DISCUSSION PAPER SERIES

No. 8714

SCATTERED TRUST DID THE 2007–08 FINANCIAL CRISIS CHANGE RISK PERCEPTIONS?

Roland Füss, Thomas Gehrig and Philipp B Rindler

FINANCIAL ECONOMICS

Centre for Economic Policy Research

www.cepr.org

Available online at: **www.cepr.org/pubs/dps/DP8714.asp**

ISSN 0265-8003

SCATTERED TRUST - DID THE 2007-08 FINANCIAL CRISIS CHANGE RISK PERCEPTIONS?

Roland Füss, EBS Business School
Thomas Gehrig, University of Vienna and CEPR
Philipp B Rindler, EBS Business School

Discussion Paper No. 8714
December 2011

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 8714

December 2011

ABSTRACT

Scattered Trust - Did the 2007-08 financial crisis change risk perceptions?*

The paper investigates whether the financial crisis did affect risk perceptions, and, hence, change structural parameters. By decomposing credit spreads of US corporate bonds into the contributions by credit, equity, and liquidity risk factors as well as structural change, the relative contribution of the change in risk perceptions can be measured. We show that this increase is mostly due to aversion to default risk for high-yield bonds. For low-yield bonds, the increase is mostly due to liquidity related factors. By means of counterfactual analysis we find that the financial crisis shifted the distribution of bond spreads almost uniformly. This evidence is consistent with changing risk perceptions as predicted by theories of ambiguity aversion or social learning in the case of rare events.

JEL Classification: C21 and G12
Keywords: ambiguity aversion, counterfactual analysis, credit spreads, quantile regression and structural models

Roland Füss
EBS Business School
Gustave-Stresemann-Ring 3
65189 Wiesbaden
GERMANY

Email: roland.fuess@ebs.edu

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=174811

Thomas Gehrig
Department of Finance
University of Vienna
Brünner Straße 72
A-1210 Vienna
AUSTRIA

Email: thomas.gehrig@univie.ac.at

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=108406

Philipp B Rindler
EBS Business School
Gustav-Stresemann-Ring 3
65189 Wiesbaden
GERMANY

Email: philipp.rindler@ebs.edu

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=174812

* A previous version of this paper was circulated under the title: Risk Decomposition of Credit Spreads. We are indebted to Dirk Antonczyk, Chris Brooks and Marcel Prokopczuk as well as the participants of the 2011 European Meeting of the Econometric Society and the International Conference on Credit Analysis and Risk Management for useful comments and helpful suggestions.

Submitted 12 December 2011

It is a well-documented fact that the financial crisis of 2007-08 did dramatically increase credit spreads for corporate bonds. It is less known though, that credit spreads did not return to their pre-crisis levels thereafter. Figure 1 documents this empirical fact for US corporate credit spreads for the period October 2004 to December 2010. How can this finding be explained? How much of the change in credit spreads has to be attributed to the variation in the underlying risk factors. How much is due to changes in market liquidity? How much of the variation is due to structural shifts in risk perception of market participants?

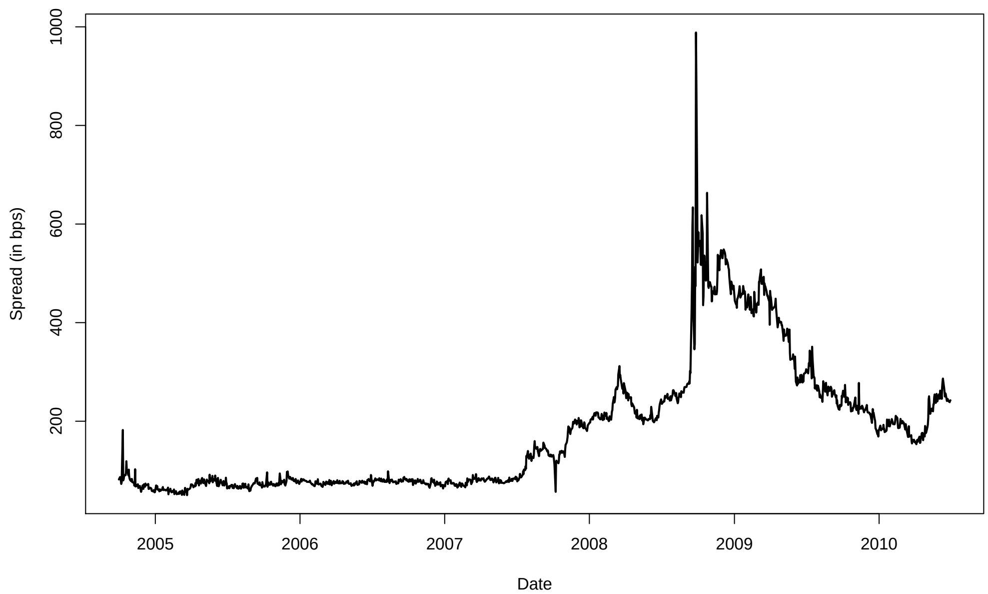
We attempt to address this question by analyzing the evolution of the whole distribution of credit spreads. In line with the current literature, we decompose the changes in spreads into factors of credit, equity, and liquidity risk. However, in contrast to (most of) the literature we also allow for changes in the underlying pricing structures. By comparing the counterfactual distribution of credit spreads with the true distribution we can identify the relative contribution of market risk and liquidity factors, while the differential in distributions is associated to changes in the underlying pricing structure. Thus, we explicitly account for the possibility that the crisis has permanently changed risk perceptions of market participants.

There may be various reasons, why large shocks may change risk perceptions permanently. First, there may be learning that small probability events have been undervalued prior to the crisis. For example, counterparty risk may have been underpriced prior to the crisis. Second, behavioral reasons might explain permanent changes in risk perceptions. Ambiguity averse investors may rationally place higher weight on the possibility of high risk scenarios after high risk events have occurred. As in the current period, deep crisis in the US bond market have been quite distant in time; hence a large crisis may have contributed to substantial updating. Possibly, also waves of optimism and pessimism might be triggered by the recent past of returns. Moreover, the crisis might have revealed weaknesses in other risk factors related to politics, regulation and the societal framework at large. While we will not be able to identify the reason of changes in market perceptions, our approach, however, will allow us to answer the question, whether changes in risk perception did actually take place, and to what extent changes in credit spreads can be attributed to such changes in market risk perceptions relative to the standard risk and liquidity factors.

In our data we find that most of the change in credit spreads has to be associated to an increase in risk perceptions. Only 30% are due to changes in the risk factors themselves. The decomposition shows that the effects of the risk factors are almost completely reversed after the crisis whereas the increases in the fundamental pricing coefficients have decreased only slightly after the crisis and remained higher than before. Hence the increase in credit spread levels is almost entirely explained by a change in risk perception of the market. Otherwise, in terms of risk factors the market has normalized soon after the crisis. This suggests that risk perceptions must have changed. In fact, our analysis suggests that the overall risk bearing capacity of the bond market has been reduced significantly and permanently.

Our findings are in line with Bao et al. (2010), Dick-Nielsen et al. (2009), Friewald et al. (2011), who also document an increase in liquidity effects during the crisis. Earlier papers like Longstaff et al. (2005) and Chen et al. (2007) find that liquidity proxies have explanatory power. All these studies, however, do not consider a change in the underlying parameters as a consequence of the crisis.

Figure 1: Development of US Corporate Credit Spreads (October 2004 - December 2010)
The chart shows the market-wide corporate bond yield spread between October 2004 and July 2010 computed as the median spread of U.S. corporate bonds. The spread is measured relative to the Treasury yield curve and reported in basis points. The data set is discussed in detail in Section 3.



As noted by Giesecke et al. (2010), bond spreads display considerable variation over time that does not appear to be closely related to economic fundamentals driving default risk. They also show the converse result, i.e., variables that help explain credit spreads have little explanatory power to forecast corporate defaults. They interpret this as an indication that credit spreads are driven primarily by changes in credit and liquidity risk premia, and only marginally by changes in objective measures of default risk. This paper investigates this proposition.

This paper also contributes to the literature on time-varying risk premia on bond returns. Chen et al. (2009) show that for common asset pricing models to explain the levels and volatilities of credit spreads time-varying risk premia are necessary. Our results extend on theirs in that we quantify the relative contribution of different risk factors. Driessen (2005) decomposes corporate bond yield spreads into tax, liquidity, interest rate risk, and risk premium components based on a reduced-form model. He finds that the ratio of risk neutral to objective default intensities is greater than one, suggesting that default event risk is indeed priced. He also obtains cross-sectional estimates of spread components and risk premia. Similar work by Berndt et al. (2004) uses expected default frequencies from Moody's KMV together with default swap prices to extract historical and risk neutral default intensities respectively. The ratio of these is interpreted as a measure of the risk premium observed in the marketplace. They document substantial time series variation in premia with a peak in the third quarter of 2002 and a subsequent dramatic drop. They show that their measure of the risk premium is strongly dependent on general stock market volatility after controlling for idiosyncratic equity volatility. They also find that their measure is increasing in credit quality.

Similar to King and Khang (2005), we use cross-sectional regressions to decompose credit spreads into risk components. This allows us to include both firm-level and bond-specific information and derive explicit estimates of the contribution of the determinants of credit spreads. We complement and extend prior studies by examining how risk factors affect the entire conditional distribution of bond spreads using quantile regressions. Similar to OLS estimates, the values of the coefficients still have a natural interpretation as rates of return to the different components of bond yields. Most studies on risk components of credit spreads rely on separate estimates for different bond classes, most commonly by rating and maturity. Since credit ratings are updated infrequently they may not fully reflect the overall riskiness of a particular bond. Bond prices, and therefore credit spreads, react immediately to new information. By estimating regressions at different quantiles of the distribution of credit spreads we therefore obtain more direct estimates of how risk factors contribute to the level of credit spreads. Instead of focusing our discussion on the impact of a particular factor (e.g., liquidity risk) we include factors related to default risk, liquidity risk, and equity risk simultaneously in order to obtain a full picture of the conditional distribution of bond spreads. Our regression results have an R^2 of around 60% from which we conclude that we can reasonably well decompose bond spreads into their risk components.

We utilize the decomposition in order to perform counterfactual analysis on the distribution of the cross-section of credit spreads. In particular, we analyze the question how much of the change in the general level of credit spreads is caused by changes in market conditions (i.e., changes of priced risk factors) as opposed to changes in risk perception (i.e., the changes in the pricing of risk premia). By estimating at a sufficient number of quantiles we obtain a semi-parametric estimator of the empirical distribution of credit spreads conditional on risk factors. By using the conditional distribution at one period in time conditional on marginal distributions of the risk factors at another, we obtain a counterfactual distribution of credit spreads that would have prevailed if risk factors had adjusted but the pricing of these factors had remained constant. The difference between the observed and this counterfactual distribution can be interpreted as the effect of market movements on credit spreads. Of the remaining difference, we use a consistent estimator to separate the effect of changes in the pricing of risk premia from residual effects that our model cannot explain. Decompositions of distributions using quantile regressions was first proposed by Gosling et al. (2000) and Machado and Mata (2005) and further developed by Melly (2005). In a recent paper, Chernozhukov et al. (2009) generalize prior work and develop formal inference theory.

We further decompose the effect that changes in risk pricing had over the prior financial crisis. By estimating a set of counterfactual distributions we are able to obtain explicit estimates of how changes in the perception of default risk, liquidity risk, and equity risk each have contributed to the increase in the level of credit spreads on financial markets. By decomposing spread changes over time into changes in risk factors and changes in risk perception, we document several notable facts: Our results show that the observed increase in credit spreads during the crisis was mostly caused by increases in the pricing implications of risk factors, i.e., risk perception. Still, we find that about a third of the increase in credit spread was caused by changes in the risk factors themselves. The decomposition results also show that the effects of the risk factors is almost completely reversed after the crisis whereas the effect of increases in coefficients (i.e., the effects of increased risk perception) have decreased only slightly after the crisis and have remained higher than before the crisis. Hence, the increased levels of credit spreads over the financial crisis can almost entirely be explained by increases in risk perception. The counterfactual effects indicate that the market for corporate bonds has normalized again as measured by the level of risk factors used to explain credit spreads. Furthermore, we find that the impact of liquidity risk on credit spreads is almost uniform for all bonds. We also find that risk perception towards default risk has actually decreased over the past years.

The remainder of the paper is organized as follows. Section 1 reviews structural models of credit risk and the implications for the theoretical determinants of credit spreads. The section reviews empirical results and motivates the proxies we use in the empirical section. Section 2 presents the method of counterfactual analysis using quantile regression. It also discusses how we use these ideas to provide a sequential decomposition of credit spreads. Section 3 discusses the data used and presents summary statistics. The results of the risk decompositions are presented in Section 4. Section 5 concludes.

1 Determinants of credit spreads

In order to price bonds structural models are needed. To the extent that the underlying economic structure is fixed, standard pricing models allow to price the underlying risk factors. To the extent that the underlying structure may change (e.g. due to model risk), the relative valuation and pricing of risk factors may change as well. Since the novel feature of our analysis is the introduction of structural risk, we will first briefly discuss the standard risk and liquidity factors for credit spreads for a given structure and then discuss possible sources of structural risk.

Credit Risk. Structural models of credit risk build on Merton (1974), who was the first to value risky bonds. Amongst many, the basic model was later extended for random times of default (Black and Cox, 1976), stochastic interest rates (Longstaff and Schwartz, 1995), dynamic capital structures (Leland and Toft, 1996) and target debt-equity ratios (Collin-Dufresne and Goldstein, 2001). The key characteristic of structural models is that default is triggered when the value of the firm falls below a given boundary. Thus, these models predict that the difference in yields of corporate bonds over Treasury bonds arises because of the possibility of the firm defaulting on its debt and the uncertain reduction in payments due to such an event.

In the original Merton model, the equity value E is given by

$$E = AN(d_+) + e^{-r\tau}DN(d_-), \tag{1}$$

where

$$d_\pm = \frac{\log\left(\frac{A}{D}\right) + (r \pm \frac{1}{2}\sigma_A^2)\tau}{\sigma_A\sqrt{\tau}},$$

where A denotes the value of the firm's assets, D the book value of debt, τ is the time to maturity, r the risk-free rate, and $N(\cdot)$ the normal distribution function. Default occurs when the leverage of a firm $\frac{D}{A}$ is larger than unity at maturity. The distance to default ($DDef$) is defined as

$$DDef = \frac{\log\left(\frac{A}{D}\right) + (\mu + \frac{1}{2}\sigma_A^2)\tau}{\sigma_A\sqrt{\tau}}, \tag{2}$$

where μ denotes the drift and σ_A the volatility of the firm value.[1] This distance to default can be interpreted as a volatility-adjusted measure of leverage. Even though it is conceivable that equity holders may find it optimal not to default when the firm value is at or below the book value of debt (Leland and Toft, 1996), it is generally hypothesized that a low firm value relative to outstanding debt is a good indicator of a firm's financial health. A related measure of the $DDef$ is the expected

[1] It should be noted that the model assumes that only one issue of debt is outstanding.

default frequency (EDF) defined as

$$EDF = N(-DDef). \tag{3}$$

A comprehensive study of the ability of this measure to predict defaults is provided by Bharath and Shumway (2008). They conclude that the measure has predictive ability and we therefore hypothesize that there should be a positive relationship between a bond's EDF and its yield spread.

As default is directly related to a company's ability to fulfill its financial commitments, a number of financial ratios have been used in the literature to proxy for the likelihood of default of a company. In this paper, we follow, amongst many, Blume et al. (1991) and Campbell and Taksler (2003) and use the following four ratios: Long-Term Debt to Total Assets (LD/TA), Total Debt to Capitalization (TD/C), Pre-Tax Interest Coverage (IC), and Operating Income to Total Sales (OI/S). Motivated by results from the bankruptcy prediction literature we also include Net Income to Total Assets (NI/TA) (Altman, 1968; Shumway, 2001).

Empirically, however, defaults occur too infrequently to be consistent with the prediction that credit spreads arise only due to credit risk. For instance, Elton et al. (2001) note that, historically, credit spreads on investment grade corporate debt had been too high to be justified by the relatively rare occurrence of defaults. Moreover, direct tests have indicated that credit spreads implied by structural models are lower than those observed on financial markets (Huang and Huang, 2003).[2] These observations have led to a large number of investigations into additional determinants of credit spreads. Based on the evidence that default risk is not the only component of credit spreads, they provide a careful analysis of the unexplained portion. They conclude that tax effects and equity risk factors have systematic influence on corporate bond spreads. In a similar spirit, Campello et al. (2008) argue that corporate bond spreads may partly reflect additional risk factors of the type typically used in equity pricing studies.[3]

As noted by King and Khang (2005), structural models technically imply that the value of debt should be independent of the expected return on the assets: Since corporate liabilities are regarded as contingent claims on the value of the firm their pricing should be independent of the expected

[2] A major reason for the low spreads implied by structural models is that they assume a diffusion process for the asset value. Hence, if a company has not defaulted to date, the probability of default becomes negligible as the maturity approaches. One possibility to circumvent this is to assume a jump diffusion process, as in Zhao (2001), for which the probability of default does not approach zero even for very short maturities. Another approach due to Duffie and Lando (2001) is to incorporate uncertainty about the true value of the company which can only be inferred from noise accounting information.

[3] In this paper, we do not explicitly attempt to measure the impact of jump risk on credit spreads. Their role is discussed, e.g., in Driessen (2005), Collin-Dufresne et al. (2010), and Cremers et al. (2008)

return on the assets of the firm. This is because any risk can be eliminated by hedging.[4] Thus, after controlling for the relevant risk factors the price of the bond should be unrelated to the value of the firm. On the other hand, several studies that have analyzed the relation between stock and bond returns conclude that each possesses explanatory power for the other (Blume et al., 1991; Campbell and Ammer, 1993; Keim and Stambaugh, 1986; Campbell and Taksler, 2003; Vassalou and Xing, 2004). Although contradictory to theory, these studies suggest that a higher return on equity decreases the likelihood that a firm will be unable to meet its financial obligation and spreads should decrease, ceteris paribus. This is confirmed by Kwan (1996) who documents that recent past stock returns have a negative effect on yield spreads. The empirical relationship between equity volatility and credit spreads is analyzed in Campbell and Taksler (2003). They find that equity volatility and credit ratings each explain about a third of the variation in corporate bond yield spreads. In accordance with their results, we expect to find a positive relationship between the volatility of equity and the spread of a bond of a given firm. These studies have contributed much to our understanding of the risk components of yield spreads on corporate bonds. However, they abstract from the influence that liquidity may have on bond spreads.

Liquidity Risk. There are two main arguments why there should be a premium for liquidity. The first dates back to the idea of Amihud and Mendelson (1986) that investors require compensation for transaction costs. Chen et al. (2007) use similar risk factors for spread components as the studies cited above and provide direct evidence that both investment and speculative bonds carry an illiquidity premium. Specifically, they use an implied measure of round-trip trading costs to proxy for liquidity. Using cross-sectional regressions over an extensive data set, they find that for investment grade bonds a 1 basis point (bp) bid-ask spread implies a 0.42 bps increase in the spread with an R^2 of 7%. For speculative grade bonds, they find a 2.3 bps increase with an R^2 of 22%. Similar results are obtained when explaining credit spread changes in time-series regressions. In complementary work, Bao et al. (2010) observe that illiquidity arises from market frictions and that its effect on market prices should be transitory. Based on this simple observation, they use the negative of the autocovariance of bond price changes as a measure for bond specific liquidity. Their results provide further evidence of the importance of liquidity as a determinant of the levels of credit spreads observed on markets.

The second theoretical rationale why liquidity is expected to explain corporate bond spreads is based on the liquidity-adjusted capital asset pricing model of Acharya and Pedersen (2005). They show that expected returns depend on the covariance of an asset with market liquidity. Thus, liquidity should be a priced characteristic on asset markets. Several recent contributions have therefore examined whether and how (il-)liquidity is priced in the cross-section of corporate bond

[4] This is the equivalent to the statement that the value of equity options are independent of the growth rate of the stock under the statistical measure.

yields. Lin et al. (2010) study the relation between corporate bond returns and systematic liquidity risk. Specifically, they use the liquidity measures proposed by Amihud (2002) and Pastor and Stambaugh (2003) estimated directly from transaction data of corporate bonds. Longstaff et al. (2005) analyze credit default swaps to determine what part of credit spreads are due to liquidity and what part is due to default risk. In concordance to structural models, they conclude that the majority of credit spreads is due to default risk. However, they also report that the non-default component is strongly influenced by (il-)liquidity.

Finally, Pedrose and Roll (1998) document that bonds with similar industries, rating categories, and maturities tend to move together. This result is not surprising as theory predicts that all credit spreads should be affected by aggregate variables such as changes in interest rates, business climate, market volatility, etc. The surprising result is that even after accounting for these effects the systematic relation persists.

Risk Perception. To the best of our knowledge the literature on credit spreads has not taken into account behavioral features like ambiguity aversion and/or investor sentiment. Ambiguity aversion may be particularly relevant, but alternative behavioral theories maybe observationally equivalent in their consequence for credit spreads. This is why we concentrate on ambiguity aversion in this paper. Ambiguity aversion arises, when investors are uncertain about the true underlying distribution from which returns are sampled. In this case, they may not even be able to measure risk. Ambiguity averse investors prefer to invest resources in order to resolve ambiguity and learn the true distribution of returns, which allows them to assess risk.

A major crisis can be seen as an event that generates information about the possibility of bad outcomes and in that sense allows to better assess risks. Essentially, it means that the observation of a deep crisis eliminates overly optimistic distributions from the set of potential distributions. In this sense, while reducing ambiguity, crises also tend to make investors more concerned about downside risk. Observationally, this is equivalent to an exogenous increase in risk perception (Alary et al., 2010), even though it is only rational inference from a crisis event. The consequences are similar to a lack of liquidity resulting in increased volatility (Ghirardato and Marinacci, 2001).

Alternatively, and almost equivalently, one might also conjecture a learning effect in case credit spreads are drawn from a mixture of distributions. For simplicity assume that one distribution is associated with rather low returns and another one with "normal" returns. The "normal" distribution dominates returns in the "crisis" regime in the sense of (first order) stochastic dominance. The crisis regime occurs with low, but unknown probability. Now assume that investors learn about this probability by means of Bayesian updating. In such a world the occurrence of any crisis will almost always have a lasting effect on the aggregate risk assessments. The change in risk perception will affect the marginal impact of the various risk and liquidity factors in any equilibrium pricing model. In our empirical implementation of a (linearized) equilibrium relationship we provide estimates of these changes.

2 Counterfactual Analysis

In order to decompose the effects caused by changes in market variables and effects caused by a change in the pricing implication of these variables over time we propose to use counterfactual distributions. In particular, we use the method proposed in Melly (2005) and further developed in Chernozhukov et al. (2009). What this method does is split the observed change of a variable of interest into three separate components.

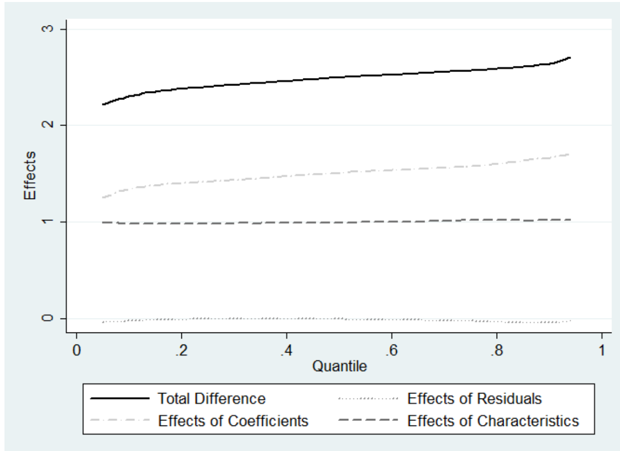
Let $\mathbf{y}_t$ be the variable of interest and $\mathbf{X}_t$ be the set of explanatory variables at times $t \in \{0, 1\}$, and let $F(\mathbf{y}_t|\mathbf{X}_s)$ be the conditional distribution of $\mathbf{y}_t$ based on $\mathbf{X}_s$. The total change of interest is then $\mathbf{y}_1 - \mathbf{y}_0$. The three components into which this is separated is the effect that is attributable to changes in the marginal distribution of explanatory variables $\mathbf{X_t}$ over time, the effect that is attributable to changes in the conditional distribution F over time, and changes in the residuals of the estimation of F. Since we are interested in the entire market of bonds, we perform this decomposition along the entire distribution. Therefore, we estimate the conditional distribution using quantile regression.

To illustrate, let $\mathbf{X}_0 \sim U[0, 1]$ and $\mathbf{X}_1 \sim U[1, 2]$ be uniformly distributed on $[0, 1]$ and $[1, 2]$, respectively. Take $\mathbf{y}_0 = \mathbf{X}_0 + \epsilon_0$ and $\mathbf{y}_1 = 2 * \mathbf{X}_1 + \epsilon_1$ where $\epsilon_i \sim N(0, 1)$ are independent standard normal error terms. In this simple setup, it is clear that $\mathbf{y}$ changes because of two things. First, the marginal distribution of $\mathbf{X}$ is shifted by one from time 0 to time 1. Second, the effect that a given level of $\mathbf{X}$ has on $\mathbf{y}$ is amplified by a factor of 2. Since the distribution of errors does not change, no residual effect should be observed.

Figure 2 illustrates the obtained counterfactual distributions in this example. The solid black line represents the actual difference while the gray lines represent the different components of the difference. As expected, we observe that the effect attributable to the change in the marginal distribution of $\mathbf{X}$ is 1 at each quantile. The estimated effect of coefficients reflects the fact that, by construction, there is a strong positive correlation between $\mathbf{X}$ and $\mathbf{y}$. Hence, the effect of changes in coefficients increases linearly along the quantiles. Finally, we can see that the residuals account for almost nothing of the observed change.

For the research question at hand, we use this procedure to generate two counterfactual distributions: The first is the distribution that would have resulted if the conditional distribution of

Figure 2: Decomposition of Differences in Distribution



bond spreads given risk factors had stayed the same over time while the risk factors themselves are allowed to change as they have. The second is the distribution that would have resulted if, in addition to the change in risk factors, the conditional distribution had changed but residuals are kept at their original level. The difference between the original (observed) distribution and the first counterfactual distribution is the effect that can be attributed to changes in market variables assuming that the pricing implications of these variables had stayed the same (i.e., assuming that the unconditional distribution did not change). The difference between the second and the first counterfactual distribution is the effect caused purely by changes in the pricing implications of the risk factors. We interpret this effect as changes in risk perception.

We use linear quantile regressions to estimate the conditional distribution of credit spreads. Hence, we specify the θth quantile of credit spreads conditional on the covariates X as:

$$q(\theta|\mathbf{X}) = \mathbf{X}\boldsymbol{\beta}(\theta), \quad \forall\, \theta \in (0,1), \tag{4}$$

where $\mathbf{X}$ denotes the N by K of covariates and $\boldsymbol{\beta}(\theta)$ the K-dimensional vector of regression coefficients at quantile θ, and $q(\theta|\mathbf{X})$ denotes the θ quantile value conditional on $\mathbf{X}$. Thus, the estimates of the various risk factors across different quantiles can be interpreted as the additional spread that a unit increase in the corresponding covariate has at a particular quantile of the distribution of credit spreads. Koenker and Bassett (1978) show that $\beta(\theta)$ can be estimated via

$$\hat{\boldsymbol{\beta}}(\theta) = \min_{\mathbf{b}\in\mathbb{R}^K} \frac{1}{N}\sum_{i=1}^{N} \rho_\theta(y_i - \mathbf{X}_i \cdot \mathbf{b}), \tag{5}$$

where $\rho_\theta(u) = u(\theta - \mathbf{1}(u \leq 0))$.

y_i denotes the i^{th} value of the response variable $\mathbf{y}$, $\mathbf{X}_i$ is the ith row of $\mathbf{X}$, and $\mathbf{1}(\cdot)$ is the indicator function. The quantile regressions allow us to analyze credit spreads conditional on bond and company specific characteristics. By estimating at a sufficiently large number of quantiles, we obtain an estimate of how the different risk components contribute to the entire distribution of credit spreads.

The methodology of using quantile regression to perform counterfactual analysis originated in Machado and Mata (2005) and Gosling et al. (2000) which is an extension of the Blinder-Oaxaca decomposition technique for differences at the mean (Oaxaca, 1973; Blinder, 1973). The recent paper by Chernozhukov et al. (2009) significantly extend this literature and also develops formal inference procedure. In this paper, we follow rather closely the ideas developed in Machado and Mata (2005) who shows that the θ^{th} unconditional quantile functions can be estimated as

$$\hat{q}_\theta(\hat{\beta}, X) = \inf\left\{ q : \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}\mathbf{1}(\mathbf{X}_i \cdot \hat{\boldsymbol{\beta}}(\theta_j) \leq q) \geq \theta \right\}. \tag{6}$$

where J denotes the number of estimated quantiles. This representation can be used to generate counterfactual distributions. Let 0 denote the initial time period and 1 the later one with observed quantile functions q_t, $t = 0, 1$. We decompose the difference as follows:

$$\begin{aligned} \underbrace{q^1 - q^0}_{\text{Observed Change}} &= \underbrace{\left[\hat{q}(\boldsymbol{\beta}^0, \mathbf{X}^1) - q^0\right]}_{\text{Covariates}} \\ &+ \underbrace{\left[\hat{q}(\boldsymbol{\beta}^{m_1,r_0}, \mathbf{X}^1) - \hat{q}(\boldsymbol{\beta}^0, \mathbf{X}^1)\right]}_{\text{Coefficients}} + \underbrace{\left[q^1 - \hat{q}(\boldsymbol{\beta}^{m_1,r_0}, \mathbf{X}^1)\right]}_{\text{Residuals}}, \end{aligned} \tag{7}$$

where, for simplicity, we have suppressed the dependence on the quantile θ. $\hat{q}(\beta^0, X^1)$ denotes the counterfactual distribution that would have prevailed if the marginal distribution of covariates had changed as they have from period 0 to 1, but the conditional distribution of spreads given covariates X had remained as in 0. It is estimated by inserting the covariates X from period 1 but the estimates β from period 0 in (6):

$$\hat{q}_\theta(\boldsymbol{\beta}^0, \mathbf{X}^1) = \inf\left\{ q : \frac{1}{N_0}\sum_{i=1}^{N_1}\sum_{j=1}^{J}\mathbf{1}(\mathbf{X}_i^1 \cdot \hat{\boldsymbol{\beta}}^0(\theta_j) \leq q) \geq \theta \right\}, \tag{8}$$

where N_t is the number of observations in period t. In the language of default risk, this change estimates the credit spreads that would have prevailed in the later period if the risk factors had changed the way they have but markets were still pricing the factors the same way as in period 0. $\hat{q}(\boldsymbol{\beta}^{m_1,r_0}, \mathbf{X}^1)$ denotes the distribution that would have prevailed if the conditional distribution had changed but residuals were still as in period 0. To do this, Melly (2005) notes that

$\mathbf{X}\left(\hat{\boldsymbol{\beta}}(\theta) - \hat{\boldsymbol{\beta}}(0.5)\right)$ is a consistent estimator of the θ^{th} quantile of the residual distribution conditional on $\mathbf{X}$. Hence, we define $\boldsymbol{\beta}^{m_1,r_0}(\theta) = \hat{\boldsymbol{\beta}}^1(0.5) + \hat{\boldsymbol{\beta}}^0(\theta) - \hat{\boldsymbol{\beta}}^0(0.5)$ which are then plugged into (8) instead of $\boldsymbol{\beta}^0$. This step separates the effect changes in risk perception (i.e., the coefficients of the covariates) have from effects that arise from residuals.

The decomposition so far only isolates the effect caused by changes in the pricing implications of all covariates considered. In order to assess how various types of risk have contributed to the market-wide increase in the levels of credit spreads we estimate a sequence of counterfactual distributions by incrementally updating the conditional distributions of the covariates. We follow the sequential approach suggested in Antonczyk et al. (2010) but explicitly account for the residual effect as described in (7). We take the perspective of the earlier period ($t = 0$) and transfer observed levels of credits spreads step-by-step to their levels observed in the later period ($t = 1$). Let $\hat{q}(\hat{\boldsymbol{\beta}}^{D_t,L_t,E_t,B_t,r_0}, \mathbf{X}^t)$ denote the estimated counterfactual quantiles of credit spreads with covariates $\mathbf{X}^t$ and

$$\hat{\boldsymbol{\beta}}^{D_t,L_t,E_t,B_t,r_0} = \hat{\boldsymbol{\beta}}^{D_t,L_t,E_t,B_t}(0.5) + \hat{\boldsymbol{\beta}}^0(\theta) - \hat{\boldsymbol{\beta}}^0(0.5),$$

where $\hat{\boldsymbol{\beta}}^{D_t,L_t,E_t,B_t}$ denotes the vector of coefficients related to default risk (D_t), equity risk (E_t), liquidity risk (L_t), and bond characteristics (B_t) from period t.

First, we adjust for changes in the pricing of default risk, which in the notation introduced above is given as $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,r_0}, \mathbf{X}^1)$. This estimates the levels of credit spreads that would have prevailed if only the pricing effects of accounting ratios and the Merton EDF had adjusted whereas liquidity, equity risk as well as the effect of bond characteristics had stayed the same. Thus, this counterfactual difference is a direct estimate of how changes in risk pricing with respect to the possibility of default have altered the levels of credit spreads observed on the market. In a similar fashion, we then update the effect of liquidity risk pricing by estimating $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,r_0}, \mathbf{X}^1)$. This change estimates the effect of changes in the pricing of liquidity risk, holding fixed the influence of other common risk factors. Third, we modify the pricing of equity risk with $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,r_1}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,r_0}, \mathbf{X}^1)$. Finally, we account for the change in the pricing of indenture data by estimating $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,r_0}, \mathbf{X}^1)$. The remaining difference, $q_1 - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,r_0}, \mathbf{X}^1)$ is then the residual effect that is not captured by our model. Note that in the sequential decomposition we do not adjust the effect of the intercept which is therefore contained in the residual component. The total decomposition can be summarized as follows:

$$
\begin{aligned}
\underbrace{q_1 - q_0}_{\text{Total Observed Change}} &= \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_0,L_0,E_0,B_0,r_0}, \mathbf{X}^1) - q^0\right]}_{\text{Effect of Covariates}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_0,L_0,E_0,B_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Default Risk}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Liquidity Risk}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Equity Risk}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Bond Characteristics}} \\
&+ \underbrace{\left[q^1 - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,r_0}, \mathbf{X}^1)\right]}_{\text{Residual}}
\end{aligned} \tag{9}
$$

The decomposition essentially entails plugging in different estimates for the coefficients in the representation in (6). It should be noted that results depend on the sequence of the decomposition.[5]

3 Data and Descriptive Statistics

The main data sources for this study are CRSP, Compustat, the Mergent FISD (Fixed Income Securities Database), and FINRA's TRACE (Transaction Reporting and Compliance Engine) database. We consider the time frame from October 2004 until July 2010. The starting point of the sample is restricted by the fact that only in October 2004 did TRACE begin to report on all US bonds irrespective of their credit rating. We match companies across the databases based on their CUSIP number. We only include non-financial corporations as indicated by their GIC code. We are able to match 1612 companies with a total of 17088 bonds. We remove all callable, putable, and convertible bonds as well as all bonds which have sinking fund features, are asset-backed, or that have any enhancing features. We also restrict the sample to fixed-rate coupon bearing bonds. This leaves us with 4972 bonds from 770 different corporations.

All accounting data comes from Compustat. Most companies in the US report their yearly accounting statements by March. To ensure that markets fully incorporate the information contained therein, we measure all yearly values as of July 1$^{\text{th}}$. Effectively, therefore, our sample begins in 2005. We measure the ratios as follows: Pre-tax Interest Coverage is the ratio of Operating Income

[5] We tried several other sequences with essentially equal results.

After Depreciation plus Interest Expense to Interest Expense, Operating Income to Total Sales is the ratio of Operating Income Before Depreciation to Net Sales, long-term debt to total assets is Total Long-Term Debt to Total Assets, Total Debt to Capitalization is Total Long-Term Debt plus Debt in Current Liabilities plus Average Short-Term Borrowings to Total Liabilities plus Market Value of Equity (which we obtain from CRSP), and finally Net Income to Total Assets is the ratio of Net Income to Total Assets.

For each company in the sample, we obtain daily equity returns as well as market values from CRSP. We estimate the mean excess return R_e and volatility σ_e for each firm as the average and standard deviation, respectively, of the daily equity returns in excess of the CRSP value-weighted index with one year of data prior to July 1^{th} of each year.

Similar to previous studies, we use the procedure suggested by Blume et al. (1998) and break the pre-tax income coverage into four categories instead of regressing on it directly. We first set every negative observation equal to 0 and any observation above 100 to 100. The four indicator variables IC_5, IC_{10}, IC_{20}, and IC_{30} used are defined as follows:

	IC_5	IC_{10}	IC_{20}	IC_{30}
$IC_i \in [0,5)$	IC_i	0	0	0
$IC_i \in [5,10)$	5	$IC_i - 5$	0	0
$IC_i \in [10,20)$	5	5	$IC_i - 10$	0
$IC_i \in [20,100]$	5	5	10	$IC_i - 20$

To calculate the distance to default, the drift and volatility of the firm's assets as well as the firm value are required. These are unobservable and we can only use equity data. We follow the iterative procedure used in Vassalou and Xing (2004) and Bharath and Shumway (2008) by iterating over (1) and (2) to solve simultaneously for A and σ_A. We start with an arbitrary initial value ($\sigma_A = \sigma_E \frac{E}{E+D}$) and use this to generate a time series of firm values using daily equity market values and (1). For the book value of debt, D, we use debt in current liabilities plus half of long-term debt. We calculate the EDF using the bond's time to maturity and the matched treasury rate as risk-free rate. We use the resulting asset value A to proxy for the financial leverage D/A.

Prior to using the TRACE data, we apply the following filters. We exclude any canceled, corrected, or duplicate interdealer trades as well as any trade for which TRACE indicates that commissions have influenced the trade price or special conditions applied. Moreover, we apply the median and reversal filters of Edwards et al. (2007). The former eliminates transactions for which reported prices deviate more than 30% from the median price of that day. The latter filter removes transactions with absolute price changes deviating from lead, lag, or average lead/lag changes by more than 10%. Finally, we exclude all trades with retail size (trade value lower than \$75000). After these filters, we measure the yearly yield on each bond as the average yield of all trades on the last day the bond traded prior to July in each year. We only use bonds which have traded in the quarter before July. As the risk-free rate, we use the constant maturity yield curve indices published by the US Treasury Department.[6] For each yield observation, we match the treasury rates on the last trading day of the bond using linear interpolation between the two closest indices to obtain the corresponding treasury rates. We measure a bond's credit spread as the difference between its yield and the corresponding treasury rate in basis points (bps).

To proxy for the liquidity of a bond, we use three separate measures of liquidity based on transaction data of bonds. The first is the Amihud (2002) measure of illiquidity (IL) which is based on the notion of the price impact of trades. It is defined as

$$IL_{i,t} = \frac{1}{N_{i,t}} \sum_{k=1}^{N_{i,t}} \frac{|R_{k,i,t}|}{\text{Vol}_{k,i,t}}, \tag{10}$$

$R_{k,i,t}$ is the return of the bond in two consecutive transactions, $\text{Vol}_{k,i,t}$ is the volume of the transaction (in million \$), and $N_{i,t}$ is the number of returns on day t. To calculate the measure on a particular day, at least two transactions need to be recorded on that day. We follow Dick-Nielsen et al. (2009) and use the median over the year as the measure of illiquidity for that year. The measure has the advantage that it only requires trading volume and transaction prices which are readily available in the TRACE database for almost all U.S. bond transactions. The measure is therefore the average of the proportional price changes in a given period. For every bond in the sample, we use all transactions in a given year prior to July to calculate the measure.

The second measure of liquidity we use is the approximation of the effective bid-ask spread (EBA) derived (under assumptions on market efficiency) by Roll (1984) as

$$EBA_{i,t} = 2\ \sqrt{-Cov(\Delta P_s, \Delta P_{s-1})} \tag{11}$$

where $\Delta P_s = P_s - P_{s-1}$ is the change in price between two consecutive trades. The idea of this measure is that bid-ask bounces induce a negative covariance between adjacent price changes. Again, we follow Dick-Nielsen et al. (2009) and estimate the daily measure using a 21-day window under the requirement that there be at least four transactions in the observation window. As yearly measure we use the median of the daily estimates within that year. In a recent paper, Bao et al. (2010) derive almost the same measure motivated by the idea of transitory price shocks. As a third measure of liquidity, we use the trading intensity (TI) of a bond defined as the percentage of days

[6] http://www.ustreas.gov/offices/domestic-finance/debt-management/ interest- rate/yield_historical_main.shtml

during a year on which the bond did not trade.

We use the bond rating provided by the FISD database. If there are multiple ratings available we give priority to the rating by Standard & Poor's, followed by Moody's, and finally Fitch. We convert all ratings to the Standard & Poor's scale. If no bond rating is available we use the company's credit rating from Campustat instead. We exclude all bonds which have a AAA rating or a rating below B. The reason for this is that there are insufficient observations for these categories. As industry dummies, we use the two-digit GIC industry codes.

We remove any observation where one of the data entries is missing. We also exclude all bonds with a time to maturity of less than one year. Finally, we remove all observations with yield spreads in the top and bottom 1% of the total sample. These are all bonds with either highly negative spreads or spreads above 5000 bps. Table 1 presents summary statistics for our sample. Although we can only cover a relatively short time frame the sample contains a similar dispersion as other papers that use similar data (e.g. Campbell and Taksler (2003); Chen et al. (2007)). We use rating dummies for each rating category and industry dummies based on the two-digit GIC industry code.[7]

The average yield spread in our sample is 213 bps with a standard deviation of 183. The spread in the first decile is 60 and the top decile 465 which indicates that most of the observations lie in a moderate range. The average time to maturity in our sample is about 11 years and our sample is roughly evenly distributed among long-, medium-, and short-term bonds. The data from equity markets reflect the fact that the sample period is concentrated around the financial crisis with an average excess return of 4.35% and average volatility of excess returns of 28.37%. Excess returns are roughly symmetrical around the mean and show a very high dispersion with a standard deviation of 33.05%.

To provide a better overview of the sample, we also report median of the data separated by credit rating and maturity in Table 2. We differentiate between short-term (1-7 years), medium (7-15 years), and long maturity (15-50 years) bonds. Consistent with the Merton (1974) model, we observe that credit spreads increase with maturity for investment grade bonds whereas they decrease for speculative grade bonds.

[7]It could be argued that the filters we apply bias our sample towards liquid bonds (see Friewald et al. (2011)). If biased, our estimates for liquidity effects should be conservative as illiquidity effects should be even more pronounced for less liquid bonds. Moreover, the results from our counterfactual analysis would not be altered since we estimate by quantile regression.

Table 1: Summary Statistics for Full Sample

The table reports the summary statistics for all variables used in the regressions and decompositions. The data sample comprises all corporate bonds without special features from TRACE for which we were able to match the corresponding accounting data from Compustat and equity data in CRSP. *Spread* is the difference between the yield to maturity on a bond to the interpolated Treasury benchmark rate measured in basis points. *Age* the time since the bond was first sold, C is the (fixed) coupon rate of each bond, and τ the time to maturity. IL is the trade impact Illiquidity measure of Amihud shown in (10) (multiplied by a million since we measure volume in million \$). EBA is the measure of the effective bid-ask spread introduced in (11). TI is the trading intensity of a bond. R_e is the annual excess return of the corresponding stock in excess of the CRSP value-weighted index. σ_e is the annualized volatility of the excess returns in the past year. IC is the pre-tax interest coverage, $LD\backslash TA$ the ratio of long-term debt to total assets, $NI\backslash TA$ is net income to total assets, $OI\backslash S$ is operating income to sales, and $TD\backslash C$ is total debt to capitalization. EDF is the Merton expected default frequency outlined in (3) and Lev is the ratio of the market value of assets to debt.

	Mean	Q10	Q25	Median	Q75	Q90	Stdev
Spread	213.43	60.37	95.94	162.47	269.26	464.51	183.35
Age	5.27	0.69	1.77	3.91	7.77	11.95	4.48
C	6.40	4.55	5.38	6.50	7.38	8.25	1.61
τ	11.19	2.38	4.09	7.46	16.55	26.27	11.2
IL	0.17	0.00	0.00	0.05	0.19	0.47	0.32
EBA	1.50	0.50	0.78	1.27	1.94	2.80	1.02
TI	0.71	0.39	0.56	0.75	0.89	0.95	0.20
$R_e(\%)$	4.35	-30.02	-14.49	1.25	19.21	39.76	33.05
$\sigma_e(\%)$	28.37	14.94	18.25	24.2	33.15	45.12	14.94
IC	8.63	2.56	4.05	6.37	10.71	16.62	15.05
$LD\backslash TA$	0.27	0.13	0.18	0.25	0.34	0.42	0.13
$NI\backslash TA$	0.05	0.00	0.03	0.05	0.08	0.11	0.07
$OI\backslash S$	0.19	0.06	0.10	0.16	0.27	0.37	0.16
$TD\backslash C$	0.23	0.09	0.13	0.19	0.30	0.42	0.13
$EDF(\%)$	6.46	0.00	0.00	0.00	0.05	13.55	20.4
Lev	0.27	0.07	0.10	0.17	0.31	0.50	0.46

Table 2: Median Observations by Maturity and Rating

The table reports the median observation of each variable. Panel A uses only observations from bonds with less than seven years to maturity, Panel B on bonds with maturity between seven and 15 years, and Panel C reports on bonds with maturities of more than 15 years. N is the number of bonds in each rating-maturity category.

Rating	Spread	Age	C	τ	IL	EBA	TI	R_e	σ_e	IC	LD\TA	NI\TA	OI\S	TD\C	EDF	Lev	N
Panel A: Short Maturities (1-7 years)																	
AA	71.44	4.96	5.06	3.69	0.21	0.89	0.48	-0.97	18.64	19.65	0.18	0.09	0.19	0.13	0.55	0.11	153
A	105.27	5.22	5.57	3.83	0.14	1.09	0.63	3.97	23.29	12.02	0.22	0.08	0.20	0.15	0.45	0.13	806
BBB	182.51	4.92	6.18	3.85	0.13	1.13	0.73	3.86	26.82	7.16	0.27	0.05	0.19	0.25	3.75	0.25	1087
BB	379.82	4.35	7.07	4.24	0.11	1.33	0.69	2.20	39.27	3.29	0.36	-0.01	0.15	0.33	15.18	0.38	500
B	399.4	3.96	6.67	4.31	0.12	1.27	0.69	9.27	42.08	2.75	0.40	-0.01	0.13	0.34	11.58	0.37	324
Panel B: Medium Maturities (7-15 years)																	
AA	92.86	4.42	5.41	9.47	0.30	1.58	0.60	-3.29	19.45	24.58	0.19	0.09	0.22	0.13	1.23	0.12	81
A	138.65	5.40	6.22	9.58	0.19	1.65	0.73	3.91	23.78	12.14	0.21	0.08	0.21	0.15	1.39	0.14	501
BBB	218.56	4.41	6.49	9.52	0.17	1.56	0.74	4.76	28.45	7.40	0.26	0.05	0.20	0.23	5.74	0.26	647
BB	363.56	3.07	7.08	9.34	0.12	1.39	0.69	4.60	38.32	4.60	0.35	0.02	0.19	0.31	17.42	0.41	243
B	419.47	4.09	7.38	8.93	0.18	1.45	0.69	3.70	38.43	3.02	0.38	0.00	0.13	0.34	16.98	0.50	126
Panel C: Long Maturities (15-50 years)																	
AA	112.44	6.16	6.33	27.37	0.34	2.02	0.65	1.13	19.03	22.74	0.18	0.09	0.20	0.12	0.00	0.11	97
A	149.21	7.28	6.75	26.42	0.21	2.13	0.79	5.70	24.07	11.54	0.21	0.08	0.19	0.15	2.30	0.16	606
BBB	219.44	6.77	6.97	25.2	0.20	2.02	0.81	7.03	25.84	7.40	0.26	0.05	0.22	0.23	7.09	0.31	692
BB	248.82	5.36	5.81	24.84	0.23	2.01	0.74	5.96	35.39	4.33	0.32	0.02	0.18	0.29	14.23	0.37	126
B	425.85	7.67	6.12	24.58	0.42	2.13	0.62	-3.92	39.29	2.98	0.37	0.00	0.11	0.42	46.32	1.94	97

4 Results of Bond Spread Decompositions

4.1 Regression Results

In order to decompose credit spreads into their components we run the following regression:

$$\begin{aligned}\text{Spread} = \alpha + &\underbrace{\beta_1 \text{ Age} + \beta_2 \text{ C} + \beta_3\ \tau}_{\text{Bond Characteristics}} + \underbrace{\beta_4 \text{ IL} + \beta_5 \text{ EBA} + \beta_6 \text{ TI}}_{\text{Liquidity Risk}} + \underbrace{\beta_7\ R_e + \beta_8\ \sigma_e}_{\text{Equity Risk}} \\ &+ \underbrace{\beta_9 \text{ IC} + \beta_{10} \text{ LD\textbackslash TA} + \beta_{11} \text{ NI\textbackslash TA} + \beta_{12} \text{ OI\textbackslash S} + \beta_{13} \text{ TD\textbackslash C} + \beta_{14} \text{ EDF}}_{\text{Default Risk}} \\ &+ \underbrace{\beta_{15} \text{ Lev} + \beta_{16} \text{ Rating Dummy}}_{\text{Default Risk}} + \underbrace{\beta_{17} \text{ Industry Dummy}}_{\text{Bond Characteristics}} + \varepsilon.\end{aligned} \tag{12}$$

As our main concern is the contribution to credit spreads of different types of risk, we group the covariates into four categories. Bond specific characteristics contain all variables which are either fixed (coupon and industry dummy) or change linearly (age and time to maturity). The other groups are variables related to liquidity, equity, and default risk, respectively.

We first report results based on OLS regression for the full sample in Table 3. We examine the marginal explanatory power of the various risk categories by consecutively excluding them from the set of regressors. We chose to report results in this way as opposed to simply regressing the subset of factors and excluding all others as results in this format might be subject to an omitted variable bias.

In the full specification, we generally find that coefficients have the right sign. All measures of illiquidity increase spreads, while the estimate for the Amihud illiquidity measure is not significant though. Excess returns are negatively related to spreads whereas equity volatility is positively related. Higher IC, $LD\backslash TA$, and $NI\backslash TA$ all decrease spreads. The pattern for the IC dummies is mixed. The coefficient for IC_5 is negative and significant at -6.16. IC_{10}, however, has a positive coefficient of 1.75 whereas IC_{20} has a coefficient of -1.16. Both estimates are insignificant however. As expected, $TD\backslash C$, EDF, and Lev are all positively related to spreads and all three estimates are significant, although $TD\backslash C$ only at the 90% level. Finally, we observe that, relative to an A rating, we do not have a significant impact of an AA rating. For BBB to B ratings, however, we find an significant and increasing effect of the ratings. The R^2 of the full regression is 64%.

The regressions which omit a class of regressors have similar explanatory power as measures by the R^2 statistic which range from 60% to 63% and are thus only slightly lower than the R^2 of the full specification. A log-likelihood test, however, rejects the restricted model in favor of the full specification for each specification. This indicates that all categories are necessary to provide a

Table 3: Regression Results for Risk Components of Yield Spreads

The table reports the coefficients from several regressions using subsets of the covariates of the regression in (12). The first column reports results of regressing only bond specific variables on yield spreads. Columns two to four use also variables related to a specific risk component in addition to the bond specific variables. The fifth column also includes rating dummies in addition to default risk related covariates. The last column reports the results for the full specification. All regressions contain (unreported) industry and year dummies. Standard errors are reported in parentheses. The second to last row reports the R^2 statistic. The last row reports the test statistic of a log-likelihood ratio test against the full specification.

	Bond Factors	Liquidity Factors	Equity Factors	Default Factors	Rating Dummies	All Factors
$Intercept$	-25.69^{*}	-133.99^{***}	-97.68^{***}	-206.00^{***}	-231.01^{***}	-157.34^{***}
	(-1.77)	(-9.44)	(-6.39)	(-20.02)	(-21.23)	(-10.34)
Age		0.35	-1.49^{***}	-0.11	-1.85^{***}	-0.92^{**}
		(0.94)	(-3.58)	(-0.26)	(-4.20)	(-2.27)
C		23.09^{***}	24.09^{***}	24.12^{***}	29.67^{***}	23.35^{***}
		(21.79)	(22.12)	(22.15)	(25.65)	(22.03)
τ		0.21	-0.44^{***}	0.27^{*}	-0.15	-0.22
		(1.59)	(-2.98)	(1.90)	(-0.97)	(-1.57)
IL	-0.22		-3.93	10.35^{*}	11.07^{*}	1.77
	(-0.04)		(-0.72)	(1.90)	(1.88)	(0.33)
EBA	19.46^{***}		16.39^{***}	13.21^{***}	15.73^{***}	15.30^{***}
	(10.69)		(8.24)	(6.63)	(7.32)	(7.91)
TI	50.49^{***}		27.79^{***}	-5.30	-12.77	17.10^{*}
	(6.01)		(3.09)	(-0.59)	(-1.35)	(1.95)
R_e	-0.20^{***}	-0.27^{***}		-0.52^{***}	-0.43^{***}	-0.26^{***}
	(-4.06)	(-5.75)		(-11.46)	(-8.95)	(-5.56)
σ_e	3.59^{***}	3.38^{***}		4.69^{***}	7.24^{***}	3.36^{***}
	(19.98)	(18.74)		(29.33)	(48.87)	(18.62)
IC_5	-10.64^{***}	-6.57^{***}	-8.70^{***}			-6.16^{***}
	(-5.17)	(-3.23)	(-4.19)			(-3.05)
IC_{10}	0.92	1.61	1.94			1.75
	(0.75)	(1.35)	(1.58)			(1.47)
IC_{20}	-1.42^{*}	-1.10	-0.40			-1.16
	(-1.93)	(-1.46)	(-0.52)			(-1.56)
IC_{30}	-0.96^{***}	-0.53	-0.40			-0.61^{*}
	(-2.64)	(-1.52)	(-1.11)			(-1.77)
$LD\backslash TA$	-63.64^{***}	-47.21^{**}	-48.77^{**}			-45.36^{**}
	(-3.18)	(-2.40)	(-2.44)			(-2.32)
$NI\backslash TA$	-16.30	-74.49^{**}	-132.02^{***}			-83.52^{**}
	(-0.49)	(-2.27)	(-3.93)			(-2.55)
$OI\backslash S$	10.35	2.49	-15.28			4.27
	(0.97)	(0.21)	(-1.28)			(0.36)
$TD\backslash C$	71.59^{***}	47.15^{*}	55.14^{**}			44.53^{*}
	(2.76)	(1.81)	(2.10)			(1.72)
EDF	0.88^{***}	0.90^{***}	1.91^{***}			0.87^{***}
	(6.98)	(7.42)	(17.37)			(7.17)
Lev	40.21^{***}	33.26^{***}	23.38^{***}			36.10^{***}
	(8.19)	(6.91)	(4.77)			(7.50)
AA	0.24	7.86	-2.24	15.32^{**}		10.37
	(0.03)	(1.10)	(-0.30)	(2.12)		(1.45)
BBB	48.92^{***}	45.83^{***}	53.22^{***}	51.79^{***}		44.07^{***}
	(12.11)	(11.70)	(13.26)	(13.96)		(11.21)
BB	131.72^{***}	117.74^{***}	143.34^{***}	133.37^{***}		116.31^{***}
	(21.75)	(19.66)	(24.17)	(24.15)		(19.50)
B	166.66^{***}	162.32^{***}	197.26^{***}	190.28^{***}		159.72^{***}
	(22.71)	(22.54)	(28.06)	(29.25)		(22.28)
R^2	0.60	0.63	0.61	0.61	0.61	0.64
logL	587.3^{***}	72.78^{***}	354.15^{***}	410.11^{***}	1357.24^{***}	

*** denotes significance at the 1%, ** at 5%, and * at 10% level.

complete picture of the components of credit spreads.

In the restricted versions, most estimates have similar magnitude and significance across all regression specifications. The estimates for the rating dummies all increase when default related variables are excluded. The restricted model is still rejected relative to the full specification based on a likelihood ratio test. This shows that ratings and accounting ratios each contain information beyond what is implied by the other.

Previous studies have noted that the influence of risk factors changes as bonds become riskier. Rather than breaking our sample into rating groups, we perform quantile regressions. Several authors have noted that ratings are a crude measure of default risk and may not always reflect all information. Assuming reasonably efficient markets, the information contained in our covariates should be contained in the level of credit spreads. Therefore, should certain risk factors be more relevant for different types of bonds this should be reflected in the coefficient estimates along the quantiles of credit spreads. Instead of relying on ratings to determine overall riskiness of a given bond we therefore use its quantile. There is, of course, a strong relation between the level of credit spreads and bond ratings. In our sample, we find a rank correlation of 0.42 (based on Kendall's τ) and 0.53 (based on Spearman's ρ) between ratings and spreads. In Figure 3 we report box plots for spreads by ratings. The figure shows that there is a good correspondence of better ratings with lower spreads.

The results of the quantile regressions for the entire sample at selected quantiles are presented in Table 4. For ease of comparison, we also include the OLS results in the first column. The following three columns are the results of the quantile regressions at the selected quantiles of 0.5 (Median), 0.1, and 0.9. Finally, the last column reports the difference between the 9$^{\text{th}}$ and 1$^{\text{st}}$ decile. The table shows the estimates of the coefficients as well as their t-values. For the quantile regressions these were obtained using bootstrapping.[8] Although the (pseudo) R^2 is a very delicate measure, the results seem to indicate that we are able to capture much of the cross-sectional variation. For the quantile regressions, we calculate a pseudo R^2 as

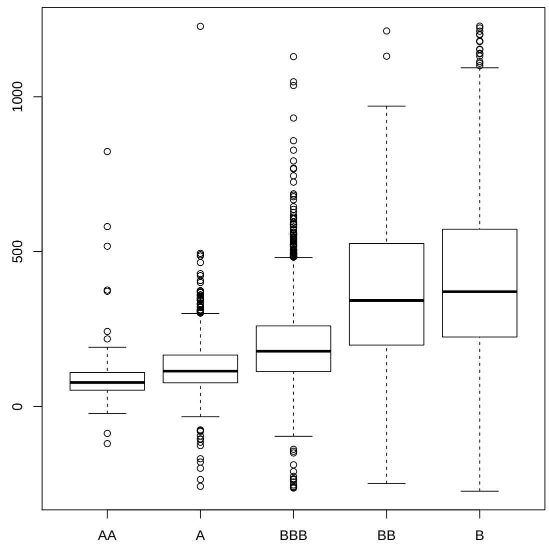
$$R^2 = 1 - \hat{S}/\tilde{S},$$

where $\hat{S}$ denotes the sum of squares of the full model in (12) and $\tilde{S}$ the sum of squares of the regression on merely an intercept. For the OLS regression, the R^2 is 64% whereas for the quantile regressions, the measure increases from 24% at the first decile to 61% at the ninth decile with an R^2 of 49% at the median. For the other (unreported) quantiles the increase in R^2 is monotonic

[8]To conserve space we do not present results for individual years. Overall, these are very similar to the full sample and available from the authors upon request.

Figure 3: Box-and-Whiskers Plot of Credit Spreads by Ratings

The chart shows Box-and-Whiskers plot for the spreads in the full sample by credit ratings. The solid black line indicates the median value and the box denotes the range of the 25% quantile to the 75% quantile. The Whiskers extend 1.5 times the interquartile range. Outliers beyond this point are indicated by black circles.



and almost exactly evenly-spaced along the deciles.

We first note that for the median and OLS regression, the signs of the coefficients mostly agree. The exceptions are τ, $LD\backslash TA$, and $OI\backslash S$. In each case, the estimate is significant in one but insignificant in the other specification. Also, the estimates are generally of a similar magnitude. Hence, both specifications provide a similar picture of the central tendency of how risk factors affect the level of credit spreads. Figure 4 provides the estimated quantile functions for all variables (excluding dummy variables).

For most covariates we find a strong quantile effect, i.e., the coefficients in the 10% decile are significantly different from the coefficients in the 90% decile. Since we only test the first against the last decile, this test can only provide indication of a linear quantile function. Other forms, such as U-shaped could result in the test being insignificant although the coefficients in between are significantly different. For eleven out of the total of 18 variables we find a significant quantile effect (at least 90% significance). This indicates that the quantile regression is indeed more appropriate to analyze the effect of various risk factors on credit spreads.

For the coupon rate (C) and $OI\backslash S$ there is a significant negative quantile effect indicating that these covariates contribute less (in absolute terms) to the spread of bonds the higher the spread is.

Table 4: Quantile Regression Results for Full Sample

The table reports the coefficients from the regression in (12) with t-values in parentheses. Standard errors are obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994). The last column reports the difference between the 9th and 1st decile. In parentheses are the F-statistic of the Wald test proposed by Bassett and Koenker (1982) to test for equality of coefficients.

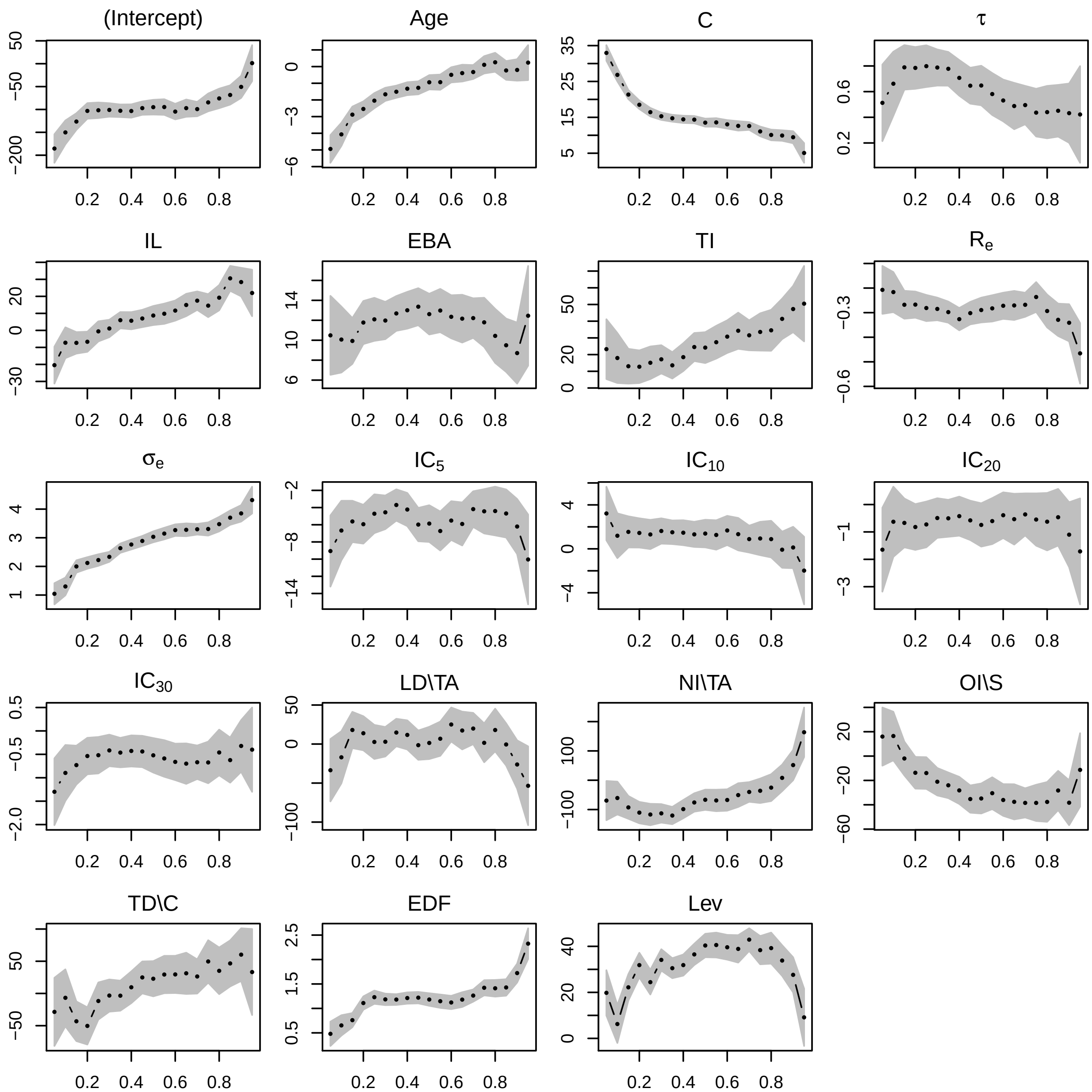
	$\hat{\beta}_{OLS}$	$\hat{\beta}(0.5)$	$\hat{\beta}(0.1)$	$\hat{\beta}(0.9)$	$\hat{\beta}(0.9) - \hat{\beta}(0.1)$
Intercept	-157.34^{***} (−10.34)	-94.98^{***} (−11.50)	-150.16^{***} (−11.17)	-50.68^{***} (−3.29)	99.48
Age	-0.92^{**} (−2.27)	-0.94^{***} (−4.27)	-4.06^{***} (−11.34)	−0.20 (−0.49)	3.86^{***} (66.14)
C	23.35^{***} (22.03)	13.52^{***} (23.50)	26.83^{***} (28.65)	9.46^{***} (8.82)	-17.37^{***} (100.03)
τ	−0.22 (−1.57)	0.64^{***} (8.19)	0.66^{***} (5.14)	0.43^{***} (2.93)	−0.22 (2.23)
IL	1.77 (0.33)	8.73^{***} (3.04)	−7.25 (−1.55)	28.40^{***} (5.30)	35.65^{***} (35.65)
EBA	15.30^{***} (7.91)	12.61^{***} (12.02)	10.06^{***} (5.89)	8.70^{***} (4.45)	−1.35 (0.38)
TI	17.10^{*} (1.95)	24.17^{***} (5.09)	17.94^{**} (2.32)	47.27^{***} (5.34)	29.33^{***} (12.04)
R_e	-0.26^{***} (−5.56)	-0.28^{***} (−11.20)	-0.21^{***} (−5.14)	-0.34^{***} (−7.08)	−0.12 (2.46)
σ_e	3.36^{***} (18.62)	3.03^{***} (30.95)	1.29^{***} (8.14)	3.85^{***} (21.08)	2.55^{***} (45.51)
IC_5	-6.16^{***} (−3.05)	-5.86^{***} (−5.34)	-6.67^{***} (−3.73)	-6.20^{***} (−3.03)	0.46 (0.02)
IC_{10}	1.75 (1.47)	1.39^{**} (2.15)	1.19 (1.13)	0.12 (0.10)	−1.06 (0.67)
IC_{20}	−1.16 (−1.56)	-0.74^{*} (−1.83)	−0.62 (−0.95)	−1.10 (−1.45)	−0.47 (0.41)
IC_{30}	-0.61^{*} (−1.77)	-0.52^{***} (−2.75)	-0.89^{***} (−2.91)	−0.32 (−0.91)	0.57^{*} (3.74)
LD\TA	-45.36^{**} (−2.32)	1.41 (0.13)	−16.99 (−0.98)	−26.20 (−1.32)	−9.21 (0.11)
NI\TA	-83.52^{**} (−2.55)	-66.66^{***} (−3.76)	-60.73^{**} (−2.10)	51.71 (1.56)	112.44^{**} (4.40)
OI\S	4.27 (0.36)	-34.83^{***} (−5.50)	16.48 (1.59)	-38.31^{***} (−3.24)	-54.79^{***} (14.93)
TD\C	44.53^{*} (1.72)	22.86 (1.63)	−6.74 (−0.29)	60.26^{**} (2.30)	67.00 (2.34)
EDF	0.87^{***} (7.17)	1.18^{***} (17.92)	0.65^{***} (6.07)	1.72^{***} (14.02)	1.07^{**} (6.35)
Lev	36.10^{***} (7.50)	40.36^{***} (15.46)	6.23 (1.46)	27.61^{***} (5.67)	21.38 (0.66)
R^2	0.64	0.49	0.24	0.61	

*** denotes significance at the 1%, ** at 5%, and * at 10% level.

We find a significant positive quantile effect for Age, IL, TI, σ_e, $NI\backslash TA$, and EDF. Most of the variables with an insignificant quantile effect, show an inverse U-shaped quantile pattern as shown in Figure 4.

Figure 4: Quantile Functions for Full Sample

The graphs plot the quantile function for the coefficient of each covariate (black dots) together with the 95% confidence band (gray area) obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994).



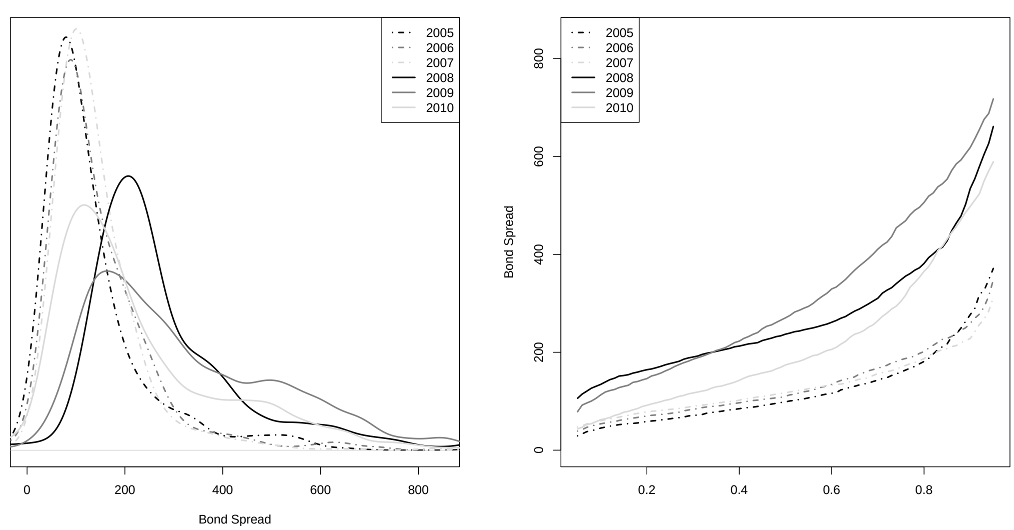
4.2 Counterfactual Experiments

The prior results indicate that with the regression specification in (12) we are able to decompose credit spreads into different risk components. Given these results, we now turn to the question of how these relations change over time. In particular, we want to determine what credit spreads would be had the financial crisis in late 2007 to early 2009 not occurred. Put differently, we want to decompose the change in credit spreads over time into the effect caused by changes of the risk factors themselves and changes caused by a revaluation of the risk implications of these factors. We use the decomposition approach discussed in section 2 to generate the counterfactual distributions of interest. Thereby, we will be mostly concerned with two questions: First, what would credit spreads look like if the financial crisis had not occurred? Second, what if risk perception and pricing of risk had remained at the pre-crisis levels?

Figure 5 presents the distributions of credit spreads for each year of our sample. The distribution of credit spreads in the years 2005 to 2007 seem to be fairly stable. By mid 2008, spreads along all quantiles have increased visibly. For 2009, there is a slight decrease in the upper quantiles (relative to 2008).

Figure 5: Mid-Year Distributions of Credit Spreads (2005 - 2010)

The figure shows the empirical density and quantile function of US corporate credit spreads measured at the end of June each year in basis points.



(a) Empirical Density (b) Empirical Quantile Function

To test whether the distribution of credit spreads has materially changed over the years we use pairwise Kolmogorov-Smirnov tests. Results are reported in Table 5. We find that we cannot reject the null of equal distributions for the pairs 2005-2006, 2005-2007, 2006-2007, and 2008-2009. Based on these results, we regard the sample from 2005-2007 as one period labeled $Pre-Crisis$, the sample from 2008-2009 as one period labeled $Crisis$, and 2010 as one period labeled $Post-Crisis$.[9]

Table 5: Results of Kolmogorov-Smirnov Tests for Equal Distributions

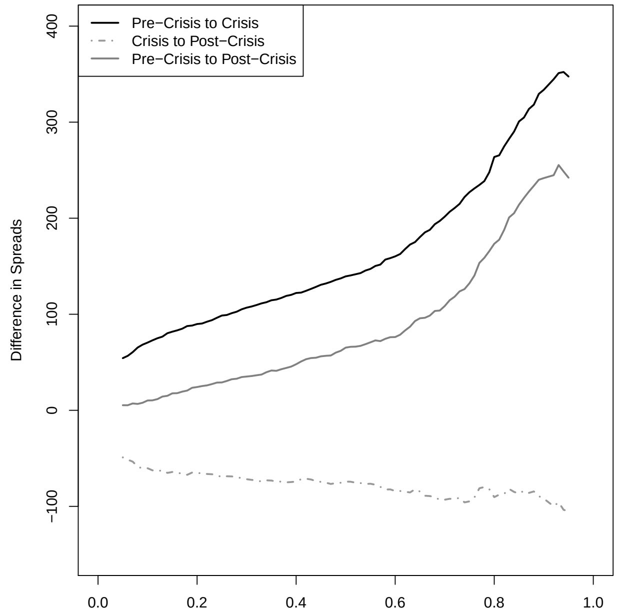
	2006	2007	2008	2009	2010
2005	0.12	0.18	0.65***	0.57***	0.34***
	(0.52)	(0.12)	(0.00)	(0.00)	(0.00)
2006		0.09	0.57***	0.51***	0.26***
		(0.88)	(0.00)	(0.00)	(0.00)
2007			0.60***	0.55***	0.30***
			(0.00)	(0.00)	(0.00)
2008				0.15	0.32***
				(0.23)	(0.00)
2009					0.27***
					(0.00)

Obviously, credit spreads increased during the crisis and subsequently decreased again. The question is what has caused this increase in spreads? How much of the change is due to changes in the risk factors, i.e., changes in the composition of bonds and business climate, and how much of the change is due to changes in risk perception, i.e., a reevaluation by markets of what the risk implications of the determinants of credit spreads are? Hence, what we propose is to decompose the quantile differences shown in Figure 6 into the component caused by market movements (i.e. changes in the covariates that give rise to credit spreads) and into the component caused by risk pricing (i.e. changes in the coefficients that determine the size of the credit spread). Hence, we perform the decomposition in (7) three times: from before the crisis (2005-07) until the crisis (2008-09) (first decomposition), from before the crisis (2005-07) until after the crisis (2010) (second decomposition), and from the crisis (2008-09) until after the crisis (2010) (third decomposition). The results of the three decompositions are reported in Figure 7. The appendix reports confidence bands in Figure B.1 to B.3 and detailed results in Table C.1.

For the first decomposition from Pre-Crisis to Crisis, we find that spreads have increased across all quantiles. Spreads in the lowest decile have increased by 66.46 bps while those in the highest deciles have increased by 310.86 bps. The difference along the quantiles is almost linear from the first to the sixth decile and then again almost linear to the last decile but with a higher slope. The counterfactual results indicate that for the lower deciles the increase in spreads is caused only to a quarter by changes in covariates. This proportion increases roughly linearly to a third for the highest decile. The counterfactual results also show that the "kink" in the differences is caused by a

[9] In unreported results, we have also apply counterfactual experiments on a year-on-year basis. These results confirm that from 2005 to 2006 and 2006 to 2007 the components of bond spreads have remained roughly constant. Similar results were obtained for 2008 to 2009. This indicates that in these periods risk perception has remained at the same level.

Figure 6: Quantile Differences of Credit Spreads



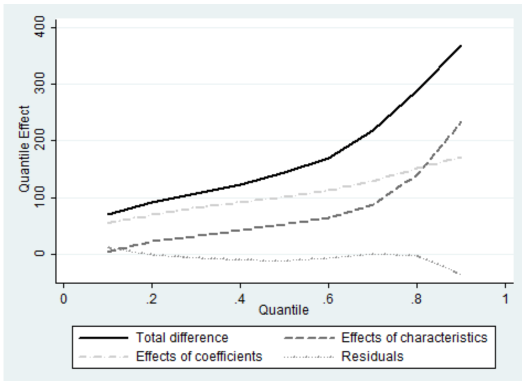
relatively stronger effect due to changes in coefficients roughly at the sixth decile. Interpreting the change caused due to coefficients as changes in risk perception, these results indicate that investors have reevaluated the risk implications of our risk proxies during the crisis. The decomposition results also show that this reevaluation was more pronounced for bonds with high credit spreads indicating a flight-to-quality. The results of the first decomposition are reported in Figures 7(a), B.1 and the first column of Table C.1 in the appendix.

In the second decomposition, from Pre-Crisis to Post-Crisis, we find that the total change is linear from the first to the sixth quantile and from the seventh to the ninth quantile with a somewhat sharper kink than in the first decomposition. In the first decile, spreads have decreased by 15.60 bps while they have increased by 228.95 bps at the ninth decile. We also find that the effects caused by changes in covariates, i.e. risk proxies, do not contribute much to the observed changes. The effect is either insignificant or economically very small. Hence, almost the entire change in the distribution is caused by changes in coefficients and the estimated effect is almost the same as the total observed change.

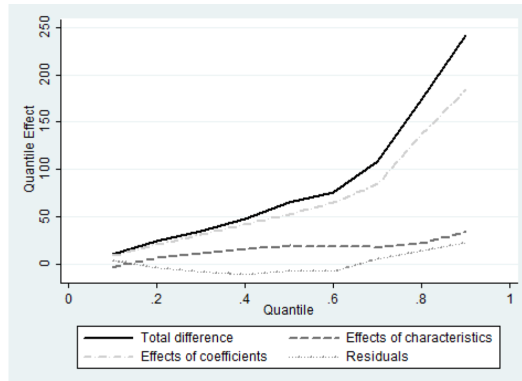
Interpreting this in financial terms, these results imply that the change in credit spreads over the financial crisis is almost entirely caused by a reevaluation of the implications of a given level of a risk factor, i.e. increases in the pricing implications of a given risk factor. This can be interpreted as an increase in risk perception caused by the crisis. The results for the second decomposition are

Figure 7: Decomposition of Credit Spreads

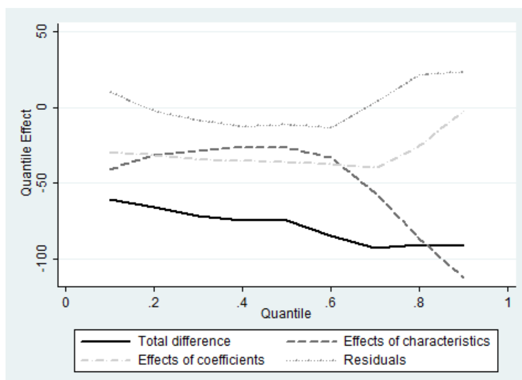
The figure presents the results of the counterfactual decomposition in (7) for the three time steps from Pre-Crisis to Crisis (Panel (a)), from Pre-Crisis to Post-Crisis (Panel (b)), and from Crisis to Post-Crisis (Panel (c)). Results on the corresponding confidence bands can be found in Appendix B.



(a) Pre-Crisis to Crisis



(b) Pre-Crisis to Post-Crisis



(c) Crisis to Post-Crisis

reported in Figures 7(b), B.2 and the second column of Table C.1 in the appendix.

For the third decomposition, from Crisis to Post-Crisis, we find that across all quantiles observed spreads have decreased in a roughly linear form with a decrease of 50.85 bps at the first decile 81.91 bps at the ninth decile. The effect of the covariates is negative and almost constant from the first to the sixth decile with values from -30.31 to -42.57 bps. For the lower quantiles, the effect is much more pronounced with an effect of -99.34 bps at the ninth decile. The results for the second decomposition are reported in Figures 7(c), B.3 and the third column of Table C.1 in the appendix.

4.3 Sequential Decompositions

In the previous section, we used counterfactual decompositions to separate how much of the observed increase in credit spreads over recent years has been caused by changes in risk factors as observed in markets (i.e., the effect caused by covariates) and how much has been caused by changes in the pricing implication of a given level of a risk factor (i.e., the effect caused by coefficients). In this section, we use the sequential decomposition described in equation (9) to analyze the influence that various types of risk categories had on the effect caused by changes in all coefficients. In particular, we analyze the separate effects that changes in the pricing of default risk, liquidity risk, and equity risk has had on bond spreads.[10]

To conserve space we only report results for the first and ninth quantile as well as the median in Table 6. We estimate the sequential decomposition for the same three time horizons as the counterfactual estimations in the previous section. The results for the four main effects in the three different decompositions is summarized in Figure 8. Panel (a) shows the total observed change in bond spreads for each time step. Panel (b) are the effects attributable to observed movements in market factors while keeping the risk pricing at their initial levels. The remaining four Panels (c) to (f) present how changes in the perception of the various risk factors have affected bond spreads.

Only in the first decomposition do we find that covariates have contributed a slight decrease for very safe bonds. What is notable, is that we do not find a strong effect for the first decomposition for most quantiles. Only for bonds in the upper quantiles is the effect of changes in risk factors substantial. Going from the crisis to after the crisis (decomposition 3) we find that the contribution is much stronger than in the previous decomposition with a substantial decrease due to the covariates at all quantiles. The effect depicted of the decomposition 2 shows that changes in market risk factors have had an exponentially increasing effect along the quantiles.

Thus far we have adjusted market conditions but have left the pricing of these conditions at their original levels. The next three steps of the decompositions adjust the pricing of these factors. The results of these decomposition should be interpreted as the difference in the risk premium associated with a particular risk at a given quantile of the distribution of credit spreads holding the level of the risk factor constant. Therefore, a quantile effect of 10 bps at a given quantile in the second decomposition would imply that markets attach a 10 bps higher premium for that risk at that quantile. Therefore, we interpret these effects as the result of altered risk perception on markets.

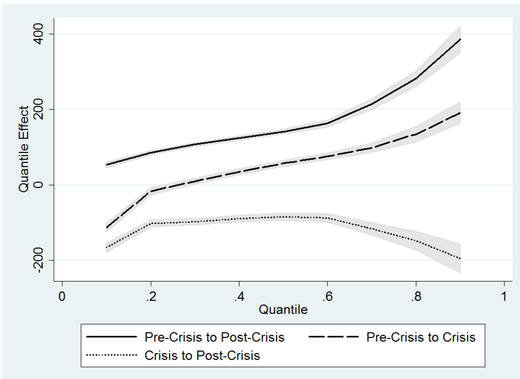
[10]This decomposition implicitly assumes that no interaction effects are present between the different components. Should this be the case, accounting for default risk first and then for liquidity risk would include the effect that liquidity effect has on default risk as the default component. In unreported results, we have varied the sequence of the decomposition with qualitatively the same results. Hence, interaction effects seem to be of only minor importance. The results are available from the authors upon request.

Table 6: Sequential Decomposition Results at Selected Quantiles

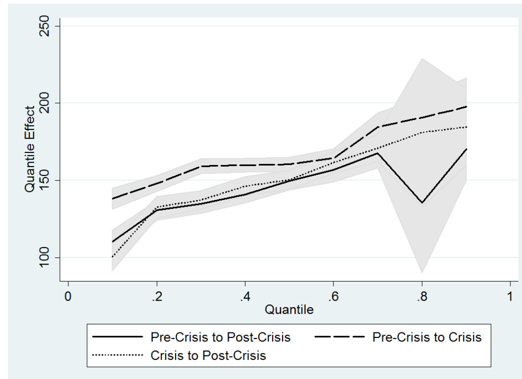
The table reports the results of the sequential decomposition described in (9) for the 10%, 50% and 90% quantile. Panel A reports results for the first decomposition (Pre-Crisis to Crisis), Panel B for the second (Pre-Crisis to Post-Crisis), and Panel C for the third (Crisis to Post-Crisis).

	Q10		Q50		Q90	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Panel A: First Sequential Decomposition						
Total Change	66.46	3.39	148.17	3.84	310.86	12.74
Change by Covariates	14.42	3.00	35.93	3.56	153.08	18.57
Change by Coefficients	59.78	3.95	105.55	4.40	135.21	23.92
Default Coefficients	-126.05	3.50	-112.87	2.40	-151.69	9.90
Liquidity Coefficients	34.43	3.23	38.04	2.04	36.43	7.24
Equity Coefficients	76.51	2.80	81.45	2.27	135.76	8.80
Characteristics Coefficients	142.78	3.41	166.42	2.36	180.12	9.49
Intercept	-67.89	4.10	-67.49	2.76	-65.41	10.74
Residual	-7.74	3.91	6.69	3.37	22.57	11.94
Panel B: Second Sequential Decomposition						
Total Change	15.60	3.34	67.96	4.68	-80.21	5.54
Change by Covariates	3.38	2.44	16.35	2.98	25.49	8.23
Change by Coefficients	9.02	3.00	52.71	4.11	184.20	11.39
Default Coefficients	-55.12	3.63	-74.52	2.71	6.37	8.02
Liquidity Coefficients	36.12	2.91	46.74	2.31	45.32	8.02
Equity Coefficients	66.53	2.95	79.07	2.09	129.48	9.47
Characteristics Coefficients	110.81	3.98	150.82	2.92	161.04	9.47
Intercept	-149.32	3.66	-149.45	3.45	-158.01	11.49
Residual	3.20	2.74	-1.11	2.97	19.26	7.61
Panel C: Third Sequential Decomposition						
Total Change	-50.85	4.38	-80.21	5.54	-81.91	16.58
Change by Covariates	-30.31	5.09	-38.51	6.00	-99.34	14.45
Change by Coefficients	-29.63	5.28	-36.24	5.16	-2.28	13.93
Default Coefficients	-99.59	4.53	-166.15	3.43	-186.11	12.47
Liquidity Coefficients	38.81	3.85	49.07	2.79	44.85	10.52
Equity Coefficients	68.82	3.80	80.91	2.65	131.27	11.74
Characteristics Coefficients	111.87	4.41	150.12	3.11	168.33	12.64
Intercept	-149.54	4.36	-150.19	3.54	-160.62	12.53
Residual	9.09	4.13	-5.46	3.59	19.71	9.66

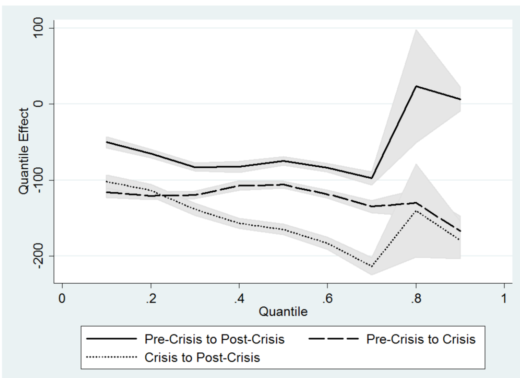
Figure 8: Decomposition Results for Different Risk Factors



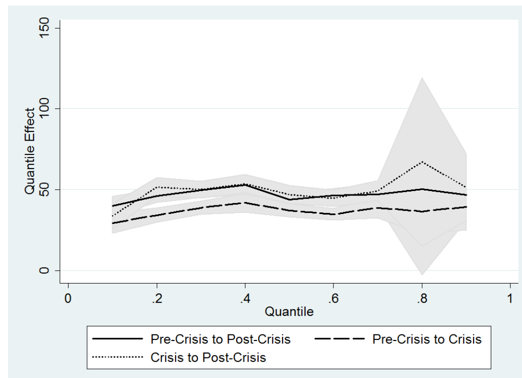
(a) Observed Change



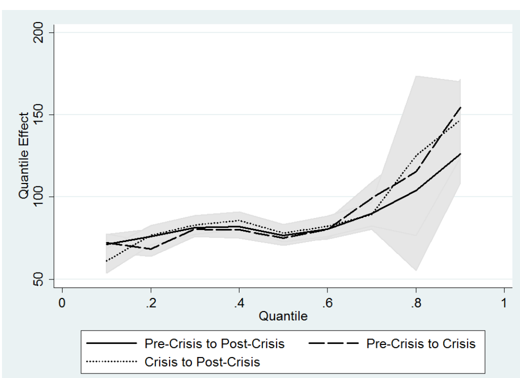
(b) Effect of Characteristics



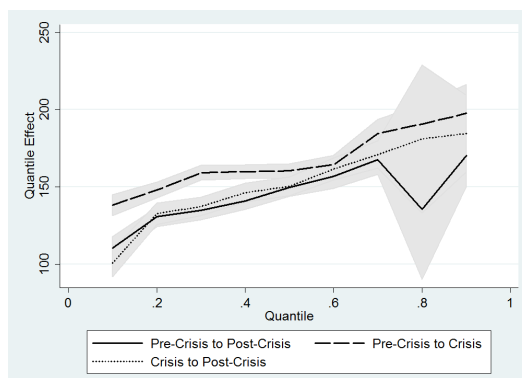
(c) Effect of Default Coefficients



(d) Effect of Liquidity Coefficients



(e) Effect of Equity Coefficients



(f) Effect of Bond Characteristics

As a first step we alter the pricing of factors related to the risk of default of a company. Figure 8(c) shows that relative pre-crisis period, the pricing implications of a given level of default risk have actually decreased. In all three decompositions, we find that aversion to default risk has decreased for most bonds with the exception of very high yield bonds. For these, default risk pricing has slightly increased from the pre-crisis to post-crisis period. As a next step, we adjusted the pricing of liquidity factors as shown in Figure 8(d). We find that the pricing of liquidity risk has increased along all quantiles in all three decompositions. Hence, we find that liquidity risk seems to play a more important role since the financial crisis irrespective of actual levels of liquidity. The effect of equity risk is presented in Figure 8(e). The graphs show that going into the crisis markets have priced equity risk at higher levels as compared to before the crisis. This effect is particularly pronounced for high-yield bonds.

Our results suggest that investors attribute more importance to liquidity and equity risk which has resulted in higher spread premia for carrying this type of risk. Default risk, however, carries a lower risk premium relative to pre-crisis levels. An alternative interpretation of these results would be that prior to the crisis, investors have been paying too much attention to default risk on the corporate bond market relative to the other risk factors. This misalignment has then been reversed during the financial crisis.

5 Conclusion

This paper investigates whether permanent shifts in risk perception are responsible for the sustained increase in corporate bond spreads from 2005 to 2010. We attempt to analyze this by explicitly accounting for changes in market risk factors and separating out the effect that the pricing of these factors have. This gives us an estimate of what spreads would have been if risk perception had not changed. The remaining difference, then, was caused by the alteration of what investors belief to be risk and how it should be compensated on markets. Using this decomposition, we find that most of the increase in bond spreads are due to changes in risk perception. While the movement of risk factors has increased spreads as the financial crisis unfolded, these effects are reversed as the crisis abated. However, bond spreads have not returned to their pre-crisis levels. This indicates that the financial crisis has caused permanent shifts in risk attitudes.

This paper uses known risk factors to decompose credit spreads into its priced risk components. Thereby, we differentiate between factors that are related to the specific bond, to its liquidity, the risk of default of the issuing company, and the equity risk of the issuing company. By estimating regressions at different quantiles of the distribution of credit spreads we therefore obtain more direct estimates of how risk factors simultaneously contribute to the level of credit spreads. Our results show that these factors can account for much of the cross-sectional variation in credit spreads and confirm several results in the literature. We find a very pronounced effect of illiquidity on credit spreads. Not unexpectedly, the quantile curves for the measures of illiquidity used clearly indicate that illiquidity premia are much higher for bonds with large credit spreads. Our results show that a large portion of credit spreads is due to illiquidity but that mean regressions may overstate its effect due to the huge premia for risky bonds with large spreads.

By using these risk factors, we provide explicit estimates of how changes in these factors have influenced credit spreads and how much of the changes in credit spreads before and after the recent financial crisis are due to changes in the pricing of these risk factors. The results of the decompositions show that most of the increase in credit spreads during the financial crisis is due to a spike in risk perception. We find an almost uniform increase along all quantiles of the effect of coefficients on credit spreads holding constant the effect of changes in the covariates. For the first decile, we find that during the crisis (i.e. from Pre-Crisis to Crisis) the effect of changes in the pricing of risk factors have increased spreads by about 100 bps. This effect increases roughly linearly over the quantiles and reaches about 150 bps for the last decile. Thus, this effect shows that markets have significantly revalued what a given risk factor should carry as a premium in the corporate bond market.

The second decomposition, from Pre-Crisis to Post-Crisis, shows that the effect of increased risk premia has diminished slightly for higher deciles and increased in the higher deciles. For this experiment, we find that for the first decile the effect of increases in risk perception is about 90 bps which increases about linearly to 250 bps for the last decile. For this decomposition, we also find that the effect of covariates has a strong influence on credit spreads. We attribute this to changes in the business environment due to the economic downturn during the time period under study. The sequential decomposition highlights the fact that liquidity and equity risk now carry higher risk premia whereas default risk premia have actually decreases once we adjust for changes in market factors and only look at the pricing effects.

An interesting further question would be to examine whether and how results differ among subsamples. For instance, one could examine if the classification into junk and investment grade bond by itself carries a risk premium above and beyond ratings and default related risk proxies. In a similar vein, Friewald et al. (2011) separate bond trades into retail and institutional trades and examine whether illiquidity has different effects depending on trade size. We leave these questions to further research.

References

Acharya, V. and Pedersen, L. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(3):375–410.

Alary, D., Gollier, C., and Treich, N. (2010). The effect of ambiguity aversion on risk reduction and insurance demand. Working Paper.

Altman, E. I. (1968). Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4):589–609.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5:31–56.

Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 2:223–249.

Antonczyk, D., Fitzenberger, B., and Sommerfeld, K. (2010). Rising wage inequality, the decline of collective bargaining, and the gender wage gap. *Labour Economics*, 17(5):835–847.

Bao, J., Pan, J., and Wang, J. (2010). The illiquidity of corporate bonds. *Journal of Finance*, forthcoming.

Bassett, G. and Koenker, R. (1982). Tests of linear hypotheses and L1 estimation. *Econometrica*, 50(3):1577 – 1583.

Berndt, A., Douglas, R., Duffie, D., Ferguson, M., and Schranz, D. (2004). Measuring default risk premia from default swap rates and EDFs. BIS Working Paper No. 173.

Bharath, S. T. and Shumway, T. (2008). Forecasting default with the merton distance to default model. *Review of Financial Studies*, 21:1339–1369.

Black, F. and Cox, J. (1976). Valuing corporate securities: Some effects of bond indenture provisions. *Journal of Finance*, 30(2):351–367.

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources*, 8(4):436–455.

Blume, M. E., Keim, D. B., and Patel, S. A. (1991). Returns and volatility of low-grade bonds: 1977-1989. *Journal of Finance*, 46(1):49–74.

Blume, M. E., Lim, F., and MacKinlay, A. C. (1998). The declining credit quality of u.s. corporate debt: Myth or reality? *Journal of Finance*, 53(4):1389–1413.

Campbell, J. Y. and Ammer, J. (1993). What moves the stock and bond markets? a variance decomposition for long-term asset returns. *Journal of Finance*, 48(1):3–37.

Campbell, J. Y. and Taksler, G. B. (2003). Equity volatility and corporate bond yields. *Journal of Finance*, 63(6):2321–2349.

Campello, M., Chen, L., and Zhang, L. (2008). Expected returns, yield spreads, and asset pricing tests. *Review of Financial Studies*, 21(3):1297–1338.

Chen, L., Collin-Dufesne, P., and Goldstein, R. S. (2009). On the relation between the credit spread puzzle and the equity premium puzzle. *Review of Financial Studies*, 22(9):3367–3409.

Chen, L., Lesmond, D. A., and Wei, J. (2007). Corporate yield spreads and bond liquidity. *Journal of Finance*, 62(1):119–149.

Chernozhukov, V., Fernández-Val, I., and Melly, B. (2009). Inference on counterfactual distributions. Working Paper, MIT.

Collin-Dufresne, P. and Goldstein, R. S. (2001). Do credit spreads reflect stationary leverage ratios? *Journal of Finance*, 56(1):29–48.

Collin-Dufresne, P., Goldstein, R. S., and Helwege, J. (2010). Is credit event risk priced? Modeling contagion via the updating of beliefs. NBER Working Papers 15733, National Bureau of Economic Research, Inc.

Cremers, K. J. M., Driessen, J., and Maenhout, P. (2008). Explaining the level of credit spreads: Option-implied jump risk premia in a firm value model. *Review of Financial Studies*, 21(5):2209–2242.

Dick-Nielsen, J., Feldhütter, P., and Lando, D. (2009). Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis. *SSRN eLibrary*.

Driessen, J. (2005). Is default event risk priced in corporate bonds. *Review of Financial Studies*, 18(1):165–195.

Duffie, D. and Lando, D. (2001). Term structure of credit spreads with incomplete accounting information. *Econometrica*, 69(3):633–664.

Edwards, A., Harris, L., and M., P. (2007). Corporate bond market transaction costs and transparency. *Journal of Finance*, 56(3):1421–1451.

Elton, E. J., Gruber, M. J., Agrawal, D., and Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance*, 56(1):247–277.

Friewald, N., Jankowitsch, R., and Subrahmanyam, M. G. (2011). Illiquidity or credit deterioration: A study in the us corporate bond market during financial crises. Working Paper.

Ghirardato, P. and Marinacci, M. (2001). Risk, ambiguity, and the separation of utility and beliefs. *Mathematics of Operations Research*, 26:864–890.

Giesecke, K., Longstaff, F. A., Schaefer, S., and Strebulaev, I. (2010). Corporate bond default risk: A 150-year perspective. Working Paper 15848, National Bureau of Economic Research.

Gosling, A., Machin, S., and Meghir, C. (2000). The changing distribution of male wages in the uk. *Review of Economic Studies*, 22(4):689–722.

Huang, J.-Z. J. and Huang, M. (2003). How Much of Corporate-Treasury Yield Spread Is Due to Credit Risk?: A New Calibration Approach. Working Paper, Penn State University.

Keim, D. B. and Stambaugh, R. F. (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics*, 17(2):357–390.

King, T.-H. D. and Khang, K. (2005). On the importance of systematic risk factors in explaining the cross-section of corporate bond yield spreads. *Journal of Banking and Finance*, 29(12):3141–3158.

Koenker, R. and Bassett, G. (1978). Regression quantiles. *Econometrica*, 46(1):33–50.

Kwan, S. (1996). Firm-specific information and the correlation between individual stocks and bonds. *Journal of Financial Economics*, 40(1):63–80.

Leland, H. and Toft, K. (1996). Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *Journal of Finance*, 51(3):987–1019.

Lin, H., Wang, J., and Wu, C. (2010). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics*, forthcoming.

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

Longstaff, F. and Schwartz, E. (1995). A simple approach to valuing risky fixed and floating rate debt. *Journal of Finance*, 50(3):789–819.

Machado, J. and Mata, J. (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics*, 20(4):445–465.

Melly, B. (2005). Decomposition of differences in distribution using quantile regression. *Labour Economics*, 12(4):577–590.

Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2):449–470.

Oaxaca, R. (1973). Male-femal wage differentials in urban labor markets. *International Economic Review*, 14(3):693–709.

Parzen, M., Wei, L., and Ying, Z. (1994). A resampling method based on pivotal estimating functions. *Biometrika*, 81(1):341–350.

Pastor, L. and Stambaugh, R. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3):642–685.

Pedrose, M. and Roll, R. (1998). Systematic risk in corporate bond credit spreads. *Journal of Fixed Income*, 8(3):7–26.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance*, 39(2):1127–1139.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business*, 74(1):101–124.

Vassalou, M. and Xing, Y. (2004). Default risk in equity returns. *Journal of Finance*, 59:831–868.

Zhao, C. (2001). The term structure of credit spreads with jump risk. *Journal of Banking and Finance*, 25(11):2015–2040.

A Results of Quantile Regressions Different Time Periods

Table A.1: Quantile Regression Results for Pre Crisis Period

The table reports the coefficients from the regression in (12) with t-values in parentheses. Standard errors are obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994). The last column reports the difference between the 9[th] and 1[st] decile. In parentheses are the F-statistic of the Wald test proposed by Bassett and Koenker (1982) to test for equality of coefficients.

	$\hat{\beta}_{OLS}$	$\hat{\beta}(0.5)$	$\hat{\beta}(0.1)$	$\hat{\beta}(0.9)$	$\hat{\beta}(0.9)-\hat{\beta}(0.1)$
Intercept	-41.67^{**} (-2.42)	-27.69^{***} (-3.68)	-51.83^{***} (-4.46)	-25.05 (-1.38)	26.77
Age	-2.76^{***} (-5.36)	-2.19^{***} (-9.74)	-4.43^{***} (-12.75)	-0.67 (-1.24)	3.75^{***} (32.86)
C	15.20^{***} (11.62)	8.54^{***} (14.95)	17.43^{***} (19.79)	8.03^{***} (5.82)	-9.40^{***} (21.72)
τ	0.61^{***} (3.76)	1.30^{***} (18.31)	1.03^{***} (9.40)	1.14^{***} (6.65)	0.11 (0.43)
IL	-4.53 (-0.54)	14.01^{***} (3.87)	-33.36^{***} (-5.97)	29.14^{***} (3.33)	62.51^{***} (8.10)
EBA	31.26^{***} (11.56)	15.76^{***} (13.35)	14.20^{***} (7.80)	21.58^{***} (7.57)	7.38^{***} (8.86)
TI	-10.73 (-1.03)	7.57^{*} (1.66)	-8.47 (-1.21)	27.87^{**} (2.54)	36.34^{***} (14.30)
R_e	-0.28^{***} (-4.44)	-0.24^{***} (-8.98)	-0.04 (-1.13)	-0.29^{***} (-4.46)	-0.25^{***} (12.26)
σ_e	1.91^{***} (6.62)	1.41^{***} (11.20)	0.21 (1.09)	2.12^{***} (6.96)	1.91^{***} (42.79)
IC_5	-7.34^{***} (-3.01)	-2.81^{***} (-2.65)	-2.42 (-1.48)	-5.10^{**} (-1.98)	-2.67 (0.51)
IC_{10}	2.54^{*} (1.89)	2.08^{***} (3.55)	0.84 (0.92)	1.44 (1.02)	0.60 (0.25)
IC_{20}	-0.08 (-0.09)	-0.72^{*} (-1.89)	0.29 (0.50)	1.27 (1.37)	0.97 (2.19)
IC_{30}	-0.66 (-1.38)	-0.46^{**} (-2.21)	-1.95^{***} (-6.08)	-0.34 (-0.67)	1.61^{***} (25.06)
LD\TA	-4.79 (-0.22)	-5.34 (-0.57)	-29.39^{**} (-2.04)	19.28 (0.85)	48.67^{**} (3.86)
NI\TA	-87.52^{**} (-2.01)	-55.73^{***} (-2.94)	-35.56 (-1.21)	-111.31^{**} (-2.43)	-75.74 (2.18)
OI\S	-17.79 (-1.14)	-24.25^{***} (-3.58)	-15.51 (-1.48)	-40.30^{**} (-2.46)	-24.78^{*} (2.86)
TD\C	6.15 (0.21)	43.69^{***} (3.53)	-10.70 (-0.56)	100.18^{***} (3.35)	110.89^{*} (3.24)
EDF	1.71^{***} (8.95)	2.32^{***} (27.73)	0.29^{**} (2.31)	2.38^{***} (11.80)	2.08^{***} (40.69)
Lev	19.80^{***} (2.59)	6.55^{**} (1.96)	39.26^{***} (7.64)	-8.78 (-1.09)	-48.04 (1.94)
R^2	0.51	0.43	0.18	0.58	

*** denotes significance at the 1%, ** at 5%, and * at 10% level.

Figure A.1: Quantile Functions for Pre Crisis Period

For each covariate, the graph plots the quantile against the coefficient estimate. The black dots denote the point estimates whereas the 95% confidence intervals are shaded in gray. They were obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994).

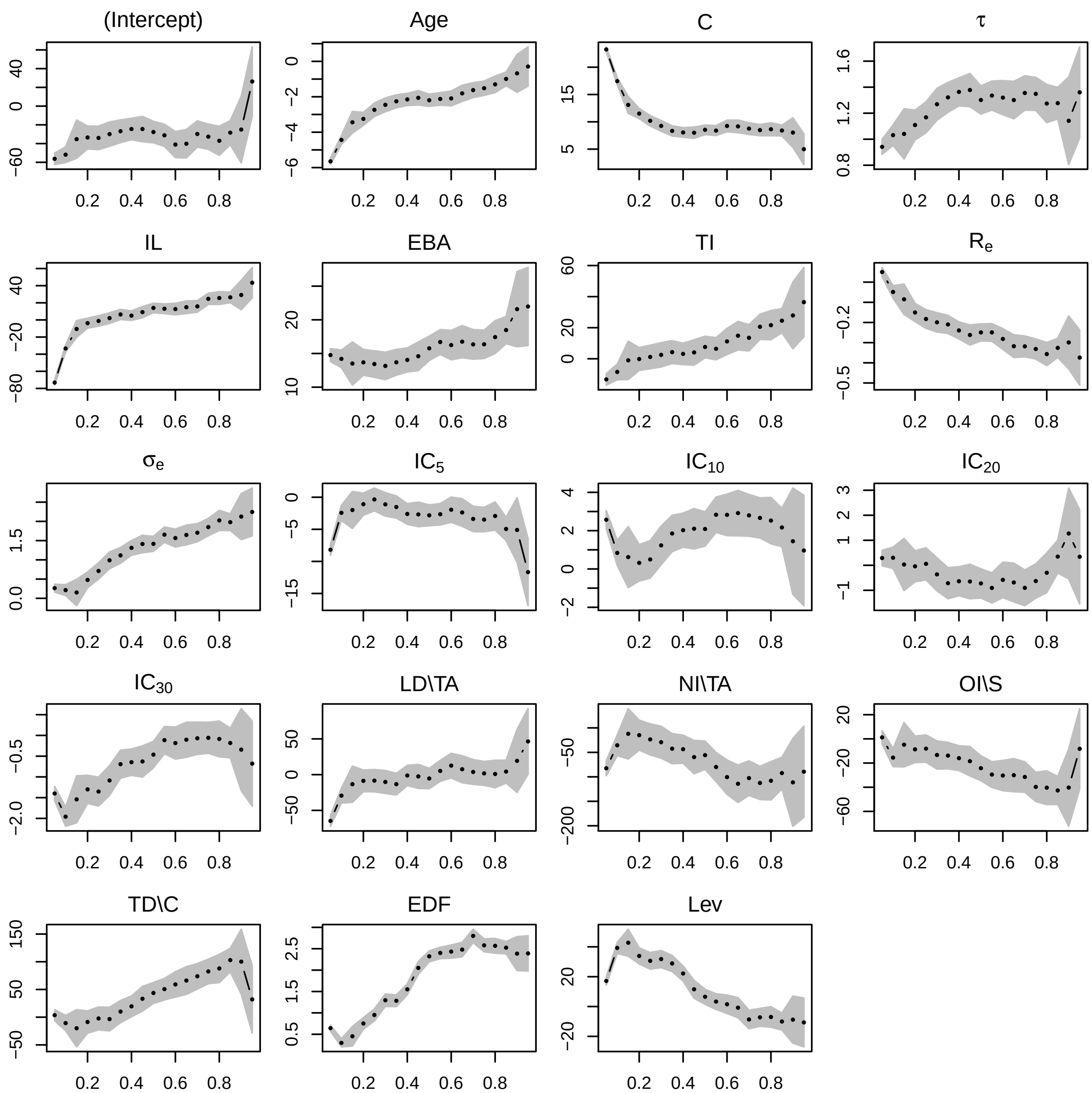


Table A.2: Quantile Regression Results for Crisis Period

The table reports the coefficients from the regression in (12) with t-values in parentheses. Standard errors are obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994). The last column reports the difference between the 9th and 1st decile. In parentheses are the F-statistic of the Wald test proposed by Bassett and Koenker (1982) to test for equality of coefficients.

	$\hat{\beta}_{OLS}$	$\hat{\beta}(0.5)$	$\hat{\beta}(0.1)$	$\hat{\beta}(0.9)$	$\hat{\beta}(0.9) - \hat{\beta}(0.1)$
Intercept	−225.09***	−114.31***	−195.06***	−200.56***	−5.50
	(−7.40)	(−7.19)	(−5.11)	(−6.31)	
Age	−1.44**	−1.16***	−6.26***	2.40***	8.66***
	(−2.10)	(−3.23)	(−7.24)	(3.33)	(75.57)
C	40.60***	23.95***	49.90***	13.72***	−36.17***
	(20.94)	(23.63)	(20.50)	(6.77)	(91.63)
τ	−1.48***	−0.59***	−0.85**	−0.61**	0.24
	(−5.28)	(−4.04)	(−2.42)	(−2.08)	(0.73)
IL	10.08	5.21	7.23	12.99	5.76
	(1.22)	(1.21)	(0.69)	(1.51)	(0.16)
EBA	6.22**	6.22***	10.33***	5.62*	−4.71
	(1.99)	(3.81)	(2.63)	(1.72)	(1.40)
TI	49.33***	44.78***	30.50	80.01***	49.50**
	(3.12)	(5.42)	(1.53)	(4.84)	(6.38)
R_e	−0.14*	−0.10**	−0.21**	−0.20**	0.00
	(−1.76)	(−2.40)	(−2.08)	(−2.47)	(0.00)
σ_e	3.47***	3.69***	1.76***	4.70***	2.94***
	(12.70)	(25.86)	(5.12)	(16.48)	(20.96)
IC_5	6.29	4.25*	−14.45***	28.23***	42.68***
	(1.49)	(1.93)	(−2.73)	(6.41)	(17.00)
IC_{10}	1.13	0.12	4.72	−0.53	−5.26
	(0.47)	(0.10)	(1.58)	(−0.21)	(2.29)
IC_{20}	−2.39*	−1.75***	−4.70***	−1.42	3.28*
	(−1.84)	(−2.57)	(−2.87)	(−1.04)	(3.80)
IC_{30}	−0.32	−0.29	−0.27	0.09	0.36
	(−0.56)	(−0.98)	(−0.38)	(0.15)	(0.06)
LD\TA	−107.20***	−48.42**	−32.04	−77.26*	−45.22
	(−2.82)	(−2.44)	(−0.67)	(−1.94)	(0.41)
NI\TA	−49.38	7.52	−23.46	72.01	95.47
	(−0.93)	(0.27)	(−0.35)	(1.30)	(0.99)
OI\S	−13.34	−51.53***	−17.04	−45.46*	−28.41
	(−0.55)	(−4.13)	(−0.56)	(−1.82)	(0.81)
TD\C	195.78***	114.15***	131.80*	230.02***	98.21
	(3.62)	(4.04)	(1.94)	(4.08)	(0.92)
EDF	0.25	0.30***	−0.08	0.62***	0.70*
	(1.33)	(2.97)	(−0.33)	(3.06)	(3.11)
Lev	33.07***	47.61***	11.58	18.48***	6.90
	(5.24)	(14.44)	(1.46)	(2.80)	(0.03)
R^2	0.67	0.51	0.31	0.62	

*** denotes significance at the 1%, ** at 5%, and * at 10% level.

Figure A.2: Quantile Functions for Crisis Period

For each covariate, the graph plots the quantile against the coefficient estimate. The black dots denote the point estimates whereas the 95% confidence intervals are shaded in gray. They were obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994).

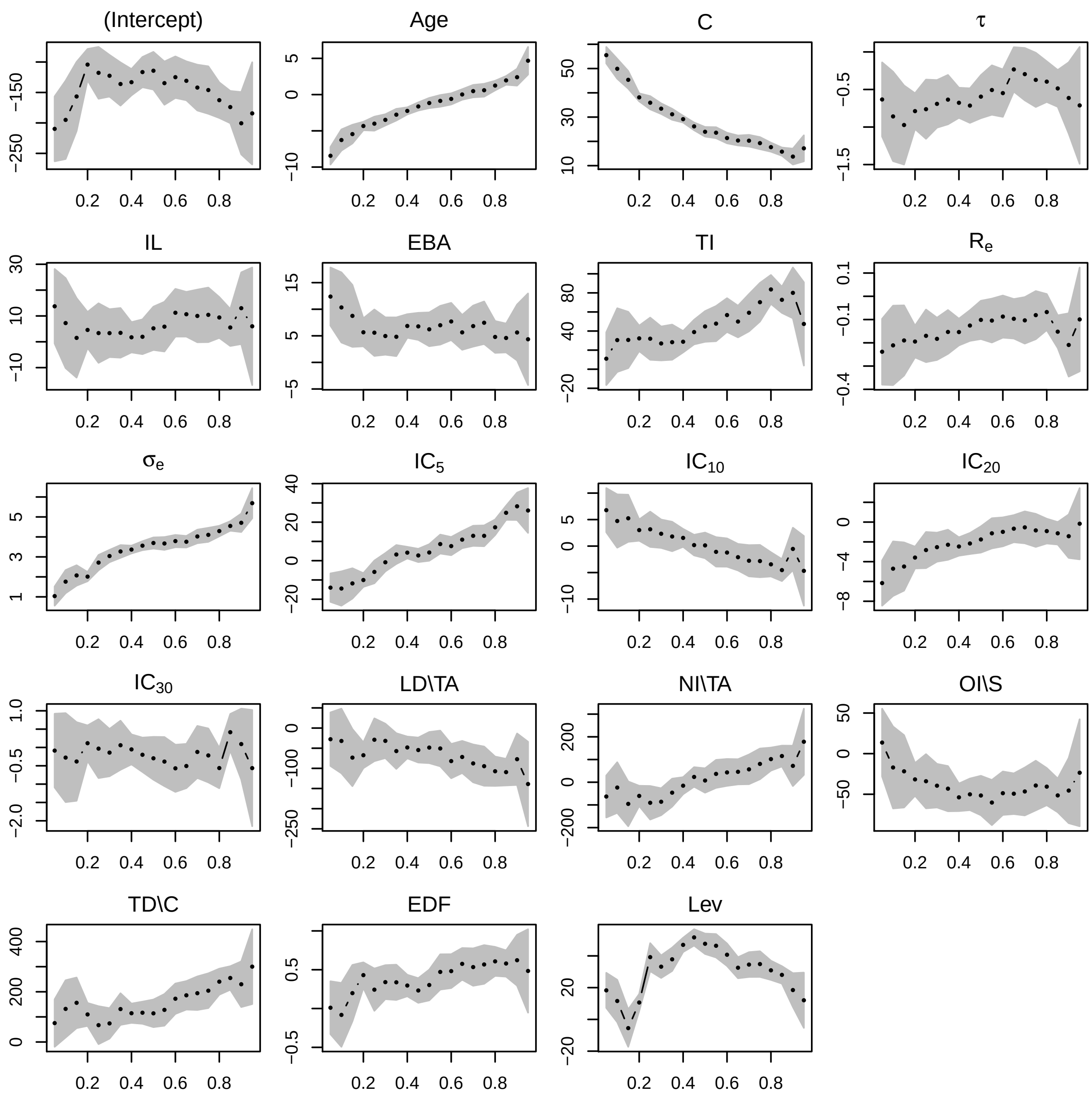


Table A.3: Quantile Regression Results for Post Crisis Period

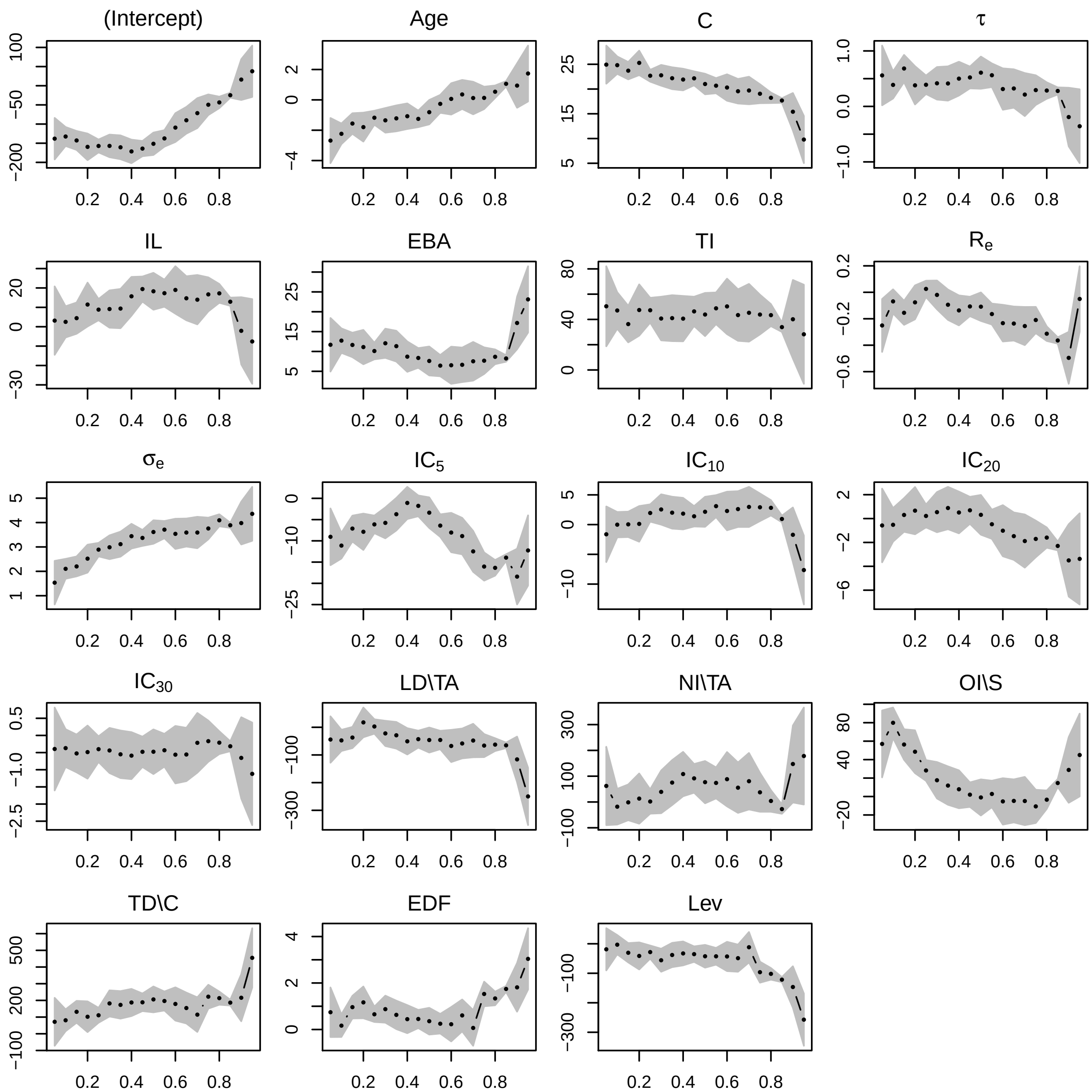
The table reports the coefficients from the regression in (12) with t-values in parentheses. Standard errors are obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994). The last column reports the difference between the 9th and 1st decile. In parentheses are the F-statistic of the Wald test proposed by Bassett and Koenker (1982) to test for equality of coefficients.

	$\hat{\beta}_{OLS}$	$\hat{\beta}(0.5)$	$\hat{\beta}(0.1)$	$\hat{\beta}(0.9)$	$\hat{\beta}(0.9) - \hat{\beta}(0.1)$
Intercept	-144.32^{***} (−4.13)	-151.47^{***} (−8.87)	-132.52^{***} (−8.58)	16.04 (0.59)	148.56
Age	−0.48 (−0.50)	-0.81^{*} (−1.73)	-2.23^{***} (−5.27)	0.94 (1.26)	3.17^{***} (13.50)
C	26.24^{***} (10.58)	21.01^{***} (17.31)	24.82^{***} (22.59)	15.41^{***} (7.98)	-9.41^{***} (7.74)
τ	−0.44 (−1.28)	0.60^{***} (3.59)	0.38^{**} (2.52)	−0.19 (−0.71)	-0.57^{**} (5.30)
IL	10.85 (0.95)	18.28^{***} (3.28)	2.51 (0.49)	−2.11 (−0.23)	−4.62 (0.07)
EBA	14.28^{***} (3.28)	7.60^{***} (3.57)	12.72^{***} (6.61)	17.17^{***} (5.07)	4.44 (0.51)
TI	24.20 (1.18)	43.87^{***} (4.39)	47.07^{***} (5.21)	40.12^{**} (2.52)	−6.95 (0.12)
R_e	−0.11 (−0.85)	-0.10^{*} (−1.72)	−0.06 (−1.20)	-0.49^{***} (−4.95)	-0.42^{**} (4.75)
σ_e	4.13^{***} (7.20)	3.61^{***} (12.84)	2.10^{***} (8.26)	3.97^{***} (8.88)	1.87^{***} (8.35)
IC_5	-11.12^{***} (−2.58)	−3.36 (−1.60)	-11.12^{***} (−5.84)	-18.42^{***} (−5.50)	−7.30 (1.65)
IC_{10}	4.41 (1.46)	2.15 (1.46)	−0.01 (−0.01)	−1.71 (−0.73)	−1.69 (0.32)
IC_{20}	−1.75 (−0.88)	0.31 (0.32)	−0.52 (−0.59)	-3.50^{**} (−2.26)	-2.98^{**} (6.28)
IC_{30}	−0.34 (−0.43)	−0.47 (−1.25)	−0.37 (−1.07)	−0.65 (−1.08)	−0.28 (0.47)
LD\TA	−45.83 (−0.84)	-46.13^{*} (−1.74)	-47.46^{**} (−1.98)	-115.99^{***} (−2.76)	−68.53 (1.33)
NI\TA	−13.41 (−0.13)	76.82 (1.60)	−18.26 (−0.42)	147.22^{*} (1.93)	165.48 (2.67)
OI\S	61.13^{***} (2.62)	−1.00 (−0.08)	79.92^{***} (7.73)	28.81 (1.58)	-51.11^{*} (2.75)
TD\C	168.43^{*} (1.82)	205.89^{***} (4.55)	80.84^{**} (1.97)	215.79^{***} (2.99)	134.94 (1.04)
EDF	1.05 (1.53)	0.35 (1.06)	0.16 (0.54)	1.81^{***} (3.39)	1.64 (0.91)
Lev	−68.98 (−1.49)	-42.41^{*} (−1.88)	−3.10 (−0.15)	-146.55^{***} (−4.08)	−143.44 (2.52)
R^2	0.6	0.53	0.27	0.59	

*** denotes significance at the 1%, ** at 5%, and * at 10% level.

Figure A.3: Quantile Functions for Post Crisis Period

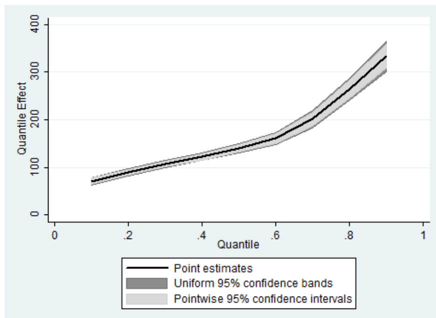
For each covariate, the graph plots the quantile against the coefficient estimate. The black dots denote the point estimates whereas the 95% confidence intervals are shaded in gray. They were obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994).



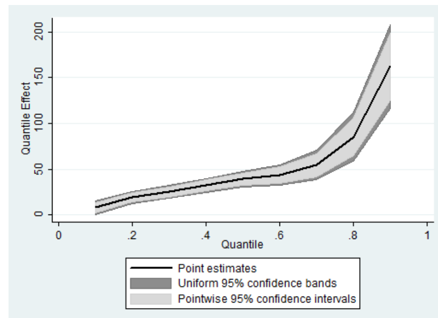
B Confidence Bands for Counterfactual Distributions

Figure B.1: Counterfactual Results from Pre-Crisis to Crisis

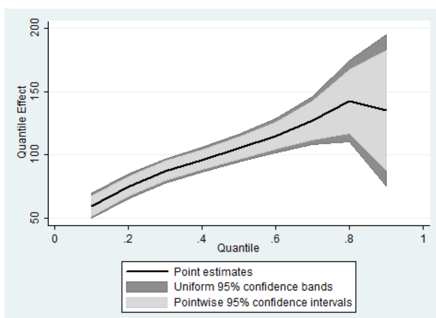
The figure presents the results and the 95% confidence bands for the counterfactual decomposition from the pre-crisis period to the crisis period. All standard errors were obtained using the bootstrap method of Chernozhukov et al. (2009) with 500 replications.



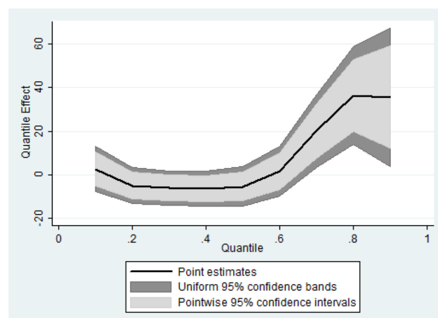
(a) Total Change



(b) Effects of Covariates

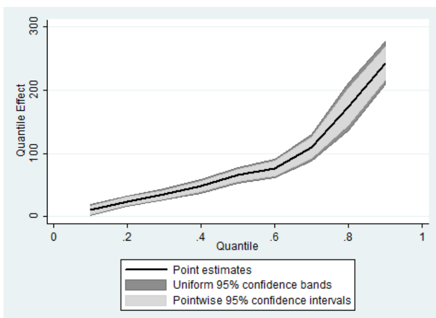


(c) Effects of Coefficients

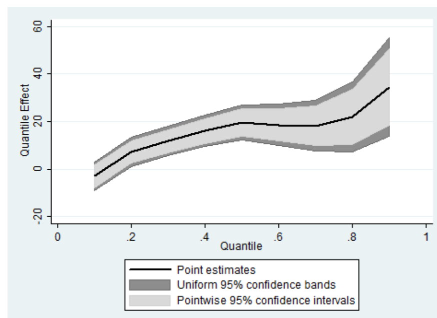


(d) Effects of Residuals

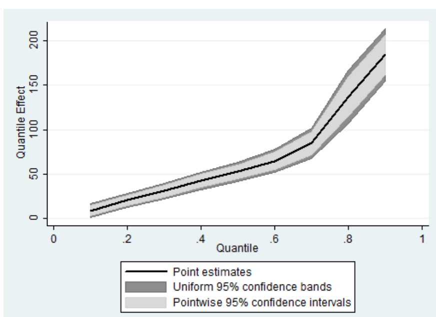
Figure B.2: Counterfactual Results from Pre-Crisis to Post-Crisis
The figure presents the results and the 95% confidence bands for the counterfactual decomposition from the pre-crisis period to the post-crisis period. All standard errors were obtained using the bootstrap method of Chernozhukov et al. (2009) with 500 replications.



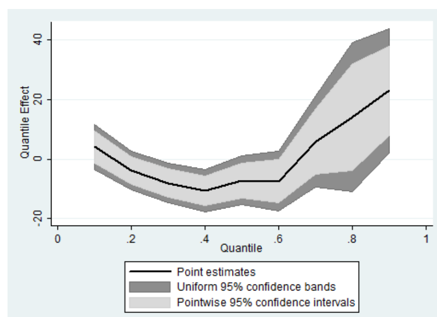
(a) Total Change



(b) Effects of Covariates



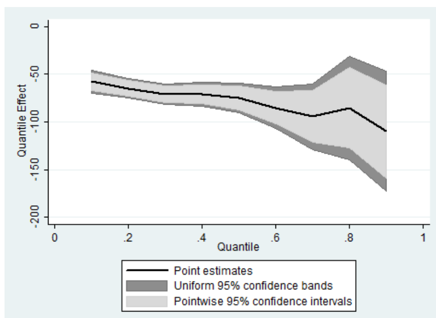
(c) Effects of Coefficients



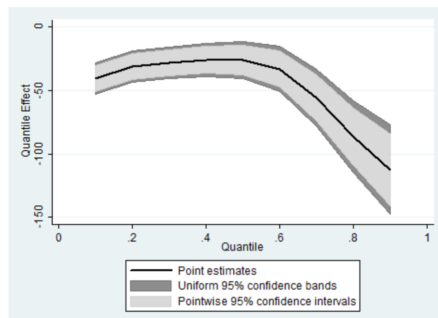
(d) Effects of Residuals

Figure B.3: Counterfactual Results from Crisis to Post-Crisis

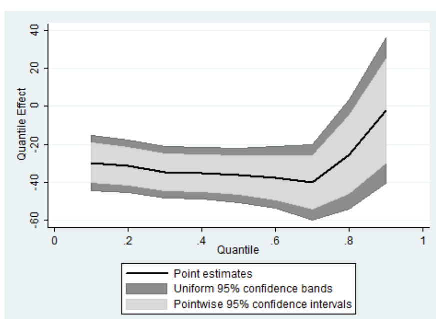
The figure presents the results and the 95% confidence bands for the counterfactual decomposition from the crisis period to the post-crisis period. All standard errors were obtained using the bootstrap method of Chernozhukov et al. (2009) with 500 replications.



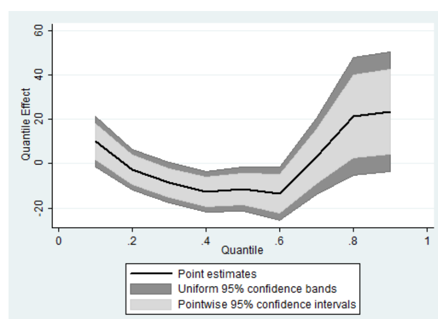
(a) Total Change



(b) Effects of Covariates



(c) Effects of Coefficients



(d) Effects of Residuals

C Full Table for Counterfactual Decomposition

Table C.1: Counterfactual Decompositions of Credit Spreads
The table reports the estimated quantile effect and standard error at each decile of the counterfactual decompositions (7) for each pair of periods. Standard errors are obtained using the bootstrap inference procedures described in Chernozhukov et al. (2009) with 500 replications.

	Pre-Crisis to Crisis		Pre-Crisis to Post-Crisis		Crisis to Post-Crisis	
Quantiles	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Differences between the observable distributions						
0.1	66.46	3.39	15.60	3.34	-50.85	4.38
0.2	92.54	2.92	28.32	3.18	-64.22	4.06
0.3	112.81	3.01	40.28	3.44	-72.53	4.35
0.4	130.20	3.27	53.68	4.12	-76.52	4.87
0.5	148.17	3.84	67.96	4.68	-80.21	5.54
0.6	169.29	5.10	83.31	5.65	-85.98	7.18
0.7	199.86	7.38	106.19	8.21	-93.67	10.33
0.8	242.32	9.70	156.56	14.71	-85.76	17.14
0.9	310.86	12.74	228.95	13.18	-81.91	16.58
Effects of Covariates						
0.1	14.42	3.00	3.38	2.44	-30.31	5.09
0.2	20.33	2.68	8.11	2.43	-33.19	5.12
0.3	24.76	2.83	11.16	2.50	-35.19	5.15
0.4	30.09	3.11	13.86	2.61	-36.53	5.36
0.5	35.93	3.56	16.35	2.98	-38.51	6.00
0.6	43.20	4.46	18.06	3.48	-42.57	7.37
0.7	55.04	6.50	18.72	4.26	-53.88	9.28
0.8	81.85	10.61	18.43	5.93	-68.61	11.58
0.9	153.08	18.57	25.49	8.23	-99.34	14.45
Effects of Coefficients						
0.1	59.78	3.95	9.02	3.00	-29.63	5.28
0.2	75.29	3.80	20.80	3.06	-31.48	5.01
0.3	87.38	3.85	31.30	3.35	-34.53	4.90
0.4	96.27	4.02	42.59	3.67	-35.18	4.97
0.5	105.55	4.40	52.71	4.11	-36.24	5.16
0.6	115.14	5.36	65.02	4.84	-37.51	5.89
0.7	127.11	7.64	84.79	6.45	-39.90	7.23
0.8	142.24	12.81	137.28	11.49	-25.32	10.49
0.9	135.21	23.92	184.20	11.39	-2.28	13.93

.... (continued on next page) ....

	Pre-Crisis to Crisis		Pre-Crisis to Post-Crisis		Crisis to Post-Crisis	
Quantiles	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Effects of Residuals						
0.1	-7.74	3.91	3.20	2.74	9.09	4.13
0.2	-3.08	3.16	-0.59	2.39	0.45	3.30
0.3	0.67	2.94	-2.18	2.38	-2.80	3.31
0.4	3.84	3.01	-2.77	2.56	-4.81	3.34
0.5	6.69	3.37	-1.11	2.97	-5.46	3.59
0.6	10.94	4.35	0.22	3.68	-5.90	4.39
0.7	17.70	6.30	2.68	5.57	0.12	6.14
0.8	18.23	8.42	0.85	9.08	8.16	9.56
0.9	22.57	11.94	19.26	7.61	19.71	9.66