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Abstract

This paper investigates, how the 2007-08 financial crisis has affected the risk perceptions of institutional bond investors. Using a methodology novel to the empirical finance literature, we quantify the impact that changes in risk perception have had on bond spreads over the course of the crisis. The relative contribution of the change in risk perceptions can be measured by decomposing changes in credit spreads of US corporate bonds into the contribution caused by changing risk factors and the contribution caused by changes in the pricing of these factors. We document that the lasting increase in credit spreads caused by the current financial crisis is almost exclusively due to increased risk aversion in bond markets. This enduring increase in perception of equity and liquidity risk, which becomes more important in periods of financial distress, is consistent with changing risk perceptions as predicted by theories of ambiguity aversion or social learning in the case of rare events.

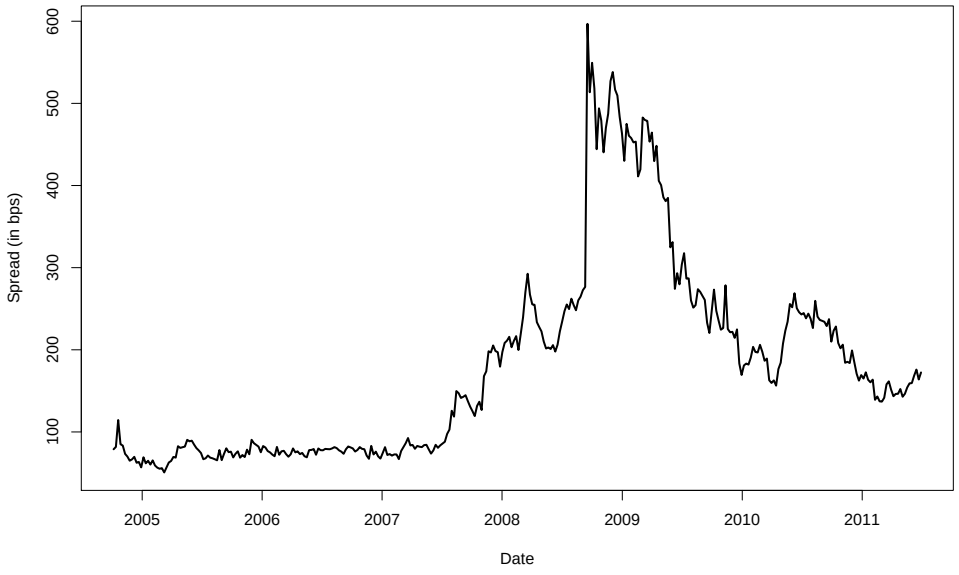
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During the 2007-08 financial crisis credit spreads for corporate bonds surged dramatically and have not returned to previous Levels.[1] Figure 1 illustrates the evolution for US corporate credit spreads for the period October 2004 to June 2011. Since credit spreads measure the riskiness of bonds as viewed by the market, two possible explanations arise: Either risk factors have risen and remain at higher levels or the yield premium that investors charge for a given level of risk has increased. Using decomposition methods, we investigate and quantify how the financial crisis has affected the risk tolerance of institutional investors in the corporate bond market. We construct estimates of the distribution of credit spreads that would have prevailed after the financial crisis if the crisis had not altered the way risk factors are priced. After controlling for changes that our model cannot account for, we obtain an explicit estimate of how much of the total increase in the level of bond spreads has been caused by a general shift in risk perception by investors.

Figure 1: Development of US Corporate Credit Spreads (October 2004 - June 2011)

The chart shows the weekly market-wide corporate bond yield spread between October 2004 and June 2011 computed as the median spread of US corporate bonds. The spread is measured relative to the Treasury yield curve and reported in basis points.



[1] In the empirical section, we define the Crisis period to last from 2008 to 2009. This is due to the fact that we use annual data measured mid-year on July 1st. Therefore, the crisis only manifests itself in our 2008 data and lasts until 2009.

There are various reasons why large shocks may have long-lasting effects on risk perceptions. First, there may be learning about the parameters that drive the economy. Papers such as Timmermann (2001), Kim (2006), or Bansal and Shaliastovich (2011) imply that once investors realize that a structural break has occurred they will start to learn about the new parameters with adaptive learning rules. This learning introduces long-run risk resulting in permanent shifts after large shocks. Second, uncertainty about the state of the economy may cause ambiguity averse investors to assign higher probabilities on the possibility of a low utility state recurring after just such an event has occurred. Gagliardini et al. (2009) show that an ambiguity about a state variable can induce a large yield premium. Boyarchenko (2012) uses a model with both ambiguity about information quality and model quality to explain the rapid increase in CDS spreads during the financial crisis. Drechsler (2013) introduces model misspecification concerns of investors into an asset pricing model. He shows that risk premia are strongly impacted by concerns about the frequency and magnitude of jump shocks. Third, as argued by Guiso et al. (2013), the crisis might have altered the determinants for variations in risk aversion such as changes in wealth, changes in habits, and changes in background risk. Finally, Bacchetta et al. (2012) show that self-fulfilling shifts in risk are made possible when asset prices depend negatively on perceived risk of future asset prices. 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 principle, bond spreads change over time because of two reasons. On the one hand, risk factors themselves change over time. On the other hand, investors change the way they price these risk factors. In our paper we are interested in quantifying the second component. The Oaxaka-Blinder decomposition (Oaxaca (1973), Blinder (1973)) and its extensions are regularly used in empirical research for such decompositions. To our knowledge, however, this methodology is novel to the empirical finance literature. The decomposition gives us an estimate of how credit spreads would have been distributed if the financial crisis had not occurred. The difference between this (counterfactual) distribution and the empirically observed distribution gives us a

direct estimate of the effect that the crisis had on risk perception. This can be seen as the result of social learning in that investors update their beliefs about which return distributions they perceive to be possible. Hence, we separate the total change in credit spreads into three components: The change caused by the risk factors themselves, the change due to a modification in the pricing relationship, and an unexplained component. We interpret the adjustment in pricing at the bond market as evidence in favor of behavioral shifts caused by the crisis.[2]

We use cross-sectional quantile regressions to model the relationship between risk factors and credit spreads. This allows us to include both firm-level and bond-specific information and derive explicit estimates of the contribution to the level of credit spreads. We favor quantile regression over the standard mean regression since it allows us to control for non-linearity in the pricing relationship of risk factors. For instance, one would expect that liquidity risk has different implications for high-yield bonds than for low-yield bonds. 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 several risk factors. Guided by the literature, we examine the impact of factors related to default risk, liquidity risk, and equity risk simultaneously in order to obtain a complete description of the conditional distribution of bond spreads.

In our data we find that most of the change in credit spreads is the result of increases in the premia of risk factors. Comparing pre-crisis to crisis levels, we find that 25 to 50% of the increase in credit spreads is caused by an actual change of risk factors (depending on the quantile

[2]Note that we do not quantify how persistent changes in risk perception and the effects on the pricing of risk factors are as our dataset ends in 2011. Because of the subsequent debt crisis in the Eurozone, the Post-Crisis period might not be an isolated incident. However, since our focus is on US corporate bonds we believe that the EMU crisis only marginally affect our main results. In addition, the bond yields during the time period considered may be influenced by the Fed's quantitative easing (QE) programs. As described later, QE1 occurred in what we call crisis period whereas QE2 coincides with out post-crisis period. Assuming these programs were successful, their effect on the bond market should be that they have lowered the level of bond spreads. Hence, our results are conservative in that observed spreads would have been higher after the crisis without the QE program of the Fed.

of the distribution). The remainder of the increase stems from the fact that the average risk premia have increased. More importantly, when we compare pre-crisis to post-crisis levels, we document that changes in risk factors had an economically insignificant effect on the level of bond spreads. 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 returned to pre-crisis levels. This implies 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. Moreover, our estimates reflect the findings from literature that a scary experience can induce a substantial increase in investors' risk aversion, and thus leads to changes in the pricing of factors from before to after the financial crisis. Our results also accord well with the questionnaire based evidence of Guiso et al. (2013) for Italian investors.

We further decompose the total effect that changes in risk pricing had into the effects due to default risk, liquidity risk, and equity risk. We find that perception of default risk has actually decreased over the time frame considered and that much of the increase in credit spreads is caused by liquidity and equity related effects. Liquidity related effects are actually larger after the crisis than during while for equity related factors we find that the effect of the crisis has mostly abated. The results confirm the dominant role of liquidity in financial crises and particularly, its effect on the pricing of risky assets (see Allen and Carletti (2008); Bacchetta et al. (2012)).

This paper also contributes to the literature on time-varying risk premia on bond returns which is summarized in Giesecke et al. (2010). These authors note that corporate bond spreads display considerable variations over time that do 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 or liquidity risk. In this paper, we investigate this proposition explicitly, while adding the role of changing market perceptions.

While time-varying beta regressions or state-space models try to answer the question how the explanatory power can be improved when we assume that coefficients are time-varying, the impact of changes in perception could not be addressed in such a framework. Since risk factors and the pricing of factors change simultaneously, these models are unable to disentangle their separate contribution to variations in credit spreads. Hence, time-varying coefficients models are based on an explicit assumption about the relationship in the dynamics of factors and coefficients, which usually are taken as independent. The use of counterfactual distributions, on the other hand, gives direct estimates of these.

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 and motivates the proxies we use in the empirical section. Section 2 discusses the data used and presents summary statistics. Section 3 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. The results on changes in risk pricing from our counterfactual experiment and the identification of the importance of risk factors by sequential decomposition are presented in Section 4. Section 5 concludes.

1 Determinants of Credit Spreads

In order to price bonds from first principle structural models are needed. To the extent that the underlying economic structure is fixed, standard pricing models allow to price the underlying risk factors.[3] To the extent that the underlying economic structure may change, the relative valuation and pricing of risk factors may change as well. In this section, we first discuss the standard risk and liquidity factors that can explain the levels of credit spreads. Since the novel feature of our analysis is the estimation of the effects of changes in the pricing structure of the bond market, we then discuss possible explanations why investors would alter their perception of the fair yield premium of a risk factors as a result of a deep financial crisis.[4]

[3]Since we are interested in analyzing changes in risk perception we focus on relative risk premia. For corporate bonds, these risk premia are expressed in the respective yield spreads. Hence, we are assuming that investors in the corporate bond market are primarily interested in the spread they earn above the risk-free rate and not the total yield.

[4]Note that we do not refer to a specific structural model in deriving the underlying risk factors of credit spreads. Instead, we specify an atheoretical credit spread model based on determinants commonly used in the literature.

Credit Risk. Structural models of credit risk are based on the idea that a company's default is triggered when the value of the firm's assets hits some boundary.[5] Thus, these models predict that the difference in yields of corporate bonds above the yield of risk-free bonds arises because of the possibility of the firm defaulting on its debt and the uncertain reduction in payments due to such an event.

Empirically, 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).[6] These observations have led to a large number of investigations into additional determinants of credit spreads.

Equity Risk. Elton et al. (2001) 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.[7] Although contradictory to theory, 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).[8] These studies suggest that a higher return on

A more formal model that is quite similar in spirit to our analysis can be found in Boyarchenko (2012).

[5]This line of reasoning was initiated by 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).

[6]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 noisy accounting information.

[7]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), Cremers et al. (2008), and Collin-Dufresne et al. (2010).

[8]As noted by King and Khang (2005), structural models 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 return on the assets of the firm. This is because any risk can be eliminated by hedging which is equivalent to the statement that the value of equity options are independent of the growth rate of the stock under the statistical measure. Thus, after controlling for the relevant risk factors the price of the bond should be unrelated to the value of the firm.

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.

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 holding illiquid assets. Hence, the level of liquidity of an asset should influence its market price. Following this argument, Chen et al. (2007) provide direct evidence that both investment and speculative bonds carry an illiquidity premium. In complementary work, Bao et al. (2011) 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 risk should be a priced characteristic on asset markets. Lin et al. (2011) study the relation between corporate bond returns and systematic liquidity risk. Longstaff et al. (2005) conclude that, even though the majority of credit spreads is due to default risk, the non-default component is strongly influenced by (il-)liquidity.

Risk Perception. One possible explanation for changes of risk pricing due to a crisis is that investors are ambiguity averse. Ambiguity aversion arises when investors are uncertain about the true underlying distribution from which returns are sampled. 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 rational inference from a crisis event.[9] Experimental evidence for this type of behavior during a deep crisis is presented in Guerreri et al. (2012). In this paper, we quantify this effect in terms of the additional increase of credit spreads that has occurred as a consequence of the financial crisis.

There are, however, few articles concerned with ambiguity aversion and/or behavioral features like investor sentiment with regards to credit spreads. One of the few papers in this regard is Boyarchenko (2012). Her model explicitly introduces ambiguity aversion into a Black and Cox (1976) type model. This addition has two effects: First, short-term credit spreads increase (relative to the ambiguity-neutral model) as ambiguity-averse investors place a higher probability of transition to low-utility states. This is similar to the effect that uncertainty about accounting information has on spread levels, as discussed in Duffie and Lando (2001). Secondly, the introduction of ambiguity aversion makes credit spreads react more strongly to new information as investors update their beliefs about default probabilities.

Ambiguity has been used to explain equity risk premia (see, for example, Olsen and Troughton (2000) and the sources therein). Several authors have linked ambiguity aversion to decision heuristics which are well documented in the behavioral finance literature. In this paper, we show that much of the variation in credit spreads over the financial crisis cannot be explained by movements in risk factors. The remaining variation has to come from investors reassessing what the fair spread premium on a given risk factor has to be. We interpret this change as a type of Bayesian updating by investors as markets incorporate the additional information generated by the crisis. A possible explanation of this is that investors were overconfident prior to the crisis. Brenner et al. (2011) show that decisions under ambiguity can be linked to overconfident behavior. The paper by Barone-Adesi et al. (2013) comes to very similar conclusions about the behavior of investors. Their model of investors' sentiment predicts inflated asset prices in good times and deep crashes in bad times. What they do not consider is how markets behave after the correcting shock. What we document in this paper is that the effect is lasting in the sense that changes in risk perception of institutional investors are observable well after the crisis has

[9] The consequences are similar to a lack of liquidity resulting in increased volatility (Ghirardato and Marinacci, 2001).

ended.

2 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 June 2011. 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 1788 companies with a total of 8411 bonds. We filter these bonds as is usual in this literature: We remove callable, putable, and convertible bonds as well as bonds which have sinking fund features, are asset-backed, or have any enhancing features. We restrict the sample to fixed-rate coupon bearing bonds and exclude all bonds with less than one year to maturity. This leaves us with 5186 bonds from 827 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^{st}. Effectively, therefore, our sample begins in 2005. For each company in the sample, we obtain daily equity returns as well as market values from CRSP.

Prior to using the TRACE data, we apply the following filters. We exclude any canceled, corrected, or duplicate interdealer trade 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%. To focus on institutional investors, we exclude all trades with retail size (trade value lower than \$100,000). Evidence by Goldstein et al. (2007) and Bessembinder et al. (2009) suggests that trades below this threshold are mainly executed by retail investors

whereas trades above it are predominantly institutional trades (see also Feldhütter (2012)). We focus on institutional investors because retail investors have to bear higher transaction costs (see, e.g., Warga (2004) and Green et al. (2007)) and thus perceive the corporate bond market to be relatively less liquid. According to Friewald et al. (2011), however, we expect that institutional investors react more strongly to changes in liquidity during the financial crisis, which might also affect their perception towards this risk factor in terms of ambiguity aversion. 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.[10] We only use bonds which have traded in the quarter before July. 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.

As the risk-free rate, we use the constant maturity yield curve indices published by the US Treasury Department.[11] As is common practice, we match the treasury rates on the last trading day of each bond using linear interpolation between the two closest indices. We measure a bond's credit spread as the difference between its yield and the corresponding treasury rate in basis points (bps).

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. We follow Blume et al. (1991) and Campbell and Taksler (2003) and use the following four ratios to measure credit risk: 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). Also, based on the results of the comprehensive study by Bharath and Shumway (2008), we include a company's expected default frequency (EDF) from the Merton model. For each company, we include the average

[10] We repeated the empirical analysis with yields measured as the median over the second quarter with little effect on the results. In addition, we recalculate credit spreads relative to swap rates instead of treasury rates to control whether our results are driven by the size of credit spreads due to lower treasury rates. Results do not change significantly to this alternative specification.

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

excess return (R_e) and volatility of excess returns (σ_e) for the prior year to account for equity risk. To proxy for the liquidity of a bond, we use the Amihud (2002) measure of illiquidity (IL), the effective bid-ask spread (EBA) of Roll (1984), and the trading intensity (TI) of a bond.[12]

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 Compustat instead. All bonds with AAA rating or a rating below B are excluded since there are insufficient observations for these categories. We use rating dummies for each rating category and industry dummies based on the two-digit GIC codes.[13]

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)). The average yield spread in our sample is 206 bps with a standard deviation of 175 bps. The spread in the first decile is 59 bps and the top decile 447 bps 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 4.47% and average volatility of excess returns of 27.00%. Excess returns are roughly symmetrical around the mean and show a very high dispersion with a standard deviation of 31.62%.

As we are mainly concerned with detecting differences in valuation before and after the crisis, we break down the sample into three period labeled Pre-Crisis (2005-07), Crisis (2008-2009), and Post-Crisis (2010-2011).[14] Summary statistics by period are shown in Table 2. The data shows that spreads more than doubled during the crisis. Comparing the Pre-Crisis and Post-Crisis levels of credit spreads we find that spreads have generally increased. For the left-tail of the

[12] See Appendix A for an extended discussion of the risk factors used in the empirical study.

[13] 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.

[14] As our yearly observations are measured in the middle of the year, the first crisis year is 2008. Section 4.2 provides statistical tests that motivate the categories.

Table 1: Summary Statistics for Full Sample

The data sample comprises all fixed-rate corporate bonds without special features from TRACE in the period October 2004 until June 2011 for which we were able to match the corresponding accounting data from Compustat and equity data in CRSP. Each variable is measured annually as of July 1^{st}. *Spread* is the difference between the yield to maturity and the interpolated Treasury benchmark rate measured in basis points. *Age* is the time since the bond was first sold, C is the (fixed) coupon rate, and τ is the time to maturity. IL is the trade impact measure of Amihud (multiplied by a million). EBA is the measure of the effective bid-ask spread and TI the trading intensity. R_e is the annual excess return of the corresponding stock in excess of the CRSP value-weighted index and σ_e 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 and *Lev* is the ratio of the market value of assets to debt. Details on the variables can be found in Appendix A.

	Mean	Q10	Q25	Median	Q75	Q90	Stdev
Spread	206.02	59.19	93.03	156.47	261.57	447.11	174.54
Age	5.17	0.68	1.73	3.75	7.56	12.07	4.50
C	6.32	4.40	5.33	6.38	7.38	8.25	1.66
τ	11.13	2.32	4.00	7.42	16.1	26.39	11.34
IL	0.17	0.00	0.00	0.05	0.20	0.48	0.32
EBA	1.51	0.52	0.82	1.29	1.93	2.80	1.00
TI	0.70	0.37	0.53	0.73	0.88	0.95	0.20
$R_e(\%)$	4.47	-27.1	-13.61	1.38	18.28	38.49	31.62
$\sigma_e(\%)$	27.00	14.38	17.47	22.8	32.19	42.36	14.22
IC	9.05	2.65	4.04	6.57	11.21	16.79	15.37
$LD\backslash TA$	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	0.38	0.16
$TD\backslash C$	0.22	0.08	0.13	0.18	0.30	0.41	0.13
$EDF(\%)$	5.40	0.00	0.00	0.00	0.00	7.71	18.66
Lev	0.26	0.07	0.10	0.16	0.30	0.48	0.43

distribution, they have returned to their original levels. At the first, second, and third quartile spreads have increased by 24%, 38%, and 49%, respectively, and at the 90%-quantile the increase is 68%. The average spread has increased by 47%. At the same time, we observe that default related risk factors, in particular EDF and Leverage, increase dramatically during the crisis but fall back to their original levels after. The pattern for measures of illiquidity and equity risk on the other hand is that they increase during the crisis and remain higher in the time after. These patterns suggest that investors' perception of different sources of risk may also have changed in differing ways. We will return to this question in the sequential decomposition in Section 4.3.

Table 2: Summary Statistics by Period

The table reports the summary statistics broken down by time period. The Pre-Crisis period comprises the years 2005, 2006, and 2007, the Crisis period 2008 and 2009, and the Post-Crisis period the years 2010 and 2011. Motivation for this division is given in Section 4.2.

	Spread	Age	C	τ	IL	EBA	TI	R_e	σ_e	IC	LD\TA	NI\TA	OI\S	TD\C	EDF	Lev
Mean																
Pre-Crisis	137.043	5.251	6.555	11.122	0.105	1.084	0.742	4.294	21.741	8.654	0.264	0.056	0.191	0.210	2.481	0.241
Crisis	303.300	5.127	6.318	11.303	0.215	1.812	0.719	2.356	38.707	9.045	0.262	0.050	0.192	0.239	14.113	0.326
Post-Crisis	201.212	5.109	6.061	10.982	0.214	1.739	0.624	6.501	22.902	9.514	0.278	0.050	0.197	0.221	1.188	0.224
10% Quantile																
Pre-Crisis	51.714	0.808	4.625	2.123	0.001	0.393	0.468	-24.321	13.731	2.727	0.127	0.010	0.064	0.077	0.000	0.059
Crisis	121.893	0.455	4.650	2.627	0.002	0.695	0.389	-41.118	20.740	2.867	0.138	-0.014	0.062	0.094	0.000	0.079
Post-Crisis	57.180	0.759	3.950	2.378	0.002	0.753	0.334	-18.066	13.976	2.157	0.148	-0.010	0.054	0.095	0.000	0.072
25% Quantile																
Pre-Crisis	73.983	2.023	5.500	3.921	0.002	0.581	0.611	-12.532	15.636	4.069	0.166	0.031	0.107	0.110	0.000	0.089
Crisis	170.600	1.458	5.400	4.378	0.010	1.038	0.568	-21.849	26.522	4.456	0.178	0.035	0.107	0.143	0.000	0.121
Post-Crisis	91.885	1.638	5.125	3.836	0.011	1.062	0.438	-11.839	16.293	3.592	0.197	0.022	0.101	0.126	0.000	0.099
Median																
Pre-Crisis	108.039	4.148	6.650	7.296	0.019	0.906	0.781	0.437	19.879	6.375	0.249	0.055	0.153	0.175	0.000	0.147
Crisis	248.005	3.734	6.350	7.756	0.076	1.573	0.764	-0.224	34.279	6.914	0.240	0.058	0.162	0.204	0.057	0.197
Post-Crisis	148.806	3.438	6.125	7.214	0.083	1.513	0.619	3.521	20.423	6.455	0.250	0.052	0.175	0.182	0.000	0.151
75% Quantile																
Pre-Crisis	172.206	7.926	7.550	16.377	0.114	1.399	0.904	16.241	26.685	11.224	0.341	0.082	0.240	0.290	0.000	0.280
Crisis	395.759	7.348	7.250	16.888	0.266	2.300	0.896	21.062	45.899	11.319	0.334	0.086	0.278	0.315	10.100	0.343
Post-Crisis	257.425	7.026	7.125	15.430	0.287	2.148	0.805	18.219	27.533	11.212	0.337	0.083	0.303	0.291	0.000	0.281
90% Quantile																
Pre-Crisis	259.886	10.518	8.500	24.914	0.274	1.972	0.959	39.756	32.182	16.623	0.415	0.110	0.35	0.374	0.017	0.428
Crisis	585.536	11.909	8.125	27.300	0.570	3.222	0.953	38.852	64.183	17.398	0.413	0.115	0.376	0.438	63.644	0.589
Post-Crisis	437.743	13.118	8.125	26.562	0.583	3.083	0.915	35.503	34.726	16.771	0.452	0.115	0.398	0.394	0.089	0.424

3 Methodology

Previous literature has focused on the explanatory power of specific risk factors on the cross-section of credit spreads. We build on that literature to explain the levels of credit spreads at one particular point in time. Our primary interest, however, is not to explain the level of credit spreads or even how they change over time but rather to attribute the change over time to changes in risk factors and changes in risk perception. We do this by estimating how credit spreads would have been distributed if risk perception had not changed over time. By comparing this counterfactual distribution to the observed distributions before and after the crisis we obtain an estimate of how much of the total change is due to either source of variation.[15]

To formally introduce the method, let $\mathbf{Y}^t$ be the variable of interest (i.e., the level of credit spreads at time t) and $\mathbf{X}^t$ be the set of explanatory variables at times $t \in \{0, 1\}$ (i.e., the risk factors used to explain credit spread levels). The total observable change in credit spreads over time is then $\mathbf{Y}^1 - \mathbf{Y}^0$. Let the conditional distribution of $\mathbf{Y}^t$ given $\mathbf{X}^s$ be denoted by $F_{\mathbf{Y}^t|\mathbf{X}^s}$. The estimated conditional distributions at times 0 and 1 are then $F_{\mathbf{Y}^0|\mathbf{X}^0}$ and $F_{\mathbf{Y}^1|\mathbf{X}^1}$. The distribution that we need to estimate is the distribution that would have resulted if only risk factors had changed (i.e., the marginal distribution of $\mathbf{X}$) but not the conditional distribution of bond spreads given the risk factors. We denote this by $F_{\mathbf{Y}(1,0)}$. It is constructed by integrating the conditional distribution of bond spreads at time $t = 0$ with respect to the distribution of risk factors at time $t = 1$:

$$F_{\mathbf{Y}(1,0)}(y) = \int F_{\mathbf{Y}^0|\mathbf{X}^0}(y|x) dF_{X^1}(x). \tag{1}$$

The difference between $F_{\mathbf{Y}(1,0)}$ and $\mathbf{Y}^0$ is the change in bond spreads resulting from changes in risk factors.[16] The difference between $\mathbf{Y}^1$ and $F_{\mathbf{Y}(1,0)}$ is the change resulting from changes in risk perception. This identifies how much of the change in the general level of credit spreads is

[15] For a recent survey of this decomposition methodology see Fortin et al. (2011).

[16] Note that we estimate the impact on the level of credit spreads and not the variance in credit spreads by using cross-sectional analyses. In contrast, Figure 1 shows the time series of weekly median credit spread with increasing volatility of credit spreads from Pre-Crisis to Crisis period. While we are interesting in the change in risk perception and hence the effect of ambiguity risk, it is also obvious that the uncertainty or risk, respectively, is higher in the Post-Crisis compared to the Pre-Crisis period. The latter might be implicitly captured by changes in the risk factors.

solely caused by changes in the pricing implications of these risk factors.[17]

We use quantile regressions to model the relationship $F(\mathbf{Y}^t|\mathbf{X}^t)$ between risk factors $\mathbf{X}^t$ and credit spreads $\mathbf{Y}^t$. We favor this specification over the standard mean regression since it allows us to control for non-linearity in the pricing relationship of risk factors. For instance, one would expect that liquidity risk has different implications for high-yield bonds than for low-yield bonds. Quantile regression can detect these differences in a natural way without any ad-hoc adjustments to the sample (such as splitting the sample by credit ratings). To be precise, we estimate the p^{th} unconditional quantile function at time t as

$$\hat{F}^{-1}(p;\hat{\boldsymbol{\beta}},\mathbf{X}^t) = \hat{q}(p;\hat{\boldsymbol{\beta}},\mathbf{X}^t) = \inf\left\{q : \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}\mathbf{1}(\mathbf{X}_i^t\cdot\hat{\boldsymbol{\beta}}(p_j)\leq q)\geq p\right\}, \tag{2}$$

where J denotes the number of estimated quantiles and $\mathbf{1}(\cdot)$ is the indicator function.[18]

For the estimation of the counterfactual distribution, we build on the work by Melly (2005) and Chernozhukov et al. (2013).[19] The distribution of bond spreads that would have resulted if no adjustment to pricing had taken place is estimated by combining the marginal distribution of the risk factors after the crisis with the pricing before the crisis. This is done by inserting the covariates $\mathbf{X}^1$ from the Post-Crisis period 1 and the estimated coefficients $\boldsymbol{\beta}^0$ from the Pre-Crisis period 0 in (2):

$$\hat{q}(p;\boldsymbol{\beta}^0,\mathbf{X}^1) = \inf\left\{q : \frac{1}{N_0}\sum_{i=1}^{N_1}\sum_{j=1}^{J}\mathbf{1}(\mathbf{X}_i^1\cdot\hat{\boldsymbol{\beta}}^0(p_j)\leq q)\geq p\right\}, \tag{3}$$

where N_t is the number of observations in period t. Hence, the change due to shifts in the market place is $\hat{q}(\boldsymbol{\beta}^0,\mathbf{X}^1) - q^0$. The remainder of the total change, $q^1 - \hat{q}(\boldsymbol{\beta}^0,\mathbf{X}^1)$, could now

[17] One concern with decomposition is the question whether the change in distributions could be due to omitted variables or unobserved characteristics. As discussed in Fortin et al. (2011), the decomposition results are valid as long as their influence on the distribution of bond spreads is the same in both time periods.

[18] Note that in a quantile regression setting the distribution of credit spreads $\hat{q}$ conditional on the covariates X, i.e. the risk factors, is given by the differences in coefficients across the quantiles which reflect the distribution of unobservable characteristics of bonds with given covariates.

[19] 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. (2013) significantly extend this literature and also develops formal inference procedure.

be interpreted as resulting from changes in risk perception. We further decompose this in order to account for variation in spreads that cannot be explained by our model, i.e. changes in the distribution of residuals. The resulting distribution, denoted by $\hat{q}(\boldsymbol{\beta}^{m_1,r_0}, \mathbf{X}^1)$, is the distribution that would have prevailed if risk factors and risk pricing had changed as it has but the distribution of residuals had remained the same. Thereby, $\boldsymbol{\beta}^{m_1,r_0}$ refers to the median estimate of the coefficients at time 1 while using the residuals at time 0. To estimate this distribution, Melly (2005) notes that $\mathbf{X}\left(\hat{\boldsymbol{\beta}}(p) - \hat{\boldsymbol{\beta}}(0.5)\right)$ is a consistent estimator of the p^{th} quantile of the residual distribution conditional on $\mathbf{X}$. Hence, we define $\boldsymbol{\beta}^{m_1,r_0}(p) = \hat{\boldsymbol{\beta}}^1(0.5) + \hat{\boldsymbol{\beta}}^0(p) - \hat{\boldsymbol{\beta}}^0(0.5)$ which are then plugged into (3) 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. Hence, our model is capable of detecting shifts in risk perceptions.

To sum up, the observed change over time, $q_1 - q_0$ is decomposed into three components:

$$\begin{aligned} \underbrace{q^1 - q^0}_{\text{Observed Change}} &= \underbrace{\left[\hat{q}(\boldsymbol{\beta}^0, \mathbf{X}^1) - q^0\right]}_{\text{Changes in Risk Factors}} \\ &+ \underbrace{\left[\hat{q}(\boldsymbol{\beta}^{m_1,r_0}, \mathbf{X}^1) - \hat{q}(\boldsymbol{\beta}^0, \mathbf{X}^1)\right]}_{\text{Changes in Pricing}} + \underbrace{\left[q^1 - \hat{q}(\boldsymbol{\beta}^{m_1,r_0}, \mathbf{X}^1)\right]}_{\text{Effect of Residuals}}, \end{aligned} \tag{4}$$

where, for simplicity, we have suppressed the dependence on the quantile p. The first component adjusts for the effect that changes in the marginal distribution of the risk factors has had. The resulting distribution, denoted as $\hat{q}(\boldsymbol{\beta}^0, \mathbf{X}^1)$, represents the distribution of credit spreads that would have prevailed if the pricing had remained unchanged before and after the crisis. The second component is the effect that changes in risk pricing had on bond spreads. We interpret this component as structural change as it represents a direct estimate of how investors have updated their risk perception over the course of the financial crisis. The final component represents an estimate of the variation in credit spreads that is not captured by our model.

The decomposition so far only isolates the aggregate effect that the crisis had. We estimate a finer set of decompositions in order to assess what types of risk where of most concern to investors. Most economists would agree that in particular liquidity risk was re-evaluated by market participants during the crisis (see, e.g., Berger and Bouwman (2009); Brunnermeier

(2009); Guiso et al. (2013)). To estimate the separate contributions of risk perception towards default, liquidity, and equity risk 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 (4). Let $\hat{q}(\hat{\boldsymbol{\beta}}^{D_t,L_t,E_t,B_t,I_t,r_0}, \mathbf{X}^t)$ denote the estimated counterfactual quantiles of credit spreads with covariates $\mathbf{X}^t$ and

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

where $\hat{\boldsymbol{\beta}}^{D_t,L_t,E_t,B_t,I_t}$ denotes the vector of coefficients related to default risk (D_t), equity risk (E_t), liquidity risk (L_t), bond characteristics (B_t), and intercept (I_t) from period t.[20]

First, we adjust for changes in the pricing of default risk, which in the notation introduced above is given as $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_0,L_0,E_0,B_0,I_0,r_0}, \mathbf{X}^1)$. 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 $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,I_0,r_0}, \mathbf{X}^1)$. 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 $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,I_0,r_0}, \mathbf{X}^1)$. Finally, we account for the change in the pricing of indenture data by estimating $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,I_0,r_0}, \mathbf{X}^1)$ and for the level shift from the intercept by estimating $\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_1,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_0,r_0}, \mathbf{X}^1)$. The remaining difference, $q^1 - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_1,r_0}, \mathbf{X}^1)$ is then the residual effect that is not captured by our model. Note that in the sequential decomposition we also adjust the effect of the intercept and the residual component. The former effect might contain macroeconomic effects for which we cannot control for in our cross-sectional regression and counterfactual decomposition

[20] Bond characteristics are variables related to indenture data such as the coupon rate.

framework. The total decomposition[21] can be summarized as follows:

$$
\begin{aligned}
\underbrace{q^1 - q^0}_{\text{Total Observed Change}} &= \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_0,L_0,E_0,B_0,I_0,r_0}, \mathbf{X}^1) - q^0\right]}_{\text{Effect of Covariates}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_0,L_0,E_0,B_0,I_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Default Risk}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_0,E_0,B_0,I_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Liquidity Risk}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_0,B_0,I_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Equity Risk}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_0,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_0,I_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Bond Characteristics}} \\
&+ \underbrace{\left[\hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_1,r_0}, \mathbf{X}^1) - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_0,r_0}, \mathbf{X}^1)\right]}_{\text{Change from Intercept}} \\
&+ \underbrace{\left[q^1 - \hat{q}(\hat{\boldsymbol{\beta}}^{D_1,L_1,E_1,B_1,I_1,r_0}, \mathbf{X}^1)\right]}_{\text{Residual}}
\end{aligned}
\tag{5}
$$

The decomposition essentially entails plugging in different estimates for the coefficients in the representation in (2). 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 would imply that markets attach a 10 bps higher premium for that risk at that quantile. We interpret this as the result of altered risk perception on markets.

[21] It should be noted that, in general, results depend on the sequence of the decomposition. We tried several other sequences with essentially equal results which are available from the authors upon request.

4 Pricing of Bond Spreads

4.1 Regression Results

Based on the large literature we use the following specification in order to explain the observed levels of credit spreads:

$$\begin{aligned}\text{Spread} = \alpha + \underbrace{\beta_1\ \text{Age} + \beta_2\ \text{C} + \beta_3\ \tau}_{\text{Bond Characteristics}} + \underbrace{\beta_4\ \text{IL} + \beta_5\ \text{EBA} + \beta_6\ \text{TI}}_{\text{Liquidity Risk}} + \underbrace{\beta_7\ R_e + \beta_8\ \sigma_e}_{\text{Equity Risk}} \qquad (6)\\ + \underbrace{\beta_9\ \text{IC} + \beta_{10}\ \text{LD}\backslash\text{TA} + \beta_{11}\ \text{NI}\backslash\text{TA} + \beta_{12}\ \text{OI}\backslash\text{S} + \beta_{13}\ \text{TD}\backslash\text{C} + \beta_{14}\ \text{EDF}}_{\text{Default Risk}}\\ + \underbrace{\beta_{15}\ \text{Lev} + \beta_{16}\ \text{Rating Dummy}}_{\text{Default Risk}} + \underbrace{\beta_{17}\ \text{Industry Dummy}}_{\text{Bond Characteristics}} + \beta_{18}\ \text{Year Dummy} + \varepsilon.\end{aligned}$$

We group the covariates into four categories. Bond characteristics contain all variables which are directly related to the bond in question. The other groups are variables related to liquidity, equity, and default risk, respectively. To control for time-varying influences, such as changes in the macroeconomic environment, we add time-fixed effects.

In order to use the linear regression (6) for the counterfactual experiment it needs to be able to explain the cross-section of bond spreads sufficiently well. The results based on OLS regression for the full sample is presented in Table 3. We generally find that the coefficients have the expected signs. All measures of illiquidity increase spreads, although the Amihud illiquidity measure is not significant. Excess returns are negatively related to spreads whereas equity volatility is positively related. Higher $LD\backslash TA$, $NI\backslash TA$, and $OI\backslash S$ all decrease spreads, although no coefficient is significant. The pattern for the IC dummies is mixed. The coefficient for IC_5, IC_{20}, and IC_{30} are negative whereas IC_{10} has a positive coefficient. Only the IC_5 is significant. As expected, $TD\backslash C$, EDF, and Lev are all positively related to spreads. 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 a significant and increasing effect of the ratings. The R^2 of the full specification is 64% which indicates that the specification in (6) is indeed an appropriate description of bond spreads.

Table 3: Regression Results for Risk Components of Yield Spreads (Full Sample)

The table reports the coefficients from several regressions using subsets of the covariates of the regression in (6) based on full sample data. In each of the first five columns are the estimates that result from omitting a risk class. 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	−12.58	−107.92***	−76.55***	−194.95***	−94.88***	−133.03***
	(−0.96)	(−8.43)	(−5.60)	(−21.20)	(−6.69)	(−9.70)
Age		0.46	−1.12***	−0.05	−1.90***	−0.71**
		(1.44)	(−3.08)	(−0.14)	(−5.16)	(−2.00)
C		21.04***	21.59***	21.99***	23.58***	21.06***
		(23.02)	(23.07)	(23.45)	(24.84)	(23.04)
τ		0.28**	−0.25**	0.36***	−0.41***	−0.08
		(2.41)	(−1.98)	(2.84)	(−3.09)	(−0.68)
IL	1.97		0.98	15.23***	6.21	6.04
	(0.39)		(0.19)	(3.05)	(1.22)	(1.24)
EBA	17.71***		12.77***	9.61***	12.99***	11.59***
	(10.71)		(6.98)	(5.22)	(6.95)	(6.49)
TI	50.69***		32.70***	5.76	31.67***	25.05***
	(6.89)		(4.22)	(0.74)	(4.07)	(3.31)
R_e	−0.20***	−0.28***		−0.52***	−0.22***	−0.27***
	(−4.59)	(−6.38)		(−12.44)	(−5.00)	(−6.30)
σ_e	3.38***	3.15***		4.44***	4.61***	3.12***
	(20.14)	(18.69)		(29.20)	(27.83)	(18.49)
IC_5	−13.15***	−9.49***	−11.75***		−19.41***	−9.16***
	(−7.10)	(−5.20)	(−6.32)		(−10.68)	(−5.04)
IC_{10}	0.03	0.70	1.00		−4.72***	0.76
	(0.03)	(0.67)	(0.93)		(−4.55)	(0.72)
IC_{20}	−0.89	−0.39	0.15		−1.07	−0.45
	(−1.41)	(−0.60)	(0.23)		(−1.59)	(−0.71)
IC_{30}	−0.70***	−0.26	−0.16		−0.36	−0.31
	(−2.68)	(−1.03)	(−0.63)		(−1.37)	(−1.26)
$LD\backslash TA$	−33.90*	−24.70	−28.40		12.23	−22.24
	(−1.93)	(−1.43)	(−1.61)		(0.68)	(−1.29)
$NI\backslash TA$	23.22	−40.31	−91.85***		−26.02	−47.18
	(0.76)	(−1.35)	(−3.03)		(−0.84)	(−1.59)
$OI\backslash S$	−2.92	−5.37	−21.57**		7.37	−3.88
	(−0.30)	(−0.50)	(−2.00)		(0.66)	(−0.36)
$TD\backslash C$	52.90**	34.50	48.91**		51.50**	32.52
	(2.22)	(1.45)	(2.04)		(2.08)	(1.37)
EDF	0.92***	0.93***	1.86***		0.63***	0.90***
	(7.75)	(8.19)	(17.85)		(5.34)	(7.96)
Lev	40.78***	32.73***	22.80***		42.11***	35.34***
	(8.76)	(7.19)	(4.94)		(8.92)	(7.76)
AA	−1.93	6.49	−1.39	12.80**		9.04
	(−0.30)	(1.06)	(−0.22)	(2.04)		(1.46)
BBB	49.77***	47.18***	54.24***	52.22***		45.03***
	(13.81)	(13.47)	(15.21)	(15.81)		(12.80)
BB	135.25***	122.17***	147.24***	139.45***		120.78***
	(24.87)	(22.76)	(27.95)	(28.46)		(22.57)
B	160.79***	157.21***	189.77***	190.14***		154.76***
	(23.97)	(23.86)	(29.69)	(32.23)		(23.55)
R^2	0.60	0.63	0.62	0.61	0.61	0.64
logLike	657.52***	61.6***	357.21***	479.95***	660.89***	

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

In order to examine the marginal explanatory power of the various risk categories we consecutively exclude 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. The regressions which omit a class of regressors have similar explanatory power as measured 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 models in favor of the unrestricted one in each case. This indicates that all risk categories are necessary to provide a complete picture of the components of credit spreads. 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. These results shows that ratings and accounting ratios each contain information beyond what is implied by the other.

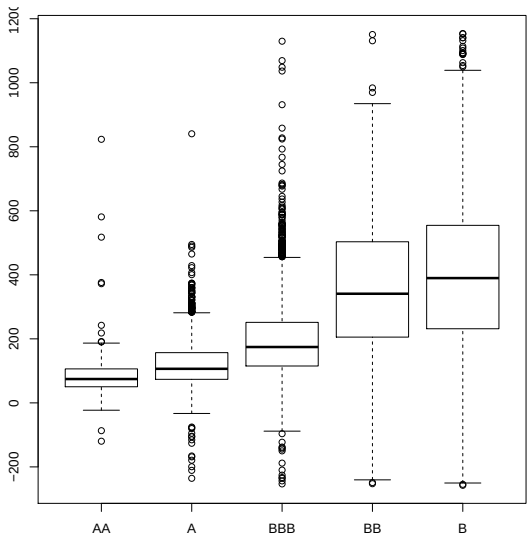
Previous studies have noted that the influence of risk factors changes as bonds become riskier. Rather than breaking our sample into rating groups, we perform quantile regressions. Several authors have noted that ratings are a crude measure of default risk and may not always reflect all information. 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 0.45 (based on Kendall's τ) and 0.57 (based on Spearman's ρ) between ratings and spreads. In Figure 2 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.[22] For the OLS regression, the R^2 is 64% whereas for the quantile regressions, the measure increases from 23% at the first decile to 61% at the ninth decile with an R^2 of 49% at

[22]The quantile estimation results for our Pre-Crisis, Crisis, and Post-Crisis sub-samples are reported in Appendix B. To save space we do not present results for individual years. Overall, these are very similar to the results for the respective sub-periods and available from the authors upon request.

Figure 2: 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.



the median. For the other (unreported) quantiles the increase in R^2 is monotonic and almost exactly evenly-spaced along the deciles. These results seem to indicate that we are able to capture much of the cross-sectional variation.[23]

We first note that for the median and OLS regression, the signs of the coefficients mostly agree. Also the magnitude of the coefficients is very similar. There is no case in which the sign is different and both estimates are significant. We conclude that both specifications provide a similar picture of the central tendency of how risk factors affect the level of credit spreads. Figure 3 provides the estimated quantile functions for all variables (excluding dummy variables).

According to the Wald test proposed by Bassett and Koenker (1982), we find a significant quantile effect for most covariates (i.e., the coefficients in the 10% decile are significantly different from the coefficients in the 90% decile). For the coupon rate (C), time to maturity (τ), and

[23]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 (6) and $\tilde{S}$ the sum of squares of the regression on merely an intercept.

Table 4: Quantile Regression Results for Full Sample

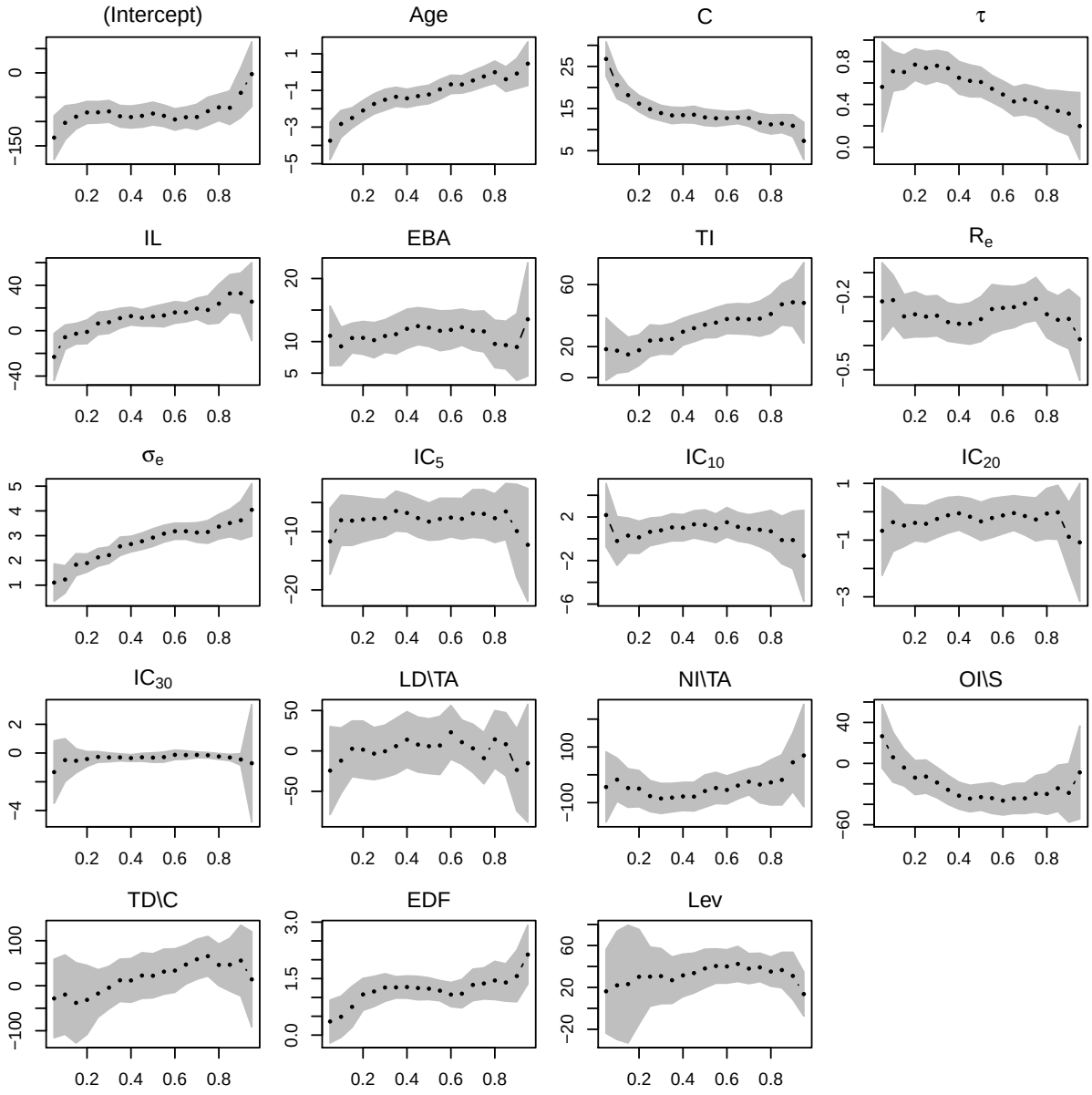
The table reports the coefficients from the regression in (6) for the full sample with t-values in parentheses. All regressions contain (unreported) industry and year dummies. The first column contains the OLS results for comparison. Columns two to four are the quantile regression results at the median, the first decile, and the last decile, respectively. Standard errors in the quantile regressions are obtained by bootstrapping 500 times using the resampling method of Parzen et al. (1994). The final column reports the difference between the 9^{th} and 1^{st} decile. The values 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	-133.03^{***}	-83.54^{***}	-102.73^{***}	-40.99	
	(-9.70)	(-6.99)	(-5.80)	(-1.63)	
Age	-0.71^{**}	-1.21^{***}	-2.82^{***}	-0.07	2.75^{***}
	(-2.00)	(-5.09)	(-7.76)	(-0.18)	(44.91)
C	21.06^{***}	12.91^{***}	20.59^{***}	10.91^{***}	-9.67^{***}
	(23.04)	(12.94)	(12.35)	(8.05)	(40.77)
τ	-0.08	0.60^{***}	0.70^{***}	0.31^{***}	-0.39^{***}
	(-0.68)	(8.59)	(7.26)	(2.93)	(15.47)
IL	6.04	12.60^{***}	-5.76	32.93^{***}	38.70^{***}
	(1.24)	(3.06)	(-0.96)	(3.49)	(62.58)
EBA	11.59^{***}	12.20^{***}	9.25^{***}	9.14^{***}	-0.10
	(6.49)	(8.54)	(6.05)	(3.33)	(0.00)
TI	25.05^{***}	34.11^{***}	17.36^{**}	48.59^{***}	31.22^{***}
	(3.31)	(7.43)	(2.23)	(5.74)	(15.84)
R_e	-0.27^{***}	-0.29^{***}	-0.21^{***}	-0.29^{***}	-0.07
	(-6.30)	(-6.17)	(-4.05)	(-4.50)	(1.02)
σ_e	3.12^{***}	2.92^{***}	1.23^{***}	3.61^{***}	2.38^{***}
	(18.49)	(15.30)	(4.16)	(9.28)	(44.76)
IC_5	-9.16^{***}	-8.28^{***}	-8.04^{***}	-9.91^{**}	-1.86
	(-5.04)	(-4.91)	(-3.52)	(-2.43)	(0.26)
IC_{10}	0.76	1.26^{*}	-0.20	-0.11	0.08
	(0.72)	(1.90)	(-0.18)	(-0.08)	(0.00)
IC_{20}	-0.45	-0.33	-0.36	-0.88	-0.51
	(-0.71)	(-0.93)	(-0.71)	(-1.41)	(0.80)
IC_{30}	-0.31	-0.31^{*}	-0.49	-0.45^{**}	0.04
	(-1.26)	(-1.92)	(-0.69)	(-2.52)	(0.01)
LD\TA	-22.24	5.84	-12.07	-23.50	-11.42
	(-1.29)	(0.33)	(-0.58)	(-0.95)	(0.21)
NI\TA	-47.18	-58.31^{*}	-17.41	44.69	62.11
	(-1.59)	(-1.89)	(-0.45)	(0.83)	(1.35)
OI\S	-3.88	-32.93^{***}	6.00	-28.85^{*}	-34.85^{**}
	(-0.36)	(-4.81)	(0.48)	(-1.94)	(6.24)
TD\C	32.52	22.11	-19.65	55.84	75.50
	(1.37)	(0.95)	(-0.42)	(1.50)	(2.65)
EDF	0.90^{***}	1.23^{***}	0.48^{*}	1.56^{***}	1.08^{***}
	(7.96)	(8.67)	(1.73)	(4.45)	(7.61)
Lev	35.34^{***}	38.00^{***}	21.93	30.94^{***}	9.01
	(7.76)	(4.22)	(0.80)	(2.85)	(0.08)
R^2	0.64	0.49	0.23	0.61	

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

Figure 3: 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).



$OI\backslash S$ 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. We find a significant positive quantile effect for Age, IL, TI, σ_e, and EDF. 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 eight out of the total of 18 variables we find a significant quantile effect (at least at the 10% significance level). However, most of the variables (IC_5, IC_{30}, $NI\backslash TA$, $TD\backslash C$, Lev) with an insignificant quantile effect show an U-shaped quantile pattern as shown in Figure 3. This indicates that the quantile regression is indeed more appropriate to analyze the effect of various risk factors on credit spreads. In addition, the quantile regression comes along with another advantage. The control for non-linearity in the covariates, i.e. risk factors, reduces the potential biases on pricing effects that are associated with changes in factors levels when going from before to after crisis period.

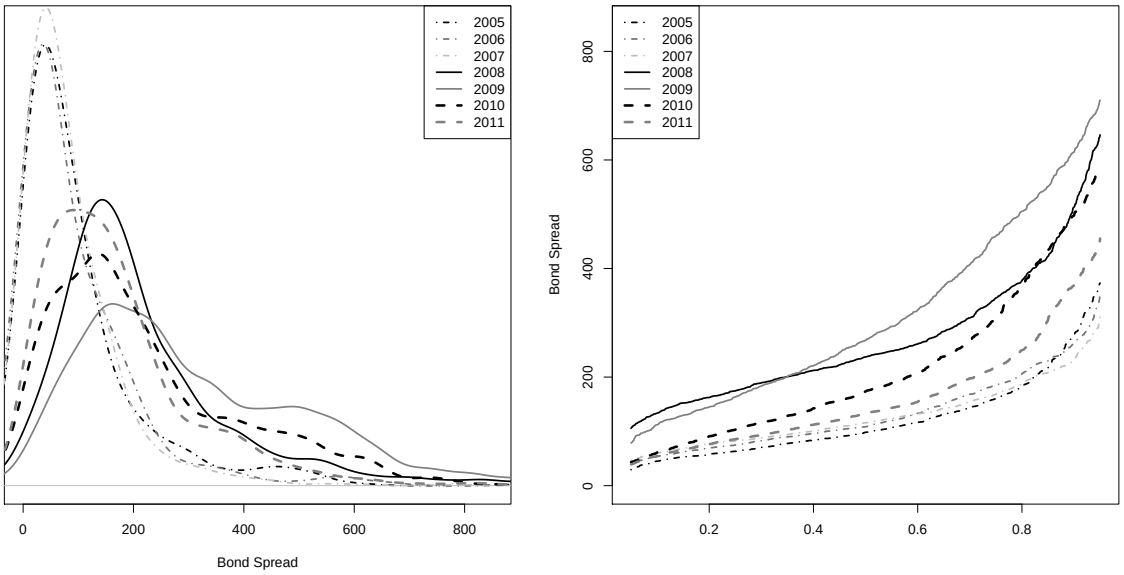
4.2 What if the Financial Crisis had not Happened?

The prior results indicate that the regression specification in (6) is able to capture a large fraction of the cross-sectional differences in credit spreads. Given these results, we now turn to the main question. Obviously, credit spreads after the crisis have remained at a higher level than they were before. The question is, what has caused this lasting 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? We use the decomposition approach discussed in Section 3 to generate the counterfactual distributions of interest.[24] Thereby, we will be mostly concerned with two questions: First, what would credit spreads look like if the financial crisis in late 2007 to early 2009 had not occurred? Second, what if risk perception and pricing of risk had remained at the levels that had prevailed before the crisis?

[24] A simple comparison of the OLS coefficients in Appendix B leads qualitatively to the same conclusions in that the coefficients show a similar pattern as described below. Although much simpler, this method is unsatisfactory for two reasons. First, it cannot distinguish between the effect of changes in the factors themselves and the pure coefficient effect. Second, we are interested in quantifying the effects. Hence, it is preferable to illustrate the effects in terms of credit spreads as this makes it easier to interpret the results economically.

Figure 4: Mid-Year Distributions of Credit Spreads (2005 - 2011)

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

Figure 4 presents the distributions of credit spreads for each year of our sample. The distribution of credit spreads in the years 2005 to 2007 are approximately equal. By mid 2008, spreads along all quantiles have increased visibly. For 2009, there is a slight decrease in the upper quantiles (relative to 2008). The distributions for 2010 and 2011 are somewhat in the middle. To test more formally 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 hypothesis 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 2010-2011 as labeled *Post-Crisis*.[25] One can argue that our Post-Crisis period also covers the economic recession in the US which may affect our results. However, if we assume that changes

[25]In unreported results, we have also applied 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. Even though we cannot reject the null of the Kolmogorov-Smirnov test for the comparisons of 2006 and 2007 to 2011, our results from counterfactual experiment and sequential decomposition confirm our assumption of similar distributions. Moreover, the year 2010 is statistically different from 2006 and 2007 but not 2011. In addition, we have repeated the analysis using only the 2010 data as the post-crisis period and discarding the 2011 data. We find that the counterfactual results are only marginally affected by this.

in the real economy have an impact on credit spreads then these effects should be reflected in changes in the risk factors and not in the pricing coefficients or risk perception, respectively.

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

	2006	2007	2008	2009	2010	2011
2005	0.11	0.15	0.59***	0.52***	0.31***	0.19*
	(0.58)	(0.21)	(0.00)	(0.00)	(0.00)	(0.05)
2006		0.07	0.52***	0.46***	0.24**	0.12
		(0.97)	(0.00)	(0.00)	(0.01)	(0.46)
2007			0.56***	0.51***	0.27***	0.13
			(0.00)	(0.00)	(0.00)	(0.36)
2008				0.14	0.29***	0.45***
				(0.28)	(0.00)	(0.00)
2009					0.24**	0.38***
					(0.01)	(0.00)
2010						0.17
						(0.11)

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

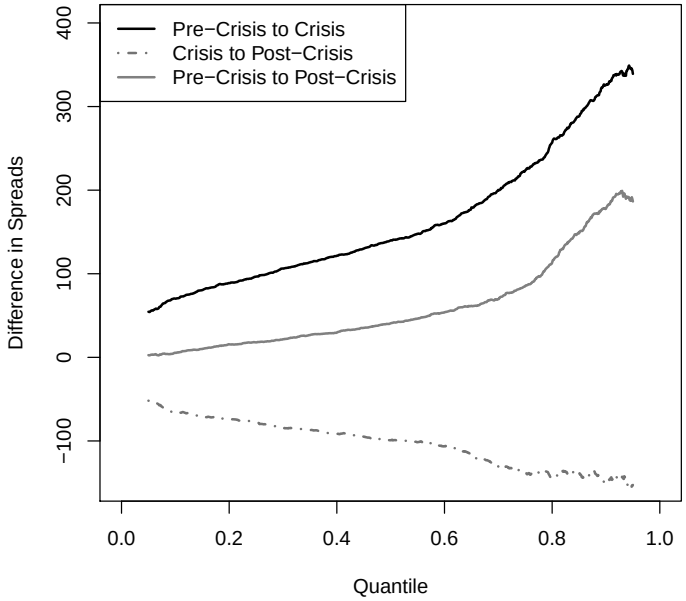
The total change in the distribution of credit spreads over the different periods is shown in Figure 5. The graph clearly shows how spreads have increased over the crisis. The increase was about 50 bps for low risk bonds and 300 bps for very risky bonds. After the crisis had ended, spreads decreased again. What can be clearly seen is that they have not returned to their initial level. For each of the three time steps we perform the decomposition into the component that is due to changes in risk factors and the component that is due to changes in risk perception described in Section 3. The results are summarized in Figure 6.[26]

For the decomposition from Pre-Crisis to Crisis (Panel (a)), the decomposition results clearly show that most of the shift of the distribution of credit spreads can be attributed to changes in risk pricing. For the lower deciles changes in market factors only account for a quarter of the observed increase in spreads. This proportion increases to about half for the highest decile. Only for the last decile is the effect due to changes in risk factors higher than the effect due to changes in the pricing of these factors. The counterfactual results also show that the "kink" in the observed differences is caused by a relatively stronger effect unexplained by the model. This could be explained as an effect of ambiguity aversion as a result of the crisis as argued by Boyarchenko (2012). Compared to the main effects, the impact of this is economically minor,

[26]The Appendices C and D report confidence bands in Figures C.1 to C.3 and detailed results on the estimates in Table D.1 for all three decompositions.

Figure 5: Quantile Differences of Credit Spreads

The Figure shows the observed differences in credit spreads over the different periods at each quantile of the distribution.

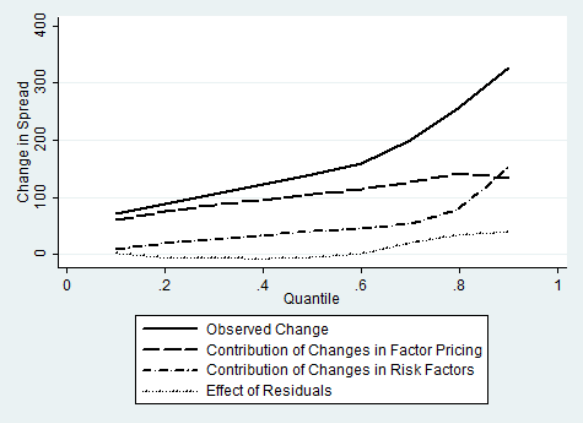


however. These results are consistent with the theories of the impact of social learning on asset prices as in Timmermann (2001); Kim (2006); Bansal and Shaliastovich (2011): As the crisis unfolds, standard risk factors lose their explanatory power because the crisis event induces a structural break in the parameters underlying the economy.

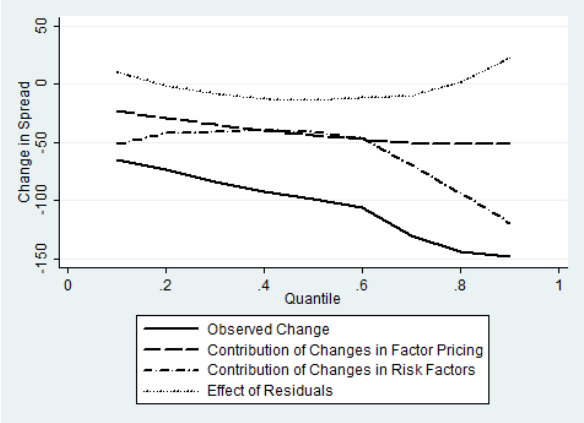
Contrary to the first decomposition, we find that for the decomposition from Crisis to Post-Crisis (Panel (b)) the effect of changes in risk factors is larger than the effect due to changes in risk pricing: The effect of the changes by risk factors is negative and almost constant from the first to the sixth decile at -50 bps. For the lower quantiles, the effect is much more pronounced. This shows that changes in market conditions have contributed to the decrease in corporate bond spreads as the effects of the crisis abated. The effect caused by changes in risk perception in this decomposition is slightly smaller than the effect by covariates. As one would expect, this result shows how institutional investors have demanded lower spread premia for a given riskiness of corporate bonds once the crisis ended. The fact that the effect due to changes in risk pricing is far smaller in this decomposition than in the first shows that investors have updated their beliefs about the riskiness of corporate bonds.

Figure 6: Decomposition of Credit Spreads

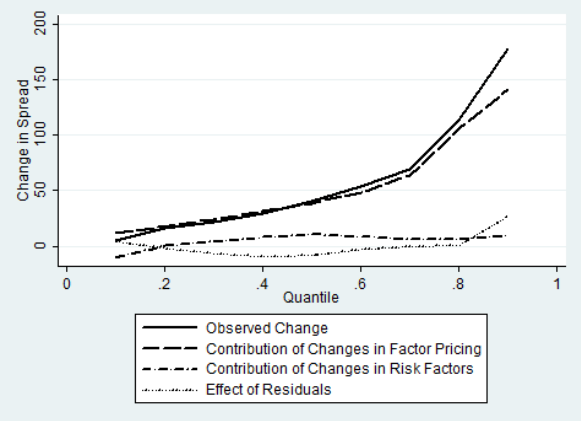
The figure presents the results of the counterfactual decomposition in (4) for the three time steps from Pre-Crisis to Crisis (Panel (a)), from Crisis to Post-Crisis (Panel (b)), and from Pre-Crisis to Post-Crisis (Panel (c)). Results on the corresponding confidence bands and estimates can be found in Appendices C and D, respectively.



(a) Pre-Crisis to Crisis



(b) Crisis to Post-Crisis



(c) Pre-Crisis to Post-Crisis

For the decomposition from Pre-Crisis to Post-Crisis (Panel (c)), we find that almost the entire increase in spreads is caused by changes in the pricing of corporate bonds. The observed change in spreads is an increase of 6 bps at the first decile while they have increased by 40 bps at the median and 178 bps at the ninth decile. The increase caused by changes in risk pricing is estimated at 12, 39, and 141 bps, respectively. On the other hand, the effect caused by changes in risk factors themselves is estimated at -10, 10, and 10 bps, respectively. The decomposition shows that changes in market factors is almost negligible and most of the change can be attributed to changes in pricing. 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 is due to an increase in risk perception caused by the crisis.

Our results are consistent with learning models of asset pricing: once investors realize that a structural break has occurred they will alter their risk pricing and start to learn about the new parameters with adaptive learning rules. This learning introduces long-run risk resulting in permanent shifts after large shocks.

In each decomposition, we find that the effect of changes in residuals are either insignificant or economically very small. This indicates that the residuals in the quantile regressions are not systematically biased and that we have not omitted a relevant latent factor (Collin-Dufresne et al., 2001) or use a misspecified model (Jaskowski, 2010). A systematic increase in residuals would indicate that changes in risk factors could have been caused by increases in the correlation of these factors. This does not seem to be the case as the residual effect in each decomposition is very small. Only for the highest quantiles is the residual effect significant, but economically the effect is negligible. Hence, we believe that the results for the effect of changes in risk factors are not driven by changes in correlation.

4.3 Effects of Different Risk Factors on Bond Spreads

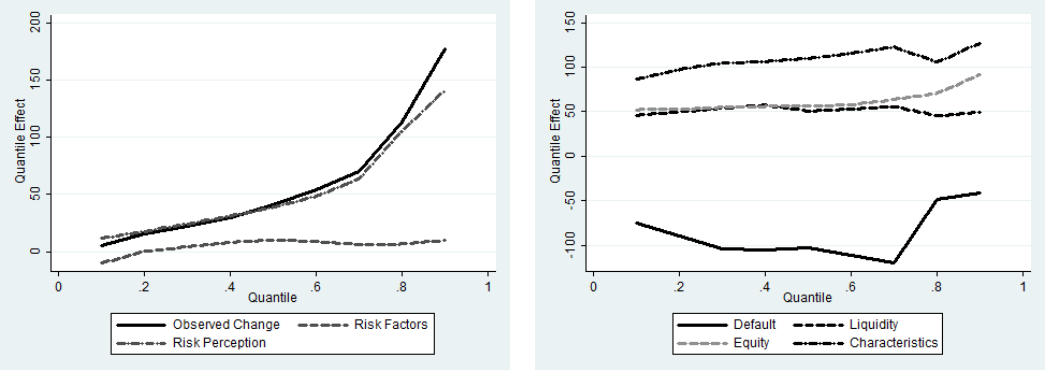
In the previous section, we used counterfactual decompositions to separate how much of the observed increase in credit spreads over recent years has been caused by changes in risk factors as observed in markets (i.e., the effect caused by covariates) and how much has been caused by changes in the pricing implication of a given level of a risk factor (i.e., the effect caused by coefficients). Motivated by the summary statistics in Table 2 we perform a sequential decomposition as described in equation (5) 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.[27] We emphasize that the interpretation of this effect does not depend on the

[27]This sequence of decomposition implicitly assumes that no interaction effects are present between the different components. In general, the cross-effects are included in the component that is added first. For instance, accounting first for default risk and then for liquidity risk implies that the effect that liquidity has on default risk is shown in the decomposition as part of the default effect. In unreported results, we have varied the sequence of the decompositions with qualitatively the same results. Hence, interaction effects seem to be of only minor

risk factors remaining constant over time. On the contrary, the methodology explicitly accounts for changes in factors. Hence, the effect that we extract is the yield premium independent of the individual riskiness of a particular bond.

Figure 7: Decomposition Results for Different Risk Factors

The figure shows results from counterfactual decomposition and the contribution of each risk factor to the change in risk perception between Pre- and Post-Crisis period.



(a) Counterfactual Decomposition (b) Contribution by Risk Factors

To save space we only report results for the decomposition from Pre-Crisis to Post-Crisis as this is the one that is central to our goal of determining the effect the crisis has had.[28] Table 6 reports results for the first and ninth quantile as well as the median change. The results for the four main effects is summarized in Figure 7. Panel (a) shows the total observed change in bond spreads (solid line) as well as the overall effects of the counterfactual decomposition (gray, dashed lines). The dashed line shows the effect attributable to observed movements in market factors while keeping the risk pricing at their initial levels whereas the dashed-dotted line shows the total effect that changes in risk perception has had. Panel (b) presents how changes in the perception of the various risk factors have affected bond spreads.

importance. Furthermore, PCA analysis on the risk factors revealed that the first principal component primarily loads on default risk whereas the second principle component loads on liquidity risk. Hence, in our sample, default and liquidity risk are orthogonal to one another. The equity component seems to interact weakly with some of the default risk variables. The results are available from the authors upon request. Note further that the choice of sequence of decompositions affects the decomposition results mainly in nonlinear models with interaction effects. We refrain from including interaction terms because the separation of covariates in main effects and interaction effects comes along with further assumptions.

[28] Results from the other two decompositions can be found in Appendix E.

Table 6: Sequential Decomposition Results at Selected Quantiles

The table reports the results of the sequential decomposition described in (5), going from the Pre-Crisis to the Post-Crisis period, for the 10%, 50% and 90% quantile.

	10% Quantile		Median		90% Quantile	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Observed Change	5.55	2.50	40.77	3.03	177.53	11.03
Contr. by Risk Factors	-10.04	2.23	10.36	2.13	9.77	5.86
Contr. by Risk Pricing	11.52	2.43	38.68	2.71	140.78	8.65
Default Coefficients	-74.66	2.44	-103.56	1.86	-41.23	6.05
Liquidity Coefficients	45.81	2.08	50.78	1.39	49.40	5.29
Equity Coefficients	52.25	1.83	56.25	1.35	92.07	6.06
Characteristics Coeff.	86.43	2.39	109.80	1.69	127.20	6.64
Intercept	-98.31	3.66	-74.59	3.45	-86.66	11.49
Residuals	4.07	2.40	-8.28	1.89	26.98	6.14

As a first step we alter the pricing of factors related to the risk of default of a company. Figure 7(b) shows that relative to the Pre-Crisis period, the pricing implications of a given level of default risk have actually decreased. Hence, we find that aversion to default risk has decreased for all bonds. This does not imply that the contribution of credit risk (which would be risk factor multiplied by its coefficient) has decreased. It does say, however, that a given ratio that we use to proxy for default risk carries a lower credit spread premium. As a next step, we adjust the pricing of liquidity factors as shown. We find that the pricing of liquidity risk has increased along all quantiles. Institutional investors seem to be more concerned with illiquidity risk than before the financial crisis irrespective of actual levels of liquidity.[29] For equity risk, we find a similar pattern as for liquidity risk: The graph shows that after the crisis equity risk carried a higher spread premium than before it. This effect is more 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

[29] Our findings are in line with Longstaff et al. (2005) and Chen et al. (2007) who find that liquidity proxies have explanatory power. More recent papers like Bao et al. (2011), Dick-Nielsen et al. (2012), Friewald et al. (2011) also document an increase in liquidity effects during the crisis. These studies, however, do not consider a change in the underlying parameters as a consequence of the crisis.

on the corporate bond market relative to the other risk factors. This misalignment has then been reversed during the financial crisis; a result which is in line with Friewald et al. (2011). Based on the arguments of Duffie et al. (2007), Dick-Nielsen et al. (2012), and Bao et al. (2011), they show empirically that during periods of financial distress the impact of liquidity measures increases significantly. In addition, they find that the parameters of their liquidity indicators are smaller for retail investors, which indicates the higher relevance of changes in liquidity for institutional investors, even though the bond market is generally more liquid for these market participants.

One should note that the change due to the intercept is significant and economically quite large as shown in Table 6.[30] A possible explanation for the size and direction of the effect is that it might capture changes in macroeconomic factors for which we cannot control by using time-fixed effects in our cross-sectional estimation setting. The negative sign could be the result of the quantitative easing program of the Federal Reserve which may have lowered bond yields to levels lower than what one would expect given a company's risk factors.

5 Conclusion

This paper investigates whether long-lasting shifts in risk perception are responsible for the sustained increase in corporate bond spreads from 2005 to 2011. We use a methodology novel to the empirical finance literature which allows us to explicitly account for changes in market risk factors and separating out the effect that the pricing of these factors has. This gives us an estimate of what spreads would have been if risk perception had not changed. The remaining difference, then, can be interpreted as an estimate of the effect that changes in the pricing structure have had on the levels of bond spreads. 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 enduring shifts in risk attitudes.

[30] This was to be expected since the intercept is highly significant in the quantile regressions for the sub-periods as shown in Tables B.1 to B.3 in the Appendix.

We use 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 default risk, 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. 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 show that most of the increase in credit spreads during the financial crisis is due to a spike in risk perception. Relative to pre-crisis levels, credit spreads have increased between 6 (first decile) and 178 bps (last decile) with an increase of 41 bps at the median of the distribution. Changes in actual risk factors have contributed to a decrease of spreads by 10 bps at the first decile and an increase of approximately 10 bps at any other decile. The remainder of the total increase in spreads is then due to changes in risk perceptions. This shows that markets have significantly revalued what a given risk factor should carry as a premium in the corporate bond market. The sequential decomposition highlights the fact that liquidity and equity risk now carry higher risk premia whereas default risk premia have actually decreased once we adjust for changes in market factors and only look at the pricing effects.

A possible explanation for this finding is provided by considering ambiguity averse investors. The financial crisis has increased the perception of model risk which has caused institutional investors to imply higher risk premia for a given level of risk as they now assign a higher probability to low utility states. A similar conclusion is reached by Boyarchenko (2012) who analyzes the impact of ambiguity on CDS spreads during the financial crisis. So far, our analysis

has been only descriptive. In order to investigate possible explanations as to why investors change their risk perception, a structural model is needed that can incorporate the salient features of bond spreads described in this paper. A possible direction would be to adapt the time-varying fear model of Drechsler (2013) to the bond market. We leave this for future research.[31]

In addition, our results provide an explanation for the structure in the residuals found by Collin-Dufresne et al. (2001). Their study looks at the determinants of changes in credit spreads using time-series regressions on each bond. They found that most of the variation in the residuals could be explained by the first principal component. From this, they concluded that bond and equity markets are segmented and that an underlying bond factor had been omitted. A number of follow-up studies have provided alternative interpretations of this result. Our study suggests that this latent factor is due to changes in risk perception over time. In a time-series regression, the estimated coefficient for each risk factor is constant. Hence, if these coefficients are in fact time-varying across the bond market, artificial cross-correlation is created in the residuals.

An interesting further question would be to examine whether and how results differ among sub-samples. 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. In our research setup, this would entail comparing the changes in risk perception of institutional and retail investors. Finally, a future study might quantify the persistence of such discovered changes in risk aversion.

[31] The questionnaire based evidence of Guiso et al. (2013) for Italy suggests that this might be a fruitful avenue to pursue.

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