.88	-1.56	-4.72	-7.85	-19.04	-23.48	-45.02*
	(0.67)	(-0.23)	(-0.75)	(-0.91)	(-1.60)	(-1.33)	(-1.79)
Pseudo R^2	0.30	0.33	0.38	0.47	0.58	0.67	0.71

Table VIII
Extended Regression: Inter-Quantile Differences and Statistical Significance

Inter-quantile differences and statistical significance *t*-tests of the extended regression reported in Table VII. The *t*-statistics in brackets, reported below each inter-quantile difference coefficient, are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors, for the inter-quantile differences, were obtained using 100 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	Implied Volatility				Put Skew			
	0.25	0.50	0.75	0.90	0.25	0.50	0.75	0.90
0.10	0.12**	0.35***	0.79***	1.45***	0.15	0.61*	1.74***	3.43***
	(2.34)	(3.59)	(4.43)	(4.56)	(0.98)	(1.92)	(2.63)	(2.85)
0.25		0.23***	0.67***	1.33***		0.46**	1.59***	3.28***
		(3.64)	(4.43)	(4.42)		(2.04)	(2.71)	(2.85)
0.50			0.44***	1.10***			1.13**	2.82***
			(3.89)	(3.92)			(2.54)	(2.73)
0.75				0.65***				1.69**
				(3.15)				(2.30)

	Stock Return				CDS Bid-Ask Spread			
	0.25	0.50	0.75	0.90	0.25	0.50	0.75	0.90
0.10	-0.01	-0.03	-0.11***	-0.25***	0.79***	1.81***	2.88***	4.02***
	(-0.66)	(-1.24)	(-2.85)	(-3.62)	(3.24)	(5.28)	(5.98)	(6.30)
0.25		-0.02	-0.10***	-0.24***		1.01***	2.09***	3.23***
		(-1.18)	(-2.81)	(-3.61)		(3.93)	(5.12)	(6.22)
0.50			-0.08***	-0.22***			1.07***	2.21***
			(-2.91)	(-3.58)			(3.39)	(4.35)
0.75				-0.14***				1.14***
				(-3.04)				(2.74)

Table IX
Sample Segmentation by Credit Rating

Pooled simultaneous quantile regression, after sample segmentation by credit rating, of 5-year CDS spreads on firm-specific factors and time-dummies. Explanatory variables include individual implied volatility, put skew, firm stock return, CDS bid-ask spread, and time-dummies. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007, obtained in Bloomberg. The sample is segmented by credit rating class: AAA/AA, A, BBB, and BB/B with 55, 136, 125, and 31 clusters, respectively. Coefficients and robust *t*-statistics are reported for the 10th, 25th, 50th, 75th, and 90th quantiles. The *t*-statistics in brackets, reported below each coefficient, are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 100 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	Rating Class: AAA/AA					
	OLS	q10	q25	q50	q75	q90
Implied volatility	0.96***	0.15*	0.26*	0.56***	0.78***	0.80***
	(6.26)	(2.44)	(2.34)	(3.56)	(4.42)	(3.26)
Put skew	0.75	0.22	0.41	1.23	1.68	2.31
	(1.09)	(1.03)	(0.94)	(1.63)	(1.58)	(1.63)
Stock return	-0.08*	-0.01	-0.02	-0.04	-0.08**	-0.09
	(-1.69)	(-0.71)	(-0.74)	(-0.92)	(-2.13)	(-1.51)
Bid-ask spread	1.53***	0.48***	0.63***	1.40***	2.09***	2.70***
	(3.11)	(3.61)	(3.36)	(3.48)	(3.36)	(4.51)
Constant	-11.12	14.06***	8.54	-3.32	-2.64	12.30
	(-1.04)	(4.36)	(1.40)	(-0.34)	(-0.16)	(0.56)
Adj. R^2 / Pseudo R^2	0.62	0.30	0.29	0.32	0.44	0.58

	Rating Class: A					
	OLS	q10	q25	q50	q75	q90
Implied volatility	0.93***	0.30***	0.35***	0.49***	0.67***	1.06***
	(4.71)	(3.82)	(3.64)	(4.34)	(4.27)	(4.04)
Put skew	0.71*	0.27**	0.32*	0.40	0.55**	0.77*
	(1.66)	(2.25)	(1.83)	(1.43)	(2.05)	(1.85)
Stock return	-0.22***	-0.06**	-0.07***	-0.09***	-0.14***	-0.27***
	(-4.86)	(-2.25)	(-3.04)	(-3.59)	(-3.74)	(-4.43)
Bid-ask spread	2.93***	1.07***	1.24***	1.94***	2.97***	3.57***
	(12.31)	(5.25)	(3.72)	(3.95)	(6.47)	(5.76)
Constant	3.61	14.06**	22.83***	26.53***	30.52**	43.73**
	(0.32)	(2.46)	(3.31)	(2.68)	(2.60)	(2.12)
Adj. R^2 / Pseudo R^2	0.64	0.24	0.27	0.33	0.43	0.52

Table IX (continued)

	Rating Class: BBB					
	OLS	q10	q25	q50	q75	q90
Implied volatility	2.25***	0.44***	0.71***	1.36***	2.13***	3.02***
	(6.25)	(3.56)	(4.13)	(6.60)	(7.90)	(4.98)
Put skew	5.12***	0.41	0.78*	1.96**	3.76***	7.04***
	(4.13)	(1.45)	(1.71)	(2.42)	(3.29)	(3.90)
Stock return	-0.43***	-0.14***	-0.18***	-0.21***	-0.33***	-0.47***
	(-4.74)	(-4.06)	(-4.34)	(-4.56)	(-3.83)	(-3.26)
Bid-ask spread	3.97***	2.71***	3.16***	4.05***	5.62***	6.41***
	(6.99)	(5.63)	(10.17)	(10.44)	(9.76)	(8.34)
Constant	-41.23*	16.52	18.23*	-0.11	-23.91	-42.22
	(-1.96)	(1.63)	(1.79)	(-0.01)	(-1.23)	(-1.40)
Adj. R^2 / Pseudo R^2	0.67	0.21	0.24	0.33	0.45	0.57

	Rating Class: BB/B					
	OLS	q10	q25	q50	q75	q90
Implied volatility	4.57**	1.29	1.98	3.23	6.64**	9.32**
	(2.19)	(1.13)	(1.41)	(1.41)	(2.09)	(2.55)
Put skew	5.39**	0.09	2.15	5.45**	5.63	12.79**
	(2.24)	(0.05)	(0.94)	(2.42)	(1.65)	(2.67)
Stock return	-0.67**	-0.05	-0.34	-0.68**	-0.54	-0.78
	(-2.70)	(-0.19)	(-1.16)	(-2.06)	(-1.45)	(-1.64)
Bid-ask spread	3.77***	4.01***	4.87***	4.95***	3.83*	2.54
	(3.41)	(4.26)	(4.12)	(3.36)	(2.04)	(1.19)
Constant	-684.7***	-305.9	-769.3*	-1016.9**	-902.6**	-881.5*
	(-5.26)	(-1.09)	(-1.90)	(-2.22)	(-2.33)	(-1.85)
Adj. R^2 / Pseudo R^2	0.56	0.30	0.32	0.37	0.40	0.45

Table X
Sample Segmentation by Credit Rating: Inter-Quantile Differences and Statistical Significance

Inter-quantile differences and statistical significance *t*-tests of the regression reported in table IX, after sample segmentation by credit rating, of 5-year CDS spreads on firm-specific factors and time-dummies. The sample is segmented by credit rating class: AAA/AA, A, BBB, and BB/B with 55, 136, 125, and 31 clusters, respectively. The *t*-statistics in brackets, reported below each inter-quantile difference coefficient, are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors, for the inter-quantile differences, were obtained using 100 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

Panel A. Implied Volatility

	AAA/AA		A		BBB		BB/B	
	0.50	0.90	0.50	0.90	0.50	0.90	0.50	0.90
0.10	0.41***	0.65**	0.19**	0.75***	0.92***	2.58***	1.94	8.03**
	(2.79)	(2.44)	(2.29)	(3.60)	(4.93)	(4.15)	(0.99)	(2.13)
0.50		0.24		0.57***		1.66***		6.09**
		(1.00)		(3.15)		(3.04)		(2.22)

Panel B. Put Skew

	AAA/AA		A		BBB		BB/B	
	0.50	0.90	0.50	0.90	0.50	0.90	0.50	0.90
0.10	1.01	2.08	0.13	0.50	1.55**	6.64***	5.36**	12.70**
	(1.53)	(1.35)	(0.48)	(1.20)	(2.02)	(3.81)	(2.33)	(2.67)
0.50		1.08		0.37		5.09***		7.34
		(0.88)		(0.83)		(3.74)		(1.46)

Panel C. CDS Bid-Ask Spread

	AAA/AA		A		BBB		BB/B	
	0.50	0.90	0.50	0.90	0.50	0.90	0.50	0.90
0.10	0.92**	2.22***	0.87**	2.50***	1.34**	3.70***	0.94	-1.47
	(2.15)	(3.62)	(2.37)	(4.02)	(2.48)	(4.20)	(0.73)	(-0.62)
0.50		1.30***		1.63**		2.37***		-2.41
		(2.83)		(2.50)		(3.67)		(-1.25)

Panel D. Stock Return

	AAA/AA		A		BBB		BB/B	
	0.50	0.90	0.50	0.90	0.50	0.90	0.50	0.90
0.10	-0.02	-0.07	-0.03	-0.21***	-0.07	-0.33**	-0.63**	-0.73
	(-0.83)	(-1.38)	(-1.04)	(-3.48)	(-1.55)	(-2.59)	(-2.37)	(-1.51)
0.50		-0.05		-0.18***		-0.26**		-0.10
		(-0.97)		(-3.37)		(-2.44)		(-0.22)

Table XI
Benchmark Regression with Macroeconomic Factors

Pooled simultaneous quantile regression of 5-year CDS spreads on firm-specific factors and macroeconomic factors. Explanatory variables include individual implied volatility, put skew, firm stock return, CDS bid-ask spread, and market wide factors - the 10-year treasury rate, the slope of the treasury yield curve, the 5-year swap spread, and the market index implied volatility. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007. Coefficients and robust *t*-statistics are reported for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The *t*-statistics in brackets, reported below each coefficient, are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 50 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Implied volatility	0.59***	0.66***	0.94***	1.48***	2.54***	4.08***	5.51***
	(6.94)	(7.53)	(7.80)	(6.68)	(8.63)	(6.03)	(4.20)
Put skew	0.39*	0.65*	1.33***	2.15***	4.01***	7.21***	9.33***
	(1.71)	(1.78)	(3.03)	(3.92)	(3.90)	(4.45)	(3.60)
Stock return	-0.03	-0.04*	-0.05***	-0.11***	-0.25***	-0.38***	-0.48***
	(-1.36)	(-1.75)	(-2.60)	(-3.57)	(-4.06)	(-3.93)	(-3.01)
Bid-ask spread	2.48***	3.07***	4.11***	6.24***	8.43***	9.81***	10.77***
	(6.90)	(12.82)	(9.65)	(11.52)	(10.85)	(8.24)	(6.05)
10y treasury rate	-2.30***	-2.80***	-2.55***	-1.53	1.86	6.00**	9.61**
	(-3.03)	(-3.97)	(-2.98)	(-1.48)	(1.13)	(2.57)	(2.24)
Slope treasury	1.17*	0.84	0.78	0.02	-0.61	0.28	0.97
	(1.70)	(1.58)	(1.28)	(0.02)	(-0.63)	(0.17)	(0.36)
5y swap spread	-0.04	-0.06	-0.11*	-0.23***	-0.49***	-0.70***	-0.77***
	(-0.73)	(-1.09)	(-1.78)	(-3.08)	(-4.03)	(-5.06)	(-3.52)
Index implied vol.	-0.54***	-0.63***	-0.94***	-1.64***	-2.64***	-3.86***	-4.91***
	(-4.41)	(-5.28)	(-4.88)	(-5.23)	(-7.39)	(-6.46)	(-4.63)
Constant	5.90*	8.01***	7.28**	5.19	-6.81	-24.87**	-42.44**
	(1.91)	(2.96)	(2.12)	(1.26)	(-1.16)	(-2.57)	(-2.43)
Pseudo R^2	0.16	0.19	0.23	0.32	0.44	0.56	0.60

Table XII
Benchmark Regression Extended with Liquidity (ETC)

Pooled simultaneous quantile regression of 5-year CDS spreads on firm-specific factors and time-dummies. Explanatory variables include individual implied volatility, put skew, stock return, and CDS bid-ask spread. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007, obtained from Bloomberg. Coefficients and robust *t*-statistics are reported for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The *t*-statistics in brackets, reported below each coefficient, are computed using bootstrapped cluster standard errors which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 50 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	OLS	q0.05	q0.10	q0.25	q0.50	q0.75	q0.90	q0.95
Implied volatility	3.80***	0.55***	0.65***	0.89***	1.51***	2.65***	4.15***	5.98***
	(5.87)	(6.40)	(7.42)	(7.29)	(7.17)	(8.58)	(5.93)	(4.43)
Put skew	5.12***	0.25	0.47	1.26***	1.76***	3.88***	7.03***	9.10***
	(3.52)	(1.09)	(1.33)	(2.90)	(3.50)	(3.46)	(4.00)	(3.33)
Stock return	-0.29***	0.01	0.01	-0.02	-0.03	-0.21***	-0.38***	-0.56***
	(-3.24)	(0.47)	(0.22)	(-0.59)	(-1.01)	(-3.72)	(-3.42)	(-3.08)
ETC	1.35***	0.57***	0.77***	1.04***	1.58***	2.15***	2.54***	2.69***
	(10.48)	(6.29)	(9.18)	(10.55)	(9.88)	(10.54)	(8.38)	(5.49)
Constant	-182.78***	-20.31***	-25.98***	-42.65***	-74.26***	-123.68***	-174.23***	-230.92***
	(-5.79)	(-2.77)	(-3.58)	(-4.80)	(-4.92)	(-6.84)	(-6.54)	(-4.97)
Adj. R^2 / Pseudo R^2	0.60	0.15	0.17	0.22	0.31	0.43	0.55	0.59

Table XIII
Benchmark Regression with Lagged Explanatory Variables

Pooled simultaneous quantile regression of 5-year CDS spreads on firm-specific factors and time-dummies. Explanatory variables include individual implied volatility, put skew, firm stock return, CDS bid-ask spread, and time-dummies. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007, obtained in Bloomberg. Coefficients and robust *t*-statistics are reported for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles. The *t*-statistics in brackets, reported below each coefficient, are computed using bootstrapped cluster standard errors, which correct for possible dependence within clusters (firms). The bootstrap cluster standard errors were obtained using 250 bootstrap replications. One, two, or three stars represent statistical significance at the 0.1, 0.05, or 0.01 levels, respectively.

	Quantile						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Implied volatility	0.50***	0.59***	0.82***	1.33***	2.24***	3.49***	5.32***
	(7.85)	(7.94)	(7.72)	(6.77)	(7.51)	(5.02)	(4.01)
Put skew	0.18	0.50*	1.05***	1.55***	3.29***	6.25***	8.79***
	(0.75)	(1.88)	(2.73)	(3.26)	(3.46)	(3.76)	(3.61)
Stock return	0.01	0.02	-0.02	-0.07*	-0.15**	-0.26**	-0.43**
	(0.57)	(0.82)	(-0.92)	(-1.71)	(-2.06)	(-2.14)	(-2.22)
Bid-ask spread	2.28***	2.64***	3.48***	5.87***	8.67***	10.27***	10.81***
	(10.51)	(12.93)	(9.37)	(11.55)	(13.75)	(10.77)	(7.63)
Constant	-14.0***	-15.4***	-27.0***	-53.1***	-91.7***	-123.3***	-183.2***
	(-3.12)	(-3.18)	(-3.50)	(-3.92)	(-5.19)	(-4.15)	(-3.90)
Pseudo R^2	0.16	0.18	0.22	0.30	0.43	0.54	0.58

Figure 1
Evolution of CDS Liquidity Measures

Time-series plot of monthly cross-sectional averages of 5-year CDS bid-ask spreads and Expected Transaction Costs (ETC). The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads collected from Aug2002 to Feb2007, amounting to 55 months, obtained in Bloomberg.

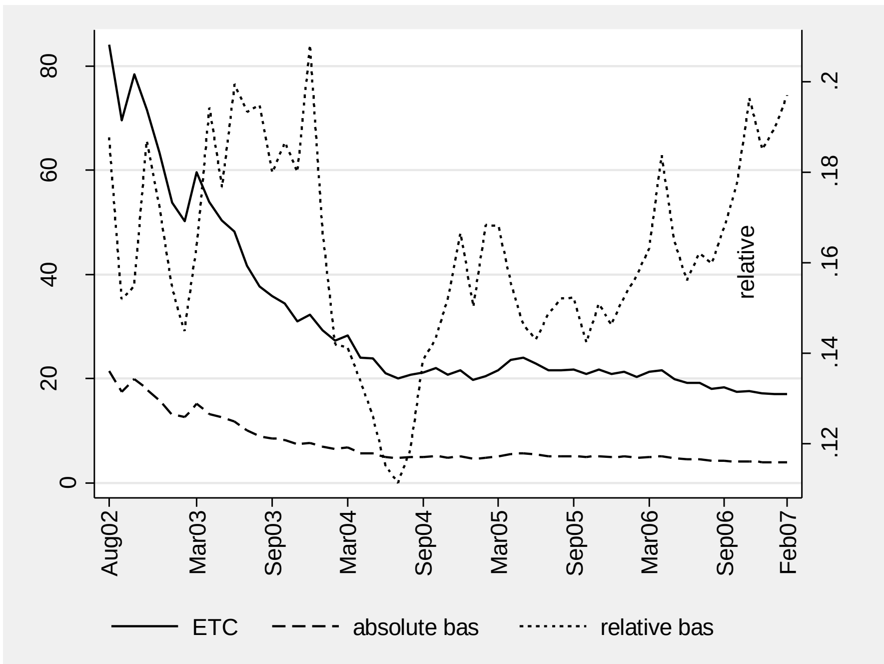


Figure 2
Evolution of CDS premiums and explanatory variables

Time-series plot with the evolution of the sample average of 5-year CDS spreads and implied volatility, put skew, and CDS bid-ask spread. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads collected from Aug2002 to Feb2007, amounting to 55 months, obtained in Bloomberg.

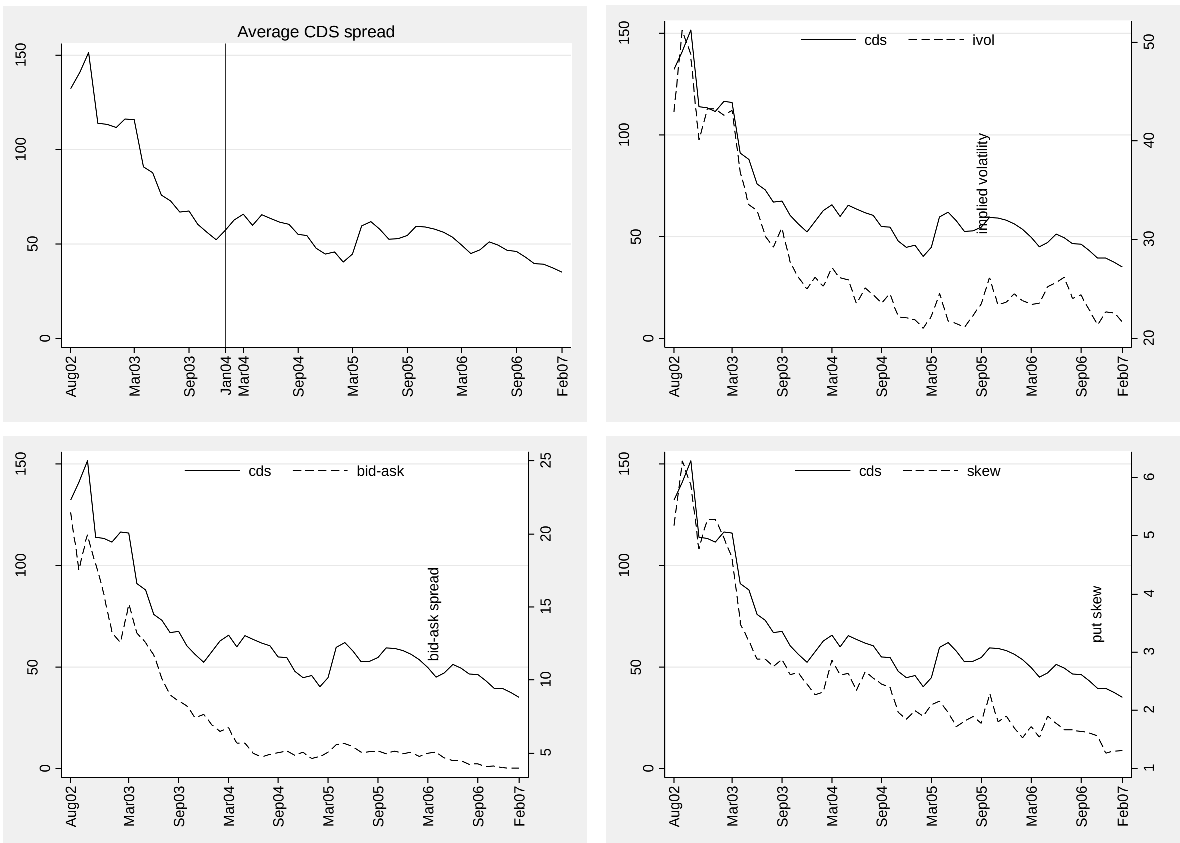


Figure 3
CDS Spread by Implied Volatility Level

Boxplot of the distribution of CDS spreads for ten groups of firms ranked by the level of implied volatility. The upper and lower limits of the "boxes" represent the first and third quartiles of CDS spreads. The median for each group is represented by the light-gray dot inside the box. The full range of the of the observed CDS spreads is represented by the horizontal bars at the end of the "whiskers". In cases where the "whiskers" would extend more than three times the interquantile range ("box"), they are truncated. For graphical reasons, the remaining outlying points are not displayed.

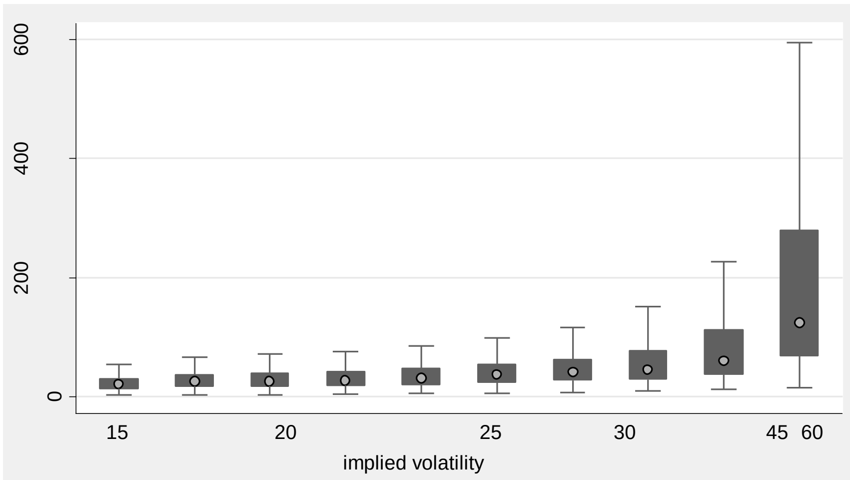


Figure 4
Histogram of Sample CDS Spreads

Histogram of sample CDS spreads and a plot of the Epanechnikov kernel density function. For graphical reasons, the x-axis was truncated at 400 bps.

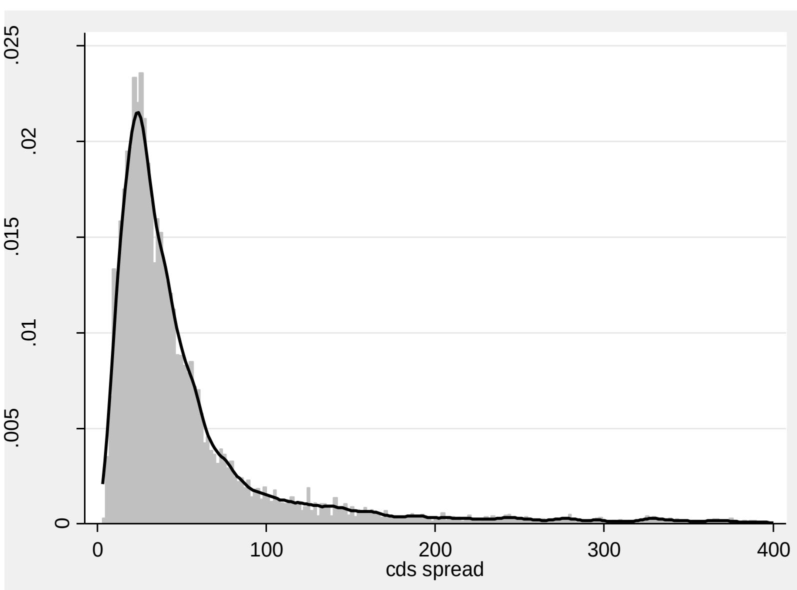


Figure 5
Relation between CDS Spreads and Firm Volatility

We use Merton's (1974) model to describe the relation between the credit spread (s) and the volatility of the firm's assets (σ). Debt matures in 5 years with a face value of 100, the risk-free interest rate is 5%, and the current value of the assets is 155. These parameters result in a leverage ratio of 0.5.

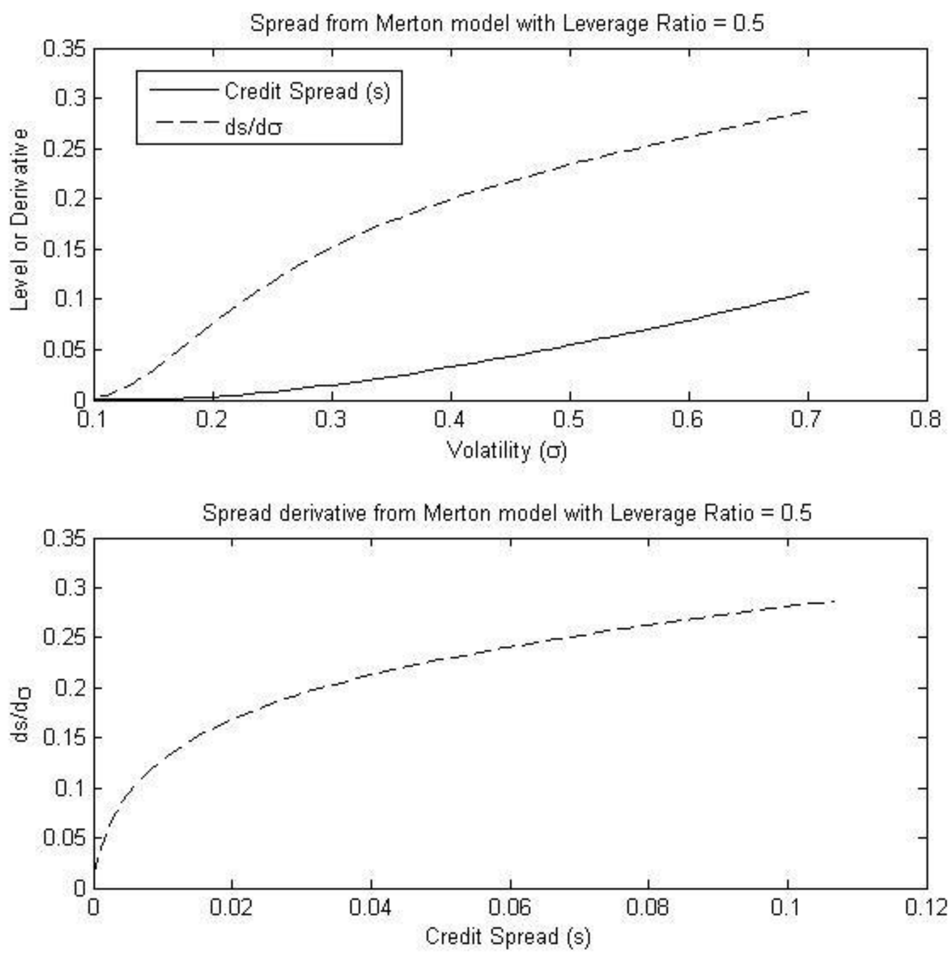


Figure 6
Quantile Plot of Estimated Slopes and 95% Confidence Interval

Quantile plots of the explanatory variables' slopes and 95% confidence interval, in the benchmark quantile regressions of 5-year CDS spreads on firm-specific factors and time-dummies, across conditional quantiles. The horizontal dash-dot and short dash lines represent the pooled OLS slope estimates and 95% confidence interval using cluster adjusted standard errors. The plots are based on the quantile regression estimates for nine deciles. Explanatory variables include individual implied volatility, put skew, firm stock return, CDS bid-ask spread, and time-dummies. The sample includes 260 firms, from the US and the EU, and comprises 13,470 monthly CDS spreads, from Aug2002 to Feb2007.

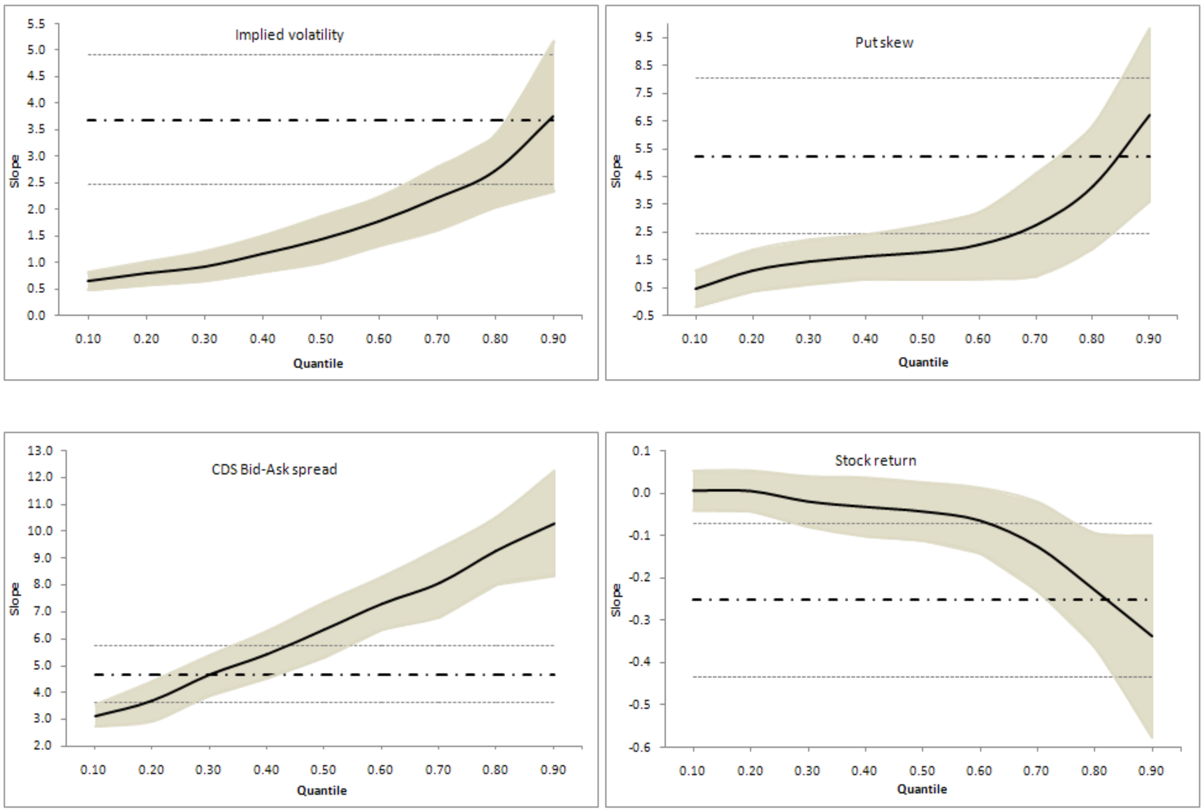


Figure 7
Time-Series Evolution of Cross-Sectional Slopes and R-Squared

Time-series plot with the evolution of the coefficients and the pseudo R-squared (and also the OLS R-Squared) of quarterly cross-sectional quantile regressions of 5-year CDS spreads to firm-specific factors. Explanatory variables include individual implied volatility, put skew, stock return, and CDS bid-ask spread. The sample includes 260 unique firms, from the US and the EU, and comprises 13,470 monthly CDS spreads collected from Aug2002 to Feb2007.

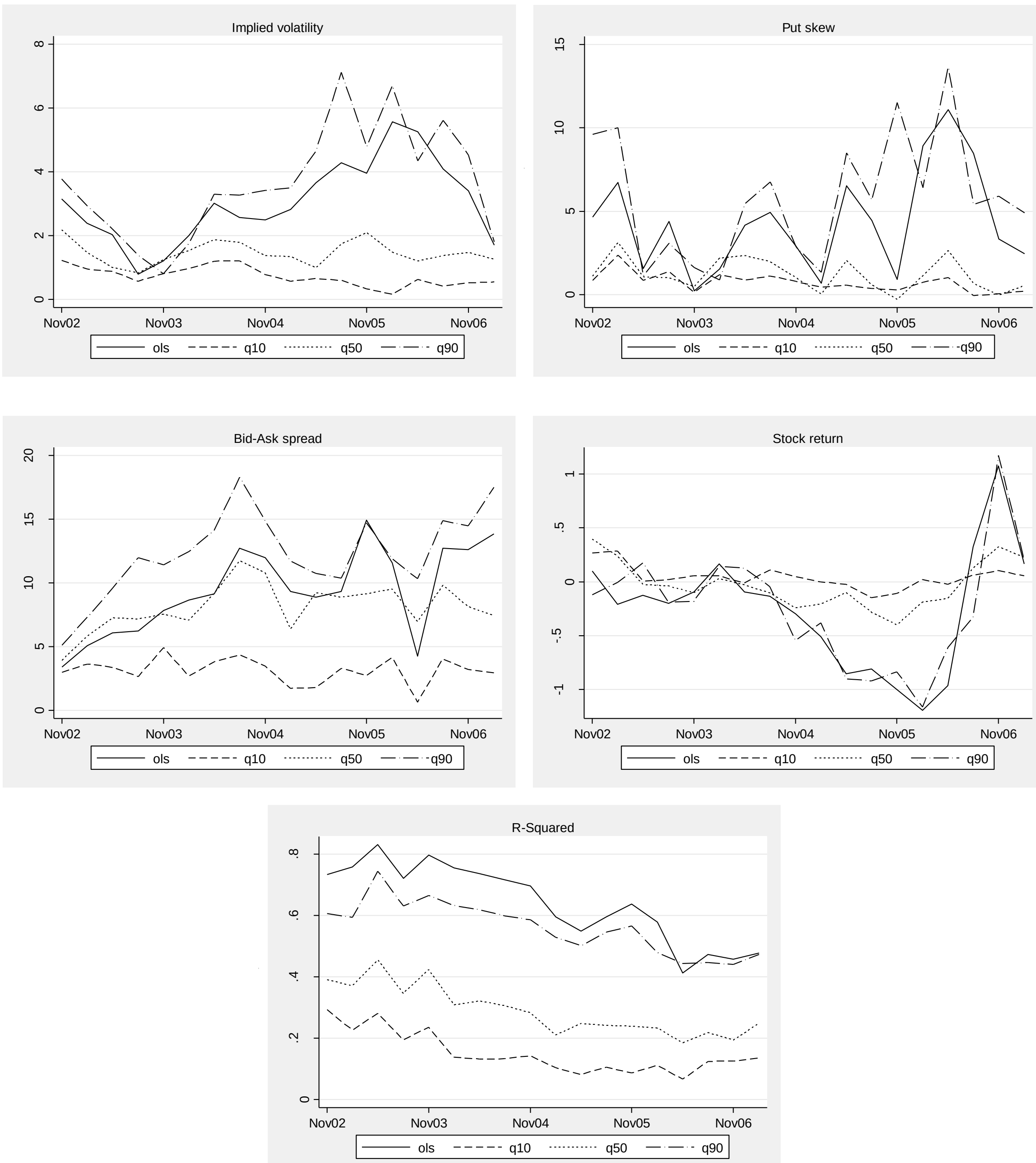


Figure 8
Conditional Density of CDS Spreads

Conditional density of CDS spreads at different values of each covariate using the model specified in equation (8) but with macroeconomic factors instead of time-dummies. Each density is fitted over 99 quantiles. Each density assumes a particular value for the key variable denoted in the title, namely the 5th, 10th, 90th, and 95th unconditional percentiles, while keeping the other regressors centered at their means.

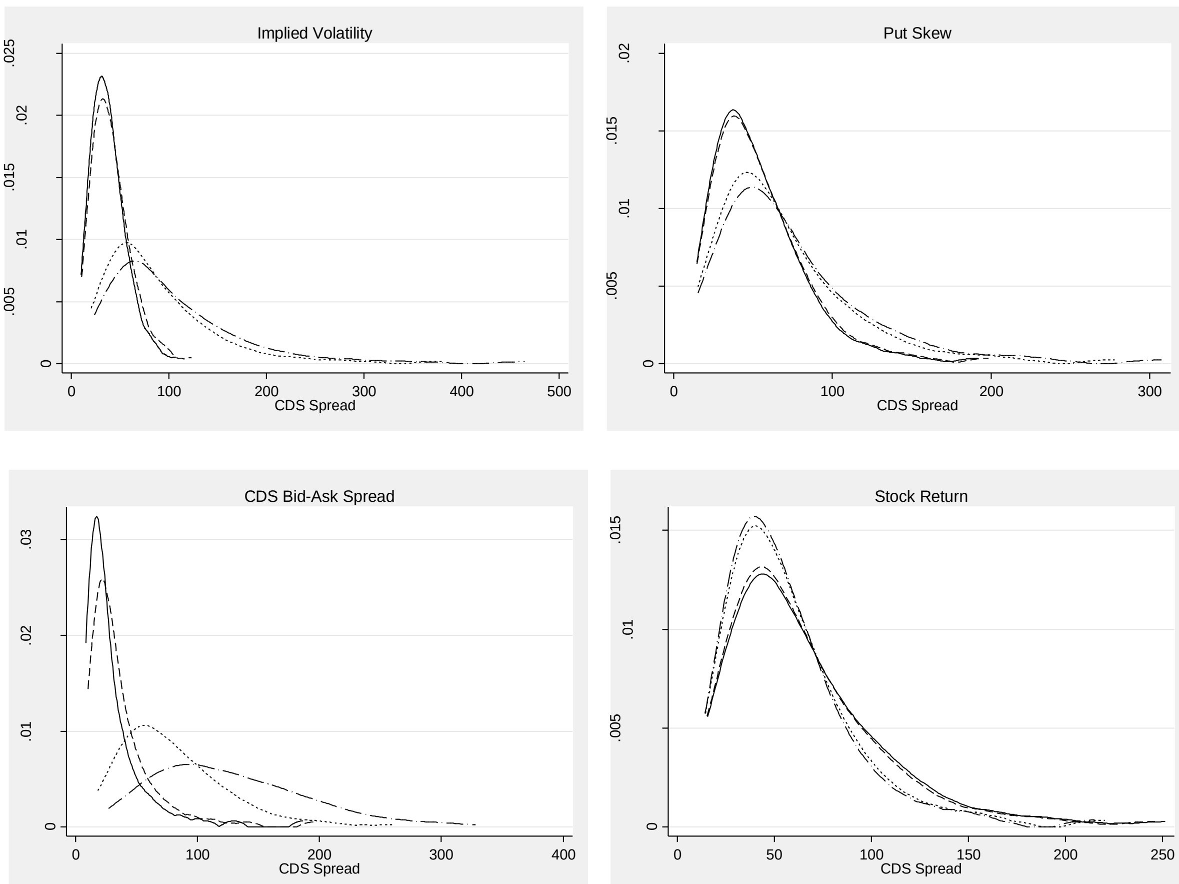
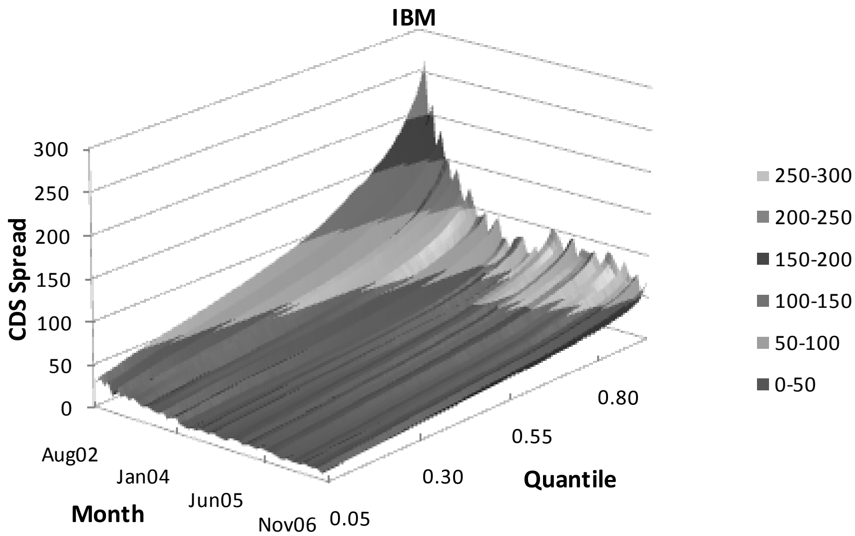


Figure 9
IBM and Alcoa: Surface of Fitted CDS Spreads

3D Surface of fitted monthly CDS spreads across quantiles for IBM and Alcoa, from Aug2002 to Feb2007. The graphs are based in the fitted results from 91 quantile regressions ranging from the 5th to 95th quantiles.



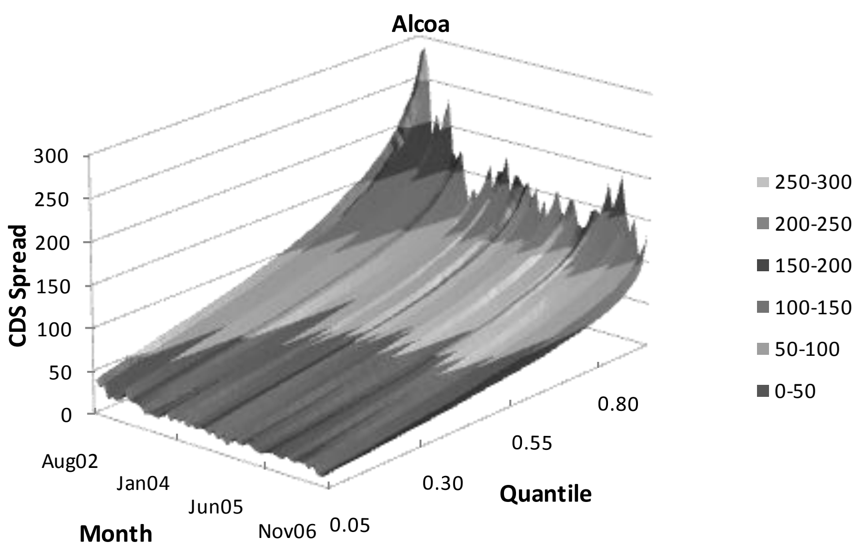


Figure 10
IBM and Alcoa CDS spreads: Observed Value and Fitted 95th Quantile

Time-series plot with the evolution of each firm's CDS spread actually observed in the market (obs) and its corresponding fitted 95th quantile (q95). The top plot is for IBM and the bottom for Alcoa. The sample includes 55 months from Aug/2002 to Feb/2007.

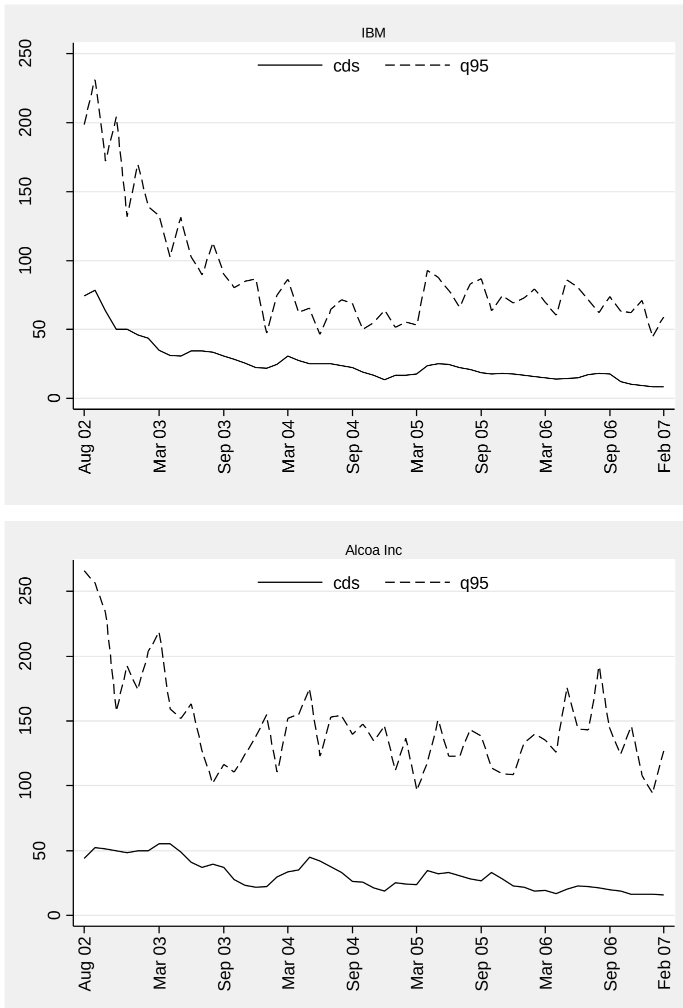


Figure 11
IBM and Alcoa: Surface of Credit VaR

3D Surface of fitted monthly Credit Value-at-Risk across quantiles, for IBM and Alcoa, for a notional exposure of $100, from Aug2002 to Feb2007. The graphs are based on the fitted results from 91 quantile regressions, ranging from the 5th to 95th quantiles, and on each firm's market observed CDS spread using the framework introduced in Section 7.