Economic Uncertainty, Disagreement, and Credit Markets

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Economic Uncertainty, Disagreement, and Credit Markets

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Abstract

Using a structural credit risk model with heterogeneous beliefs, this paper derives testable implications for the role of common and firm specific components of economic uncertainty in the determination of equilibrium credit spreads and asset prices. In an economy where agents with different subjective perception of economic uncertainty disagree about future firm cash flows, we obtain: (i) a positive relation between uncertainty and belief heterogeneity, (ii) a positive relation between belief heterogeneity, credit spreads, and their volatility, (iii) a positive relation between belief heterogeneity and the frequency of arbitrage-free credit market violations, and (iv) an ambiguous relation between belief heterogeneity and stock returns. Using a merged data-set of firm-specific differences in beliefs, credit spreads and stock returns, we test the model predictions and obtain a number of novel results for the empirical credit risk literature: (a) Counter-cyclical uncertainty is strongly positively related to a common dynamic component in the cross-section of individual differences of earning forecasts provided by financial analysts; (b) The dynamic common component in the individual differences of earning forecasts is the most significant variable for the time-series of credit spreads. At the same time, firm-specific difference in beliefs is the most significant variable in explaining the cross-section of credit spreads; (c) Uncertainty induces a significant co-movement between credit spreads and stock volatility; (d) During the 2008 Credit Crisis, the link between uncertainty and credit spreads was stronger than in previous crisis periods; (e) Uncertainty and belief heterogeneity have significant explanatory power for no-arbitrage violations of single factor models in credit markets.

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Structural credit risk models with additive preferences find it difficult to explain the average level and the dynamics of corporate bond spreads when calibrated to historical default and recovery rates. This paper studies whether economic uncertainty and belief heterogeneity can help to better explain the dynamic and cross-sectional features of credit spreads. Economic uncertainty surges in recessions and during periods of financial crises, when there is less confidence about future macroeconomic conditions and the firm’s cash flows. Kurz (1994) discusses this link and explains how higher uncertainty can lead economic agents to have more disperse beliefs. We study the asset pricing implications of this mechanism starting from an equilibrium model of credit risk, in which the interaction of investors with different perceptions of economic uncertainty and future cash flows generates novel implications for equilibrium credit spreads.

To motivate the relation between uncertainty/beliefs disagreement and credit spreads from a time-series perspective, Figure 1 (left panel) plots from January 1990 to December 2007 the (detrended) common dynamic component of the difference of analysts forecasts about future earnings for a large cross-section of U.S. firms. It is estimated using dynamic factor analysis (for convenience, we call the difference in analysts forecasts of future earnings “Uncertainty-DiB” thereafter, where DiB stands for Differences-in-Beliefs).

Three interesting properties in the data emerge. First, Uncertainty-DiB has a systematic counter-cyclical component, which peaks near real economic recessions or (temporary) financial crises and is highly time-varying. Consider for instance the case of the 1991 recession. Twelve months before it’s inception the common dynamic component of Uncertainty-DiB was around 0.01. At the peak of the crisis it increased to 0.3, but twelve months after, it dropped by 66% to 0.1. The counter-cyclicality of Uncertainty-DiB is supported by a broader comparison in Table 1 which reports the average increase/decrease of the common component of Uncertainty-DiB during financial crises from 1990 to 2007: In each crisis, Uncertainty-DiB increased before and decreased after the crisis peak.

The second characteristic of Uncertainty-DiB is its large time series co-movement with financial variables like credit spreads. Figure 1 (right panel) plots the monthly average of the de-trended common component of Uncertainty-DiB together with the default spread, defined as the difference between Moody’s Baa and Aaa bond yields, before, during, and after a crisis event. The common component of Uncertainty-DiB and average credit spreads peak together at crisis times and their monthly unconditional correlation of 60% is quite substantial, e.g., in comparison to the one with the VIX index, which is often interpreted as a measure of risk appetite: The unconditional correlation between the default spread and the VIX index around crisis times is only 28%.

The third distinctive property of Uncertainty-DiB is that it contains a firm-specific component that is correlated with credit spreads in the cross-section: For instance, if one sorts credit spreads of investment grade bonds according

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1Using dynamic factor analysis, we estimate the dynamic common component from individual belief disagreement proxies derived from single firm earnings forecasts. Individual proxies are calculated as the mean absolute difference of individual forecasts on one-year ahead earnings. We then de-trend this series using a Hodrick-Prescott filter.

2Much like the 2007-2008 credit crunch, the 1991 recession began with a housing bubble burst that generated uncertainty about the solvency of a significant portion of the financial sector. In the late 1989, the US congress passed the Financial Institutions Reform, Recovery and Enforcement Act of 1989 (FIRREA), which was part of a program of reforms set up by the Resolution Trust Corporation (RTC) to liquidate hundreds of insolvent institutions. By 1994, more than 1,600 thrifts were closed or received financial assistance.
to firm-specific differences in Uncertainty-DiB for the “crisis” year 1998, the difference in the average credit spread between the highest quintile and the lowest quintile is as large as 17 basis points, which is half the standard deviation of investment grade credit spreads in our data. The strong cross-sectional relationship between credit spreads and disagreement is illustrated in more detail by Figure 2 (lower panel), where we plot the average asset swap spread and Uncertainty-DiB proxies for six different sectors. These two variables are strongly related across sectors and their average unconditional correlation of 0.59 is highly significantly different from zero. A one standard deviation change in the average Uncertainty-DiB increases the asset swap spread by 57 basis points and those sectors that experienced the largest surge in the asset swap spread also experienced the largest ascent of Uncertainty-DiB: For example, the spread in the banking sector increased by a factor of 15 since the beginning of the credit crisis in late spring 2007. In the same period, Uncertainty-DiB in this sector increased almost threefold.

Why is dispersion in analysts’ forecasts so strongly related to credit spreads in the cross-section and the time series, and what are the major asset pricing implications of this link? We address these questions starting from a structural equilibrium model of credit risk, in which agents have different perceptions of future cash flows and their degree of uncertainty, captured by the volatility of expected cash flows growth. Agents form beliefs about expected cash flow growth using a common set of observable variables and agree to disagree about future firm cash flows. These common variables include a firm-specific signal (the firm’s cash flows themselves) and a systematic (market-wide) signal correlated with the firm’s cash flow growth.

Our economy with uncertainty and belief disagreement extends Merton’s (1974) credit risk model along three main dimensions. First, the equilibrium stochastic discount factor is driven by an additional state variable, the ratio of the marginal utilities of optimistic and pessimistic investors in the model, which is directly linked to the degree of uncertainty and belief heterogeneity. Thus, heterogeneity in beliefs implies in equilibrium a stochastic firm value volatility and risk-neutral skewness. Since in good (bad) states the stochastic discount factor depends more heavily on the marginal utility of the optimistic (pessimistic) agent, a higher uncertainty or belief heterogeneity is linked to a lower equilibrium firm value, a higher firm value volatility, and a more negative firm value risk-neutral skewness. These features together imply a positive relation between uncertainty, belief heterogeneity and the market price of default risk in our economy.

Second, due to the larger market price of default risk, a higher uncertainty or belief heterogeneity is unambiguously linked to higher credit spreads in our model. Since this effect arises mostly via the price of default risk, and less so through the probability of default events, we can find parameter choices implying realistic credit spreads without excessively increasing measures of distance to default or the physical default probability. The positive link between Uncertainty-DiB and credit spreads is a useful result, because it is known that standard structural models such as Merton (1974) tend to under-estimate corporate bond spreads on average; see Huang and Huang (2004), among

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3The asset swap spread is the difference between the yield on the corporate bond and the LIBOR. Sectors are defined following Standard & Poors Global Industry Classification Standard.
many others. Moreover, since the common Uncertainty-DiB component in the data is strongly counter-cyclical this finding suggests the presence of a potential counter-cyclical credit spread component driven by Uncertainty-DiB.

Third, the endogenous link between Uncertainty-DiB and equilibrium firm value affects the equilibrium price of any derivative on the capital structure of the firm, like corporate bonds and stocks. Thus, Uncertainty-DiB emerges as an additional common risk factor for credit spreads, stock returns, and stock volatility. Starting with the work of Fama and French (1993), an increasing literature suggests that common risk factors affect both stock and bond returns. However, while some factors such as the Fama and French factors have been successful at explaining the cross-section of stock returns, they are much less effective in explaining the cross-section of corporate credit spreads; See Collin-Dufresne, Goldstein, and Martin (2001) and Schaefer and Strebulaev (2008), among others. Our model suggests that Uncertainty-DiB has explanatory power both for credit spreads and stock returns, a prediction that we can study and test in the data.

Fourth, the relation between Uncertainty-DiB and equilibrium stock volatility is positive, because stock volatility is mostly driven by the level of the firm value volatility. As a consequence, we obtain a positive co-movement between credit spreads and stock volatility, which gives theoretical support to the empirical positive relation observed in the data. Campbell and Taksler (2003) show that firm-level equity volatility explains as much of the variation in corporate credit spreads as credit ratings. In related work, Cremers, Driessen, and Maenhout (2008) use the at-the-money implied volatility of individual stock options as a proxy for volatility risk, the implied volatility of out-of-the-money puts as a proxy for jump risk, and link them to the dynamics of credit spreads.

Fifth, the relation between Uncertainty-DiB and stock returns is ambiguous and depends on the degree of leverage: It is negative for highly levered firms, but it can turn positive for moderately levered firms. This finding follows from the different skewness sensitivities of the default options embedded in the stock: For low (high) leverage companies, this option is far out-of-the-money (closer to be in-the-money) and its value is more (less) sensitive to changes in skewness. Overall, this feature implies an ambiguous relation between credit spreads and stock returns, which can potentially explain the frequent violations of basic capital structure arbitrage relationships implied by single factor structural models. Moreover, this finding can help reconcile in a frictionless economy with heterogenous beliefs the mixed sign of the cross-sectional relation between Uncertainty-DiB and stock returns found in the literature.

We study the previous testable model implications by constructing proxies of firm-specific Uncertainty-DiB for a large cross-section of 337 US firms, using earning forecast data from the Institutional Brokers Estimate System (I/B/E/S) in the period from 1996 to 2008: For each firm and each month, we obtain a measure of individual Uncertainty-DiB.

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5 Diether, Malloy, and Scherbina (2002) find a negative relation between dispersion in analysts’ earnings forecasts and stock returns. They interpret this finding as evidence in support of Miller’s (1977) conjecture that binding short-selling constraints imply stock prices reflecting the view of the more optimistic investor. Johnson (2004) argues that if dispersion is a proxy for idiosyncratic risk then the stock return of a levered firm should decrease with dispersion. Qu, Starks, and Yan (2004) find a positive relationship between disagreement and returns using a different scaling variable. Anderson, Ghysels, and Juergens (2005) and Banerjee (2007) also estimate a positive relation. Avramov, Chordia, Jostova, and Philipov (2009) suggest that the negative relation between expected stock returns and dispersion could be a manifestation of financial distress.
In a second step, we build an empirical proxy for the systematic component of Uncertainty-DiB, by estimating with dynamic factor analysis a common dynamic component for the whole cross-section of individual Uncertainty-DiB proxies. We find that this common component is highly counter-cyclical and that it explains a large fraction of the variation in individual proxies, thus supporting the conjecture that cross-sectional firm’s cash flow uncertainty contains a large common component. We test the main model implications for the relation between credit spreads and Uncertainty-DiB using a variety of pooled panel and Logit regressions that include our firm-specific and common Uncertainty-DiB proxies as explanatory variables. We obtain the following findings.

First, Uncertainty-DiB has a positive impact on credit spreads, both via its firm-specific and its systematic components. The significance and the direction of the effect is robust even after controlling for several other explanatory variables. A one standard deviation increase in firm-specific Uncertainty-DiB increases credit spreads by approximately 18 basis points, which is more than one third the credit spread sample standard deviation in our data. A one standard deviation increase in systematic Uncertainty-DiB increases the average credit spread by about 10 basis points. Overall, Uncertainty-DiB consistently improves the explanatory power of empirical credit risk models using explanatory risk factors previously suggested in the literature. For instance, in a regression with option-implied volatility related factors the $R^2$ increases by about 10% when our Uncertainty-DiB proxies are added to the regression model. Finally, when studying in more detail the recent 2008 credit crisis, we find that the positive link between Uncertainty-DiB and credit spreads in the data is even stronger than during previous crisis periods.

Second, firm-specific Uncertainty-DiB has explanatory power for stock returns, but the sign of this empirical relation depends on leverage: One third of the firms with lowest leverage features a negative relation, but the remaining two thirds of firms imply instead a positive relation. Together with the results for credit spreads, we find that Uncertainty-DiB is a risk factor that explains the joint behavior of credit spreads and stock returns.

Third, Uncertainty-DiB helps to explain the empirical violations of capital structure no-arbitrage restrictions implied by single-factor structural models. Merton’s and similar structural models imply a negative relation between credit spreads and stock prices, which is the basis of different capital structure arbitrage strategies used in the industry. This relationship is often empirically violated in our data, with a frequency between 14% and 19% that tends to decrease with firm leverage. Our model suggests that Uncertainty-DiB acts as a priced risk factor that can potentially explain such violations. We investigate this conjecture in more detail in a number of Logit panel regressions and find that indeed Uncertainty-DiB significantly increases the conditional likelihood of credit market violations.

We study the robustness of our results using various econometric techniques. We estimate regressions with year and firm fixed effects, to ensure that our results are not driven by spurious time-series or cross-sectional correlation, and find that the economic and statistical significance of Uncertainty-DiB is unchanged. We also consider proxies of idiosyncratic volatility as control variables and find that the effect of our Uncertainty-DiB proxies is not weakened by idiosyncratic volatility.

Recently, Kapadia and Pu (2008) give further support to our findings by showing that the frequency of violations in credit default swap markets can be as large as 35%.

These findings are robust towards the inclusion of other risk factors such as liquidity or option implied volatility. Our findings are related to, but distinct from, the results of the literature on equity index options. While the Black-Scholes model implies a positive (negative) link between call (put) option prices and stock prices, the empirical evidence shows that arbitrage-free relations are violated in the data; See, e.g., Bakshi, Cao, and Chen (2000) and Pérignon (2006). The frequency of no–arbitrage violations for individual call (put) stock options is lower and it ranges between 3% and 10% (between 2% and 10%), depending on the option’s maturity and moneyness.
Our structural credit risk model motivating the link between economic uncertainty, beliefs disagreement, and credit risk borrows from a large literature studying the equilibrium relation between heterogeneity in beliefs and asset prices in default-free economies. The introduction of credit risk and leverage in the economy with heterogeneous beliefs delivers interesting implications for the relation between Uncertainty-DiB and asset prices, which cannot be generated by similar economies without default. The modeling of an explicit capital structure also allows us to formulate novel cross-sectional asset pricing predictions for credit spreads and stock returns, in dependence of the joint characteristics of firm leverage and firm-specific Uncertainty-DiB. As a consequence, we can derive the economic link between beliefs heterogeneity, the ambiguous cross-sectional relation between credit spreads and stock returns, and the frequency of credit market violations in the data. These empirical features are novel with respect to the implications of models for an unlevered firm, as for instance in Buraschi and Jiltsov (2006), which simply imply a monotone link between Uncertainty-DiB and stock prices. Our work is also related to the recent literature investigating the implications of counter-cyclical systematic risk factors for credit risk modeling. However, we have a different purpose and follow a distinct approach than other models in this literature. First, instead of introducing additional model sophistication at the level of either the underlying process for firm cash flows, investor’s preferences or strategic default, we consider a structural economy with standard separable preferences and a simple default structure, in order to focus exclusively on the additional novel implications of uncertainty and belief-heterogeneity for understanding the pricing of credit risk. This already gives us novel empirical predictions on (i) the positive relation between credit spreads and Uncertainty-DiB, (ii) the ambiguous relation between Uncertainty-DiB and stock returns and (iii) the potential link between counter-cyclical credit spreads and the counter-cyclical common component of Uncertainty-DiB extracted from the cross-section of individual earning forecasts. Second, the additional state variable driving the market price of credit risk in our model, Uncertainty-DiB, has a concrete economic interpretation linked to economic uncertainty, which naturally motivates our use of empirical proxies of firm-specific and market-wide belief heterogeneity extracted from earning forecast data of financial analysts.


10In a different context, Longstaff and Wang (2008) emphasize this point using an economy populated by agents with heterogeneous risk aversions.

The remainder of the paper is organized as follows. Section I introduces our structural equilibrium model of credit risk with uncertainty. It then presents and discusses the equilibrium solutions for asset prices. Section II investigates in detail the empirical model predictions. Section III describes our data set and Section IV presents the empirical findings. Section V provides robustness checks and Section VI concludes. Proofs are collected in the Appendix.

I. The Economy with Uncertainty and Disagreement

In order to motivate our testable implications for the relation between heterogeneity in beliefs and credit risk, we consider a structural model where economic uncertainty is linked to investors’ heterogeneous beliefs on the growth opportunities of a firm financed by equity and debt. The growth rate of future earnings or cash flows is typically unknown, and financial analysts often largely disagree on it, since it depends on several variables that are difficult to predict, like future sales and costs, the regulatory environment, and general business conditions. We consider a standard Bayesian inference framework, in which investors observe the same piece of information. To circumvent the no-trade theorem and induce trading in equilibrium, we follow the standard assumption that heterogeneous priors are not motivated by private information, so that it is rational for agents to “agree to disagree”.

A. State Dynamics

We develop an extended version of Merton’s (1974) model by taking the dynamics of the asset cash flows of the firm as a primitive and assuming that investors disagree on it. Investors are identical in all other aspects. The firm has a simple capital structure consisting of equity and two defaultable bonds with different seniority and identical maturity. The equilibrium value of equity and debt depends on the probability that the firm will generate enough cash flows to cover its liabilities. Cash flows, $A(t)$, follow the process:

$$
d log A(t) = \mu_A(t)dt + \sigma_A dW_A(t),$$
$$
d\mu_A(t) = (a_{0A} + a_{1A}\mu_A(t))dt + \sigma_{\mu_A} dW_{\mu_A}(t),$$

where $\mu_A(t)$ is the cash flow's expected growth rate, $\sigma_A > 0$ its volatility, $a_{0A} \in \mathbb{R}$ the growth rate of expected cash flow growth, $a_{1A} < 0$ its mean-reversion parameter and $\sigma_{\mu_A} > 0$ the volatility. ($W_A(t), W_{\mu_A}(t)$) is a standard bivariate Brownian motion.

Cash flows $A(t)$ are observable, but expected growth rate $\mu_A(t)$ is unknown and has to be estimated. We interpret $A(t)$ as a direct signal about the firm’s future growth opportunities, and the volatility parameter $\sigma_{\mu_A}$ as the degree of uncertainty about the growth rate of cash-flows.

Our preliminary empirical analysis in the introduction has shown a strong commonality in belief heterogeneity proxies derived from forecasts of individual future cash-flows. In order to specify parsimoniously such a common business

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12Merton’s (1974) model of credit risk assumes an exogenous firm value process with constant volatility. Even if we treat the firm value as endogenous, the predictions of our model for the case in which there is no disagreement are identical to those of Merton (1974).
cycle component influencing investors beliefs about future earnings, we introduce an unobservable market-wide indicator $\mu_z(t)$ of overall economic growth, potentially related to the business cycle and the competitive landscape. Investors observe a signal $z(t)$ reflecting information about both firm-specific and market-wide growth $\mu_A(t)$ and $\mu_z(t)$, and use it to improve their forecasts of future cash flows. The signal dynamics is given by:

$$dz(t) = (\alpha \mu_A(t) + \beta \mu_z(t))dt + \sigma_z dW_z(t),$$
$$d\mu_z(t) = (a_{0z} + a_{1z} \mu_z(t))dt + \sigma_{\mu_z} dW_{\mu_z}(t),$$

where $\sigma_z > 0$ is the signal volatility, $a_{0z} \in \mathbb{R}$ the long-term growth rate of expected signal growth, $a_{1z} < 0$ the mean-reversion parameter and $\sigma_{\mu_z} > 0$ the uncertainty of overall economic growth. $(W_z(t), W_{\mu_z}(t))'$ is a standard two-dimensional Brownian motion independent of $(W_A(t), W_{\mu_A}(t))'$. If $\beta = 0$, $z(t)$ contains pure firm-specific information about cash flows. When $\beta \neq 0$, $z(t)$ reflects mixed information about both firm-specific and market-wide growth. There exist several well established theories that motivate why investors might use information beyond historical cash flows in order to forecast the firm’s future prospects, and we take our specification of $z(t)$ as a reduced form description of these theories.\textsuperscript{13} The main implication of this assumption is that the information provided by signal $z(t)$ will be indeed used by heterogenous investors in order to build their beliefs about future cash flows. In this way, uncertainty about market-wide information will affect individual optimal consumption and investment plans and have a real impact on the equilibrium stochastic discount factor, thus asset prices, even when the signal $z(t)$ does not directly affect the structural dynamics of each firm’s technology $(\mu_A$ and $\sigma_A)$.\textsuperscript{14} This specification will motivate the empirical analysis of the role of firm specific and common uncertainty factors, linked to the $z(t)$ process, for the time-series and cross-sectional properties of the credit spreads of multiple firms.

### B. The Disagreement Process

Investors update their beliefs based on the available information using Bayes’ rule. Given the Gaussian state dynamics of $A(t)$ and $z(t)$, the Bayesian updating rule of each agent follows via a standard application of the Kalman Bucy filter and the heterogeneity in beliefs can be summarized by the differences in posterior means and covariance matrices across agents.

Let $m^i(t) := (m^i_A(t), m^i_z(t))' := E^i \left(\left((\mu_A(t), \mu_z(t))'\right|\mathcal{F}^A_z, t\right)$, where $\mathcal{F}^A_z$ is the information generated by cash flows and signals up to time $t$ and $E^i(\cdot)$ denotes expectation relative to the subjective probability of investor $i = 1, 2$. As

\textsuperscript{13}Boyd, Hu, and Jagannathan (2005) and Beber and Brandt (2006), show that it can be optimal for analysts to use information beyond direct historical cash flows. Malmendier and Tate (2005) find that especially during the new economy boom in 2000 the accounting values of some companies were not very reliable. An imprecisely observed firm value is also modeled by Çetin, Jarrow, Protter, and Yildirim (2004), who assume that investors can access only a coarsened subset of the manager’s information set. Giesecke (2004) develops a model with an imperfectly observed default boundary. Collin-Dufresne, Goldstein, and Helwege (2003) assume that

\textsuperscript{14}See, for instance, Basak (2000) for a detailed explanation of this aspect in relation to different forms of extraneous risk.
shown in Buraschi and Jiltsov (2006), the posterior covariance matrix of \((\mu_A(t), \mu_z(t))\)' agent one solves a matrix Riccati differential equation, in which the solution is directly linked to the time 0 prior covariance matrix of this agent. We consider for simplicity the steady state solution of this differential equation, denoted by \(\gamma^1\), which is independent of agents’ initial prior. \(\gamma^1\) solves the algebraic matrix Riccati equation:

\[
a_1\gamma^1 + \gamma^1 a_1 + b^1 b^{1\prime} - \gamma^1 A'(BB')^{-1}A\gamma^1 = 0,
\]

where \(b^1 = \text{diag}(\sigma^1_{\mu_A}, \sigma^1_{\mu_z})\), \(a_1 = \text{diag}(\alpha_{1A}, \alpha_{1z})\), \(B = \text{diag}(\sigma_A, \sigma_z)\) and \(A = \begin{pmatrix} 1 & 0 \\ \alpha & \beta \end{pmatrix}\). \(\gamma^1\) is a function of investor one’s subjective perception of the uncertainty about firm cash-flow and overall economic growth, parameterized by \(\sigma^1_{\mu_A}, \sigma^1_{\mu_z}\). The (posterior) belief dynamics of agent one follows as:

\[
dm^1(t) = (a_0 + a_1 m^1(t)) dt + \gamma^1 A'B^{-1} dW^1(t) ; \ m^1(0) = m^1_0,
\]

where \(W^1(t)\) is the innovation process induced by investor one’s belief and filtration and \(a_0 = (a_{0A}, a_{0z})'\). Let \(\Psi(t)\) be the standardized process of the difference in the posteriors of the two agents, namely:

\[
\Psi(t) := (\Psi_A(t), \Psi_z(t))' = B^{-1}(m^1(t) - m^2(t)).
\]

Thus, \(\Psi_A(t)\) directly measures the disagreement about the growth rate of future cash flows while \(\Psi_z(t)\) measures the disagreement about the market-wide signal \(z(t)\). Since the dynamics of each individual belief \(m^i(t)\) are functions of the individual perception of the uncertainty in the economy, parameterized by \(\sigma^i_{\mu_A}\) and \(\sigma^i_{\mu_z}\), the stochastic properties of the disagreement process depend on the overall uncertainty of firm-specific and market-wide economic growth:

\[
d\Psi(t) = B^{-1} \left( a_1 B + \gamma^2 A'B^{-1} \right) \Psi(t) dt + B^{-1}(\gamma^1 - \gamma^2) A'B^{-1} dW^1(t) ; \ \Psi(0) = \Psi_0,
\]

where \(\gamma^2\) solves the same matrix Riccati equation as \(\gamma^1\), but with agent specific uncertainty parameter \(b^1\) replaced by \(b^2\). Under our assumptions, the heterogeneity in beliefs is stochastic when \(\gamma^1 \neq \gamma^2\), i.e., when investors perceive the degree of uncertainty in the economy differently. This relation between economic uncertainty and the stochastic properties of the belief heterogeneity motivates the analysis of the link between common belief disagreement proxies and macroeconomic uncertainty in our empirical tests. When \(\gamma^1 = \gamma^2\), the disagreement process is deterministic and completely determined by the initial difference in priors \(m^1(0) - m^2(0)\) across investors. We investigate the credit risk implications of a stochastic disagreement dynamics and solve the model for the general case \(\gamma^1 \neq \gamma^2\).

C. The Link Between Uncertainty and Belief Disagreement

A characteristic of the data is an apparent relation between crisis periods and variations in a common dynamic component of Uncertainty-DiB, highlighted in Figure 1 and Table 1. To study in more detail this empirical link, it

\[\text{15 A formal proof of this result can be found in Liptser and Shiryaev (2000); See also the technical Appendix.}\]
is useful to look at the properties of the diffusion process for the disagreement $\Psi(t)$. A higher average subjective uncertainty tends to increase the average disagreement and the disagreement variability in our economy. Therefore, a larger uncertainty about the market-wide growth factor $\mu_z(t)$ tends to be associated with a larger degree of heterogeneity in beliefs. This result follows from the form of the dependence of the (Gaussian) distribution of $\Psi(t)$ on the investor specific uncertainty parameter $\sigma_{\mu_z}^i$, $i = 1, 2$, which is explicit in our model through the link between the individual posterior variances $\gamma^i$ and uncertainty parameters $\sigma_{\mu_z}^i$:

$$
\Psi(t)\mid \Psi(0) \sim \mathcal{N}\left( e^{tM} \Psi(0), t e^{tM} B^{-1} \left( \gamma^1 - \gamma^2 \right) A' (BB'^{-1}A) \left( \gamma^1 - \gamma^2 \right) B^{-1} e^{tM} \right),
$$

where $M = B^{-1} \left(a_1 B + \gamma^2 A'^{-1} \right)$. We find that the first moment of the probability distribution of $\Psi(t)$ is increasing in the average subjective uncertainty, measured by $\bar{\sigma}_{\mu_z} \equiv \frac{1}{2} \left( \sigma_{\mu_z}^1 + \sigma_{\mu_z}^2 \right)$. The variance of this distribution is positively related to the cross sectional uncertainty heterogeneity, parameterized by $\Delta \sigma_{\mu_z} \equiv \sigma_{\mu_z}^1 - \sigma_{\mu_z}^2$. Figure 3 presents the comparative statics of the mean and standard deviation of $\Psi_z(t)$ with respect to $\bar{\sigma}_{\mu_z}$ and $\Delta \sigma_{\mu_z}$.

[Insert Figure 3 approximately here.]

An increase in $\bar{\sigma}_{\mu_z}$ ($\Delta \sigma_{\mu_z}$) increases the expectation (variance) of the probability distribution of $\Psi_z(t)$. $\Delta \sigma_{\mu_z}$ has virtually no effect on the expected value of $\Psi_z(t)$, so that average disagreement is indeed mostly driven by the the average subjective uncertainty in the economy. The variance of $\Psi_z(t)$ is mostly driven by the heterogeneity in subjective uncertainty. As expected, when $\Delta \sigma_{\mu_z} = 0$ the variance of the disagreement vanishes. $\bar{\sigma}_{\mu_z}$ also increases the variance of $\Psi_z(t)$ and this effect is more pronounced for settings of low average uncertainty and large uncertainty heterogeneity.

These findings suggest that periods of high average uncertainty and uncertainty heterogeneity are associated with the largest disagreement and disagreement variability over time. Therefore, the model suggests a direct link between economic uncertainty and heterogeneity in beliefs, which motivates our interpretation of common belief disagreement as an empirical proxy for market-wide economic uncertainty. This insight useful for empirical work, given the notorious difficulty of obtaining satisfactory proxies of uncertainty.

D. Investors’ Preferences, Financial Markets and Equilibrium

We work in a standard two-agent economy populated by investors with heterogeneous beliefs. Agents maximize life-time expected power utility subject to their budget constraint:

$$
V^i = \sup_{c_i} \mathbb{E}^i \left( \int_0^\infty e^{-\rho t} c_i(t)^{1-\gamma} \frac{dt}{1-\gamma} \left| \mathcal{F}^A_z \right) \right),
$$

(1)

where $c_i(t)$ is the consumption of agent $i = 1, 2$ at time $t$ and $\gamma, \rho > 0$ are the common relative risk aversion coefficient and time preference rate, respectively. Investors finance their consumption plans by trading in financial assets. Belief heterogeneity across agents influences the prices of all financial assets, which – from the perspective of agent one – can be written as functions of the two-dimensional filtered Brownian motion $W^1(t)$. In this economy, at least two risky financial assets are needed to determine a unique stochastic discount factor. We study a model including corporate bonds and equity. We denote by $r(t)$ the interest rate on the risk-less bond, in zero net supply, by $S(t)$ the price of the stock of the firm, in positive net supply, and by $B^s(t)$ ($B^j(t)$) the price of a senior (junior) bond, in positive supply. $V(t)$ denotes the value of the single firm in our economy.

**Definition 1** (Equilibrium). An equilibrium consists of a unique stochastic discount factor such that: (I) given equilibrium prices, all agents in the economy solve the optimization problem [1], subject to their budget constraint. (II) Goods and financial markets clear.

Optimal consumption policies are of the form $c_i(t) = (y_i \xi^i(t))^{-1/\gamma}$, where $y_i$ is the Lagrange multiplier associated with the static budget constraint of agent $i$ and $\xi^i$ is the state-price density of this agent. Closed-form expressions for agent specific state price density $\xi^i(t)$ follow with standard computations\(^{17}\):

\[
\xi^1(t) = \frac{e^{-\rho t}}{y_1} A(t)^{-\gamma} \left( 1 + \lambda(t)^{1/\gamma} \right)^\gamma, \quad \xi^2(t) = \frac{e^{-\rho t}}{y_2} A(t)^{-\gamma} \left( 1 + \lambda(t)^{1/\gamma} \right)^\gamma \lambda(t)^{-1},
\]

where weighting process $\lambda(t) = y_1 \xi^1(t)/(y_2 \xi^2(t))$ follows the dynamics:

\[
\frac{d\lambda(t)}{\lambda(t)} = -\Psi_A(t) dW^1_A(t) - \left( \alpha \Psi_A(t) \frac{\sigma_A}{\sigma_z} + \beta \Psi_z(t) \right) dW^1_z(t).
\] (2)

The dynamics of $\lambda(t)$ is completely described by the disagreement process $\Psi(t)$, which determines the volatility of $\lambda(t)$, and in contrast to Merton’s (1974) structural model the stochastic discount factor depends on the additional stochastic state variable $\Psi(t)$. When $\Psi(t) = 0$, we obtain as a special case Merton’s economy with identical agents: In this case, the relative weight $\lambda(t)$ is constant and the consumption plans across investors are proportional. However, when agents have different subjective beliefs they implement different consumption plans. Optimistic (pessimistic) investors consume more (less) in states of high aggregate cash flows, at a lower (higher) marginal utility, because they perceive those states as more (less) likely: The consumption share of the optimist is higher (lower) in states of high (low) aggregate cash flows. This feature has direct implications on the equilibrium stochastic discount factor and the price of any future aggregate consumption state. Since the volatility of the stochastic discount factor is a direct function of the disagreement across agents, the market price of risk of cash-flow and signal shocks features a different structure than in the Merton (1974) model. Intuitively, this is due to the fact that when beliefs are heterogeneous, agents face both absolute and relative consumption share risk: Belief-dependent state prices and market prices of risk are necessary in order to support belief-dependent consumption shares. Importantly, in the

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\(^{17}\) The equilibrium is solved using the martingale approach, originally developed by Cox and Huang (1986). The extension to the case of heterogeneous beliefs has been studied, among others, by Cuoco and He (1994), Karatzas and Shreve (1998), and Basak and Cuoco (1998). In this extension, a stochastic weighting process $\lambda(t)$ captures the equilibrium impact of belief disagreement.
economy with heterogeneous beliefs, market-wide signal shocks are priced, because agents use the signal to construct their beliefs on future cash flows and to determine their belief-dependent optimal consumption plans. The market prices of risk perceived by the optimist are greater than those perceived by the pessimist. The economic intuition is simple: In order to finance ex-ante the different individual consumption plans, pessimistic investors have to buy financial protection against low aggregate cash-flow states from optimistic investors. This demand lowers the price of securities with positive exposure to cash-flow shocks, and the risk implied by bad cash-flow states is transferred to the optimist investors. If a negative state occurs ex-post, optimistic investors are hit twice: First, because the aggregate endowment is lower. Second, because their consumption share is lower due to the protection agreement. The size of this risk transfer is proportional to the degree of disagreement among agents.

**Remark:** The asset pricing implications of economic uncertainty have been studied from a different angle by Bansal and Yaron (2004), among others, who show that time varying (objective) uncertainty is priced when the representative agent has Epstein-Zin utility. In our setting, subjective uncertainty across investors directly influences the dynamic properties of the disagreement process. This feature generates a premium for Uncertainty-DiB also in heterogeneous beliefs economies where investors have homogenous time-additive preferences. Economic uncertainty in our setting also has a distinct role vis-à-vis the growing literature on (recursive) multiple-priors utility; see, for instance, Gilboa and Schmeidler (1989) and Epstein and Schneider (2008). In our setting, a premium for Uncertainty-DiB arises also when investors make their decisions using a single, but individual specific, prior.

### E. Pricing of Financial Assets

We assume that the firm repayment structure satisfies a strict priority rule, in which payments to the junior bond holders are made only if the contractual payments to the senior bond holders have been made. As in the Merton (1974) model, default occurs only at maturity of the corporate bonds, if the value of the assets of the firm is less than the face value of these bonds. To focus on the implications of Uncertainty-DiB in credit risk, we do not explore more general default rules or liquidation procedures. In our setting, the price of the senior bond is the sum of the prices of the zero-coupon bond and the price of a short put option on the firm value. Similarly, the price of equity is the firm value residual in excess of the price of the total corporate debt.

Given the expressions for the individual state price densities $\xi_1(t)$ and $\xi_2(t)$, one can price any security by computing expectations of its contingent payoffs weighted by the state price density. Let $K_s$ be the face value of the senior

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18 Since the signal is not an explicit argument of consumer preferences, the economy generates dynamics that could be interpreted or labeled as having “excess volatility”. It is also interesting to notice that even if there would be no disagreement on the dynamics of the market-wide signal $z(t)$, but agents were to disagree on the firm’s factor loadings $\beta$, then the risk of unexpected innovations in the signal would still affect agents optimal behavior and equilibrium market prices.

19 There is also a number of important applications of multiple-priors utility in the context of robust optimal control (Hansen, Sargent, and Tallarini, 1999, Cagetti, Hansen, Sargent, and Williams, 2002, Maenhout, 2004, Leippold, Vanini, and Trojani, 2008). None of these papers studies the equilibrium interaction of heterogeneous agents. In most of these models, ambiguity averse investors typically act as if assuming a worst case scenario in terms of mean earnings.

20 As in Merton (1974), we assume zero-bankruptcy costs. Therefore, in the event of default, equity holders are left with a zero price of equity and the corporate bond holders share the residual firm value according to the pre-specified seniority rules. See, e.g., Black and Cox (1976) for a model with premature default. Anderson and Sundaresan (1996) and Mella-Barral and Perraudin (1997) model strategic debt service. Broadie, Chernov, and Sundaresan (2007) propose a setting that incorporates Chapter 7 and Chapter 11 issues.
corporate debt and let $B(t, T)$ be the equilibrium price of risk-free zero coupon bond. The value of a senior corporate bond is given by $B^*(t, T) = K_s B(t, T) - E^t_1 \left( e^{-\rho(T-t)} \frac{\xi(T)}{g(t)} (K_s - V(T))^+ \right)$, which is the difference between the value of a risk-free discount bond and a put option on firm’s value: $K_s B(t, T, \Psi(t)) - P(V(t), \Psi(t); K_s, t, T)$. Both quantities are affected, in equilibrium, by Uncertainty-DiB. Since the equilibrium stochastic discount factor $\xi(t)$ is a function of $A(t)$ and $\lambda(t)$ only, in order to compute the expectations in all relevant pricing expressions the joint density of $A(t)$, $\lambda(t)$, and the contingent claim payoff is needed. The joint density of $A(t)$ and $\lambda(t)$ is typically unavailable in closed-form. However, we can calculate its joint Laplace transform in closed-form, which can be used, in a second step, to price more efficiently all securities using Fourier transform methods. For convenience, we compute this Laplace transform for the case $\sigma_{\mu A}^1 = \sigma_{\mu A}^2$, $\sigma_{\mu z}^1 \neq \sigma_{\mu z}^2$, which admits a stochastic dynamics for the disagreement process $\Psi(t)$. The next technical Lemma, which draws upon Dumas, Kurshev, and Uppal (2009), gives the required result.

**Lemma 1.** The joint Laplace transform of $A(t)$ and $\lambda(t)$ under the belief of agent one is given by:

$$
E^1_t \left( \left( \frac{A(T)}{A(t)} \right)^c \left( \frac{\lambda(T)}{\lambda(t)} \right)^\chi \right) = F_{m_A}(m_A^1, t, T; \epsilon)F_{\Psi_A, \Psi_z}(\Psi_A, \Psi_z, t, T; \epsilon, \chi), \quad (3)
$$

where

$$
F_{m_A}(m_A^1, t, T; \epsilon) = \exp \left( \frac{\epsilon}{a_{1A}} \left( -a_{0A} \tau + \left( \frac{a_{0A}}{a_{1A}} + m_A^1 \right) \left( e^{\alpha_{1A} \tau} - 1 \right) \right) + \frac{1}{2}(\epsilon - 1)\sigma_A^2 \tau 
+ \frac{\epsilon^2}{4a_{1A}^2} \left( \frac{a_{1A}^2 \tau}{\sigma_A^2} \right)^2 \left( 3 - 4e^{\alpha_{1A} \tau} + e^{2\alpha_{1A} \tau} + 2\alpha_{1A} \tau \right) 
+ \frac{\epsilon^2 \sigma_A^2}{a_{1A}^2} \left( -\tau + \frac{1}{a_{1A}^2} \left( e^{\alpha_{1A} \tau} - 1 \right) \right) \right), \quad (4)
$$

with $\tau = T - t$ and

$$
F_{\Psi_A, \Psi_z}(\Psi_A, \Psi_z, t, T; \epsilon, \chi) = e^{A_0(t)}B_1(t)A_1(t)B_2(t)C_1(t)A_1(t)C_2(t)A_2(t)D_0(t)A_1(t)\Psi_A\Psi_z, \quad (5)
$$

for functions $A_0, B_1, B_2, C_1, C_2$ and $D_0$ detailed in the proof.

The Laplace transform in Lemma 1 depends on $m_A^1(t)$, $\Psi_A(t)$, and $\Psi_z(t)$. The dependence on $m_A^1(t)$ is exponentially affine. The dependence on $\Psi_A(t)$ and $\Psi_z(t)$ is exponentially quadratic. Using the closed–form characteristic function of $A(t)$ and $\lambda(t)$, we can now price the corporate bond spreads as a function of the Uncertainty-DiB by Fourier inversion and Monte Carlo methods. The spirit of the Fourier inversion approach is similar to the one used to price derivatives in stochastic volatility models, such as Heston (1993), Duffie, Pan, and Singleton (2000), and Carr, Geman, Madan, and Yor (2001), or in interest-rate models, such as Chacko and Das (2002). The pricing expressions

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21In this way, we can avoid a pricing approach that relies exclusively on Monte Carlo simulation methods, which would be too computationally intensive in our setting, especially in the computation of corporate credit spreads and stock prices, which are functions of derivatives on the endogenous firm value.

22We reduce the system of ordinary differential equations for functions $A_0, B_1, B_2, C_1, C_2$ and $D_0$ in Lemma 1 to a system of matrix Riccati equations, which can be linearized using Radon’s Lemma. In this way, we obtain explicit expressions for the coefficients in the exponentially quadratic solution of the Laplace transform.
for the contingent claims in our economy are summarized in Lemma 2 of the Appendix. Firm value and risk-less zero bond prices are in semi-closed form, up to a numerical integration. However, corporate bond and stock prices, which are options written on the firm value, require a Monte Carlo simulation step in their computation.

Using the pricing formulas in Lemma 2, we can study in more detail the dependence of corporate bond spreads on the degree of Uncertainty-DiB about future cash flows and the market-wide signal in our economy. In this way, we motivate a number of testable empirical hypotheses for the relation between market-wide uncertainty, belief disagreement, credit spreads, and stock returns. We focus on the following main questions, which give rise to the null hypotheses tested empirically in this paper:

Q1. What is the relation between uncertainty, belief disagreement, and credit spreads?
Q2. Does the interaction of uncertainty and disagreement create a structural link between stock return volatility and credit spreads?
Q3. What is the link between stock returns, uncertainty, and belief disagreement?
Q4. Does heterogeneity in beliefs help to explain capital structure no arbitrage violations of (single factor) credit risk models?

II. Model Predictions

We compute equilibrium quantities for a version of our model calibrated to the cash–flow dynamics of a representative firm in our sample. Table 2 summarizes the calibrated parameters. We assume a risk aversion of 2 and a firm cash-flow volatility of 7\% (Zhang, 2006). The calibrated parameters of the learning dynamics are consistent with the estimates obtained in Xia (2001) and Brennan and Xia (2001). In our comparative statics, we consider disagreement $\Psi_A(t)$ and $\Psi_S(t)$ between 0 and 0.2. The median difference in beliefs of firms’ future earnings in our I/B/E/S forecast data is 0.22.

A. Credit Spreads and Stock Return Volatility

We first study the joint relation of belief heterogeneity, credit spreads, and stock returns. This relation is driven by the effect of belief heterogeneity on the equilibrium firm value and the associated market price of default risk.

A.1. Disagreement and Credit Spreads.

What is the relation between belief disagreement and credit spreads? We find that in our model credit spreads and belief heterogeneity are in an unambiguous positive relation: An increase in the difference in beliefs reduces firm value and increases the risk premium of the default event, by lowering the risk-neutral skewness of the firm. These
mechanisms generate the higher credit spreads. To illustrate quantitatively these effects, the right panel of Figure 4 shows that as $\Psi_A(t)$ and $\Psi_z(t)$ increase from zero to 0.2, the senior credit spread increases by 29%, from 123 to 159 basis points, even for moderate levels of risk aversion. This increase is more than one standard deviation of the corporate credit spreads in our sample. Such an increase is economically significant, especially for senior secure investment grade bonds.

These findings give rise to a testable empirical prediction, which is directly related to the question Q1 raised at the end of Section I:

- Uncertainty-DiB and credit spreads are unambiguously positively related.

Remark: Standard structural credit risk models have difficulties in explaining the level of credit spreads, especially for firms with high credit ratings; See, e.g., Eom, Helwege, and Huang (2004), Huang and Huang (2004) and David (2007) for an alternative explanation. This is known as the “credit spread puzzle”. Ultimately, the question remains whether belief heterogeneity can help to provide at least part of an explanation to the puzzle. More precisely, the credit spread puzzle refers to the fact that it is difficult to reconcile high credit spreads with moderate probabilities of default and/or large credit spread volatilities. Table 3 summarizes the evidence about the credit spread puzzle in the context of our economy.

We consider a parameter choice $\overline{\mu}_\sigma = 0.008$ for the average market-wide uncertainty, which is reasonable in comparison to the calibrated “economic uncertainty” parameter of 0.0078 in Bansal and Yaron (2004). For the heterogeneity in uncertainty, we consider parameter values $\Delta \sigma_{\mu_x} = 0.001$, and 0.0015. This parameter choice yields a model-implied average disagreement of approximately 0.3.

We find that the model can generate reasonable credit spreads, default probabilities, and credit spread volatilities, even when risk aversion is not excessively high: For $\gamma = 2$ ($\gamma = 4$) the average credit spread is between 148 and 160 (152 and 165) basis points, while the model-implied probability of default is always less than the 4.3% default probability in the data. At the calibrated parameters, the model is also able to generate a substantial credit spread volatility, which can be as high as 32 basis points for a risk aversion $\gamma = 4$. As expected, the standard Merton (1974) model (i.e. $\Psi_A(t) = \Psi_z(t) = 0$) fails along these dimensions: For moderate risk aversion parameters, $\gamma = 2$ or 4, it delivers realistic default probabilities at the cost of abnormally low credit spreads and a credit spread volatility that is only slightly above half the volatility in the data. In order to obtain credit spreads levels comparable to the data, it is necessary to rise the risk aversion parameter to $\gamma = 12$. However, this at the same time rises the model implied default probability to an unrealistic level of 8.12%, which is about twice the default probability of the senior secured bonds in the data.
In summary, the results of this simple calibration show that the economic impact of Uncertainty-DiB on credit spreads can be substantial, via its influence on the equilibrium stochastic discount factor, thus creating an important potential link between credit markets and Uncertainty-DiB. These findings motivate a careful empirically analysis. In what follows, we first study the other joint implications of the model.

A.2. Credit Spreads and Stock Volatility

A second implication of the model is that disagreement increases equity volatility. This is a useful finding because Campbell and Taksler (2003), among others, have documented empirically a positive co-movement between credit spreads and the volatility of stock returns. Moreover, this co-movement exceeds the co-movement predicted by standard structural models and follows endogenously from the time-variation of the difference in beliefs. The left panel of Figure 4 illustrates quantitatively these effects: The volatility of equity increases from 7% to 29% as disagreement increases. For firms with lower leverage, not shown in Figure 4, the volatility increases to 20%. These volatilities are consistent with the average volatility of stock returns in our data set. Overall, these findings give rise to a second testable empirical prediction, which is related to question Q2 at the end of Section I:

- As Uncertainty-DiB varies, credit spreads and stock volatility co-move positively.

A.3. The Link between Difference in Beliefs and the Price of Default

In order to understand the economic mechanism linking belief disagreement, stock volatility, and the price of default risk, we investigate in more detail the firm value process in our economy. In Merton’s (1974) structural model \( (\Psi_A(t) = \Psi_z(t) = 0) \), the calibrated parameters imply a firm value of 161 and a (constant) firm value volatility of 7%. Figure 5 (left panel) shows that the firm value decreases as disagreement about cash flows or the signal increases: An increase in \( \Psi_A(t) \) and \( \Psi_z(t) \) from zero to 0.2 reduces the equilibrium (asset) value of the firm by approximately 1.5%. This effect lowers corporate bond prices, which contain a short put position on the firm value.

To understand this finding, it is convenient to write the stochastic discount factor of the optimistic investor in our economy as the marginal utility of a stochastic share \( s_i(t) \) of total consumption \( A(t) \):

\[
\xi_i(t) = \frac{1}{y_i} e^{-\rho t} A(t)^{-\gamma} s_i(t)^{-\gamma},
\]

where \( s_i(t) = c_i(t)/A(t) \) is investor’s \( i \) total consumption share. In the economy with homogeneous beliefs, \( s_i(t) \) is constant and the discount factor is proportional to the marginal utility \( A(t)^{-\gamma} \) of aggregate consumption. In the

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23Similar findings have been documented by Zhang, Zhou, and Zhu (2006), and Avramov, Jostova, and Philipov (2007), using reduced form models. Chen, Collin-Dufresne, and Goldstein (2008) and Bhamra, Kuehn, and Streubel (2008) obtain similar effects from a consumption-based equilibrium model.
economy with disagreement, $s_i(t)$ is greater (lower) in good (bad) aggregate cash-flow states and the marginal utility of the optimist has a larger (lower) impact on the stochastic discount factor in those states. Since in good (bad) states the marginal utility of the optimist (pessimist) is lower, the present value of future cash flows is lower, implying a lower equilibrium firm value than in the economy with homogeneous beliefs.\(^{24}\)

An important feature of the stochastic discount factor \(\Psi(t)\) is that its volatility is stochastic when the consumption share is stochastic. The volatility of $s_i(t)$ is stochastic and proportional to $\Psi(t)$, because it depends on the volatility of the ratio of individual marginal utilities of optimal consumption. Therefore the endogenous firm value process features a stochastic volatility that is increasing in the degree of belief disagreement. Figure \(\text{[middle panel]}\) illustrates quantitatively the effects of belief heterogeneity on the firm value volatility: At the calibrated parameters an increase in $\Psi_A(t)$ and $\Psi_z(t)$ from zero to 0.2 increases the equilibrium firm value volatility from 7\% to approximately 12.5\%. Since equity is a call option on the firm value, this mechanism generates a positive relation between belief heterogeneity and the stock volatility. At the same time, it further reduces the price of the short put position embedded in corporate bonds.

The negative endogenous co–movement of firm value and firm value volatility implies a moderate negative skewness of the physical firm value distribution, which implies at the calibrated parameters a moderate increase of the physical probability of default from 3.2\% (5.6\%) to 4\% (7.1\%) for low (high) leverage firms in the model with heterogenous beliefs.\(^{25}\) More importantly, the structure of the stochastic discount factor in the economy with heterogenous belief implies a positive relation between belief disagreement and firm value risk-neutral skewness, which directly increases the price of default states. Using Itô’s Lemma, the diffusion term in the dynamics of the stochastic discount factor is:

$$d\xi(t)/\xi(t) - E_\xi[d\xi(t)/\xi(t)] = - (\gamma \sigma_A + (1 - s_i(t))\Psi_A(t)) dW_A^1(t) - (1 - s_i(t)) \left( \alpha \Psi_A(t) \frac{\sigma_A}{\sigma_z} + \beta \Psi_z(t) \right) dW_z^1(t).$$

The volatility of the individual state prices is asymmetrically related to the consumption share in the economy: A positive cash-flow or signal shock lowers the volatility of the individual stochastic discount factor and vice versa. This feature follows from the decreasing marginal utility of consumption of the two investors. Figure \(\text{[right panel]}\) illustrates the positive link between belief heterogeneity and negative risk-neutral skewness quantitatively: An increase in $\Psi_A(t)$ and $\Psi_z(t)$ from zero to 0.2 decreases the firm value risk-neutral skewness from 0 to -0.5.\(^{26}\) This feature is important because it generates a substantial disagreement-induced risk premium for the default event,

\(^{24}\)To implement the optimal consumption plan, the optimist (pessimist) buys financial assets that finance the higher future consumption share in good (bad) cash-flow states. Therefore, in the competitive equilibrium the optimist sells financial protection against low cash-flow states to the pessimist. The additional risk of the stochastic consumption share is compensated in an asymmetric way because individual state prices are proportional to different marginal utilities.


\(^{26}\)Negative skewness can also be obtained in partial equilibrium models with jumps. See Pan (2002) for an application in option pricing, and Zhang, Zhou, and Zhu (2006), Cremers, Driessen, and Maenhout (2008) and Tauchen and Zhou (2006), for applications in credit risk. In our model, negative skewness arises endogenously, even if cash-flows and security prices do not include a jump component. To compute the risk-neutral skewness, we follow Bakshi and Madan (2000), who show that any payoff function can be spanned by a continuum of out-of-the-money calls and puts. The expression for the risk-neutral skewness is provided in the technical Appendix.
which can have a substantial impact on the price of default-dependent securities, even if the physical probability of default at the calibrated parameters is moderate.

B. Capital Structure Arbitrage

Single factor models inspired by the structural approach of Merton (1974) imply a negative correlation between stock prices and credit spreads. This link forms the basis of capital structure arbitrage strategies, which are based on relative value analysis and implemented using different parts of the capital structure, as well as over-the-counter contracts such as CDS. In our economy, the volatility and risk-neutral skewness of the firm value are stochastic. For firms with different degrees of leverage, we find that the price of equity can either increase or decrease with disagreement. This feature has important implications for the co-movement of credit spreads and stock prices, which is crucial for the successful implementation of capital structure arbitrage strategies. Figure 6 documents the ambiguous effect of an increase in the disagreement $\Psi_A(t)$ and $\Psi_z(t)$, conditional on a low or a high firm leverage.

For high leverage firms, an increase in $\Psi_A(t)$ and $\Psi_z(t)$ to 0.2 lowers the price of equity by 1 percent. For low leverage firms, the price increases by 3.1 percent. From our previous results, it follows that in the first case stock prices and credit spreads co-move negatively, while in the second case the co-movement is positive. This is an important departure from Merton’s (1974) model, because it implies that the standard hedge ratio might even change sign.

To understand the economic mechanism behind these effects, note that the stock price can be written as the price of a portfolio consisting of a long position in the firm value $V(t)$, a short position in $K_1$ risk-less zero bonds with price $ZCB(t)$, and a long position in an out-of-the-money put on the firm value, with strike $K_1$ and price $P(t, K_1)$ (we consider for brevity of exposition a firm without junior debt, with $K_1$ being the face value of the senior debt):

$$S(t) = V(t) - K_1 \cdot ZCB(t) + P(t, K_1).$$

$V(t)$ is independent of leverage and decreasing in disagreement. $ZCB(t)$ can be shown to be decreasing in disagreement for a relative risk aversion parameter greater than one. Thus, the effects of the first two components of the price of equity tend to offset each other, with the second component increasing proportionally to firm leverage. The price of the put option $P(t, K_1)$ has a positive impact on the price of equity, but the size of the effect depends significantly

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27 In this approach, corporate debt and equity are (non-linear but monotonic) contingent claims collateralized by the same balance sheet. Since the firm's cash-flows act as the single pricing factor, negative cash-flow shocks reduce the value of any claim in the capital structure. The correlation between corporate bond spreads and equity prices is restricted, by no-arbitrage, to be negative at all times and states.
and in a non-monotonic way on firm’s leverage. We find that for some regions of leverage this effect can be large enough to reverse the negative impact of the change in the value of the firm:

\[
\frac{dS}{d\Psi} = \frac{dV}{d\Psi} - K_1 \cdot \frac{dZCB}{d\Psi} + \left[ \frac{dP}{d\Psi} \cdot \frac{d\sigma_v}{d\Psi} + \frac{dP}{d\Psi} \cdot \frac{d\delta_v}{d\Psi} + \frac{dP}{d\Psi} \cdot \frac{dSkv}{d\Psi} \right].
\]

(7)

When leverage is high, the dominating effect on the price of equity comes from the first two terms in (7), as the Delta, Vega, and Skewness effects on the put price are all small. For very low leverage values, the put option and the position in the zero bond are a small fraction of firm value. Therefore, the price of equity is dominated by the first term in (7). For the intermediate leverage region, however, the price of the embedded out-of-the-money put option can be a non-negligible fraction of the firm value, and its sensitivity to increases in negative skewness (the last term in square brackets) is high. Figure 7 illustrates the trade-off between these effects as \( \Psi_A(t) \) changes from 0 to 0.20, dependent on firm leverage.

[Insert Figure 7 approximately here.]

For levels of leverage between approximately 0.01 and 0.03 the effect of the higher negative skewness is large enough to increase the price of equity as beliefs dispersion increases. The leverage region in which disagreement and stock price have a positive co-movement depends on the calibrated parameters in the model. For instance, for a relative risk aversion parameter \( \gamma = 4 \) this region is broader and contains leverage ratios between 0.01 and 0.06.

Overall, the following testable empirical predictions arise from our analysis, which are the direct counterparts to question Q3 and Q4 in Section I:

- The relation between stock returns and heterogeneity in beliefs is negative for highly levered firms, but it can switch sign for firms that are moderately levered.
- The co-movement of credit spreads and stock returns tends to be positive for highly levered firms, but is more likely to turn negative for firms that are less levered when Uncertainty-DiB is higher.

Remark: Similar to the findings for the firm value, the endogenous stochastic co-movement between the price and the volatility of equity generates an asymmetric physical stock price density. However, in contrast to the unambiguously negative sign of the skewness of firm value, the skewness of stock returns can be both positive or negative in our model: The positive (negative) co-movement between the price and the volatility of equity tends to generate stock returns that are positively (negatively) skewed.

Skewness has been found by several authors to be a key determinant of stock returns. Kraus and Litzenberger (1976) study a CAPM with investors that have preferences for skewness. Harvey and Siddique (2000) show that stocks with increasing prices when volatility spikes up have a positive skewness. Moreover, investors with preferences for skewness bid up the prices of assets with positive (co)skewness. Dittmar (2002) studies the impact of a non-linear pricing kernel in an economy, in which agents are averse to kurtosis and prefer positive skewness. Barberis and Huang (2007) study the impact of a preference for skewness in a Prospect Theory-type model with exogenously distorted beliefs. Brunnermeier, Gollier, and Parker (2007) analyze preferences for skewness in general equilibrium and find that positively skewed assets have lower expected returns. Recently, Conrad, Dittmar, and Ghysels (2007) link the higher prices of assets with positive skewness to the existence of stock market bubbles.

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III. The Data Sets

To empirically test the main implications of our model, we merge four data sets and match, for each firm, information on professional earnings forecasts, balance-sheet data, corporate bond spreads, stock returns, and stock option prices. The merged data set contains monthly information on 337 firms for the period 1996 – 2005.

A. Bond Data

The bond data is obtained from the Fixed Income Securities Database (FISD) on corporate bond characteristics and the National Association of Insurance Commissioners (NAIC) database on bond transactions. The FISD database contains issue and issuer-specific information for all U.S. corporate bonds. The NAIC data set contains all transactions on these bonds by life insurance, property and casualty insurance, and health maintenance companies, as distributed by Warga (2000). This database is an alternative to the no longer available database used by Duffee (1998), Elton, Gruber, Agrawal, and Mann (2001), and Collin-Dufresne, Goldstein, and Martin (2001). U.S. regulations stipulate that insurance companies must report all changes in their fixed income portfolios, including prices at which fixed income instruments were bought and sold. Insurance companies are major investors in the fixed income market and, according to Campbell and Taksler (2003), they hold about one-third of outstanding corporate bonds. These data represent actual transaction data and not trader quotes or matrix prices.

Initially, we eliminate all bonds with embedded optionalities, such as callable, putable, exchangeable, convertible securities, bonds with sinking fund provisions, non-fixed coupon bonds, and asset-backed issues. The data set contains information on the seniority level of the bonds. We are thus able to divide our data sample into senior secured and junior subordinated bonds. We manually delete all data entry errors. Moreover, to control for the possibility of residual errors, we windsorize our database at the 1% and 99% level. We are then left with a final database of 337 firms with senior secured bonds and junior subordinated bonds. Finally, to compute corporate bond credit spreads, we use zero-coupon yields available from the Center for Research in Security Prices (CRSP).

B. Uncertainty-DiB Proxies

To obtain our proxies of belief disagreement, we use analyst forecasts of earnings per share, from the Institutional Brokers Estimate System (I/B/E/S) database. This database contains individual analyst’s forecasts organized by forecast date and the last date the forecast was revised and confirmed as accurate. To circumvent the problem of using stock-split adjusted data, as described in Diether, Malloy, and Scherbina (2002), we use unadjusted data. In an initial step, we match analysts forecast data with the bond data. We extend each forecast date to its revision date. If an analyst makes more than one forecast per month, we take the last forecast that was confirmed.

29 Earlier data sets offered only indirect information about actual market prices, since values of non-traded bonds were estimated based on matrix algorithms.
30 E.g., if a forecast is made in July and last confirmed in September, then we use this information for the months July, August, and September.
C. Option Data

The option data is taken from OptionMetrics, LLC. This database covers all exchange listed call and put options on U.S. equities. With each trade, OptionMetrics reports the option’s implied volatility. Implied volatilities are calculated using LIBOR and Eurodollar rates, taking into account European and American exercise styles. We apply the following data filters to eliminate possible data errors. First, we exclude options which mature in the given month, since it is known (see, e.g., Bondarenko, 2003) that they suffer from illiquidity. Second, we eliminate all observations for which the ask is lower than the bid, for which the bid price is equal to zero, or for which the bid ask spread is lower than the minimum ticksize. In a first step, we take implied volatilities of single-stock options which are closest to at-the-money since these are known to be the most liquid ones. The implied volatility skew is calculated as the difference between the implied volatility of a put option with moneyness 0.92 and the implied volatility of an at-the-money put, scaled by the difference 0.92 − 1 in strike to spot ratios.

D. Control Variables

A large empirical literature has studied the determining factors of credit spreads and stock returns. A first obvious control variable in all our regressions is firm leverage, which is defined as total debt divided by the sum of total debt and the book value of shareholders’ equity. In the regression for credit spreads, we additionally control for firm size, defined as the log total book value of assets. Leverage and firm size data are retrieved from the COMPUSTAT database. We also add to our regressions earnings volatility, defined as the time-series sample standard deviation of quarterly earnings per share over the last eight quarters, scaled by lagged stock price. A second set of natural control variables captures business-cycle and term structure effects, as well as further systematic pricing factors. To this end, we include in the regressions for credit spreads and stock returns a NBER dummy, the monthly S&P500 returns and non-farm payroll. The NBER dummy is taking the value 1 in expansion periods, as defined by the NBER. A third set of control variables are the Fama and French factors. Fama and French show that a zero-cost factor mimicking portfolio exposed to the size and value premia can explain a considerable component of the cross-section of equity returns. Although corporate bonds and equity are different non-linear contingent claims, they are written on the same firm’s balance sheet. Thus, one might expect their dynamics to be driven by the same value/risk drivers and the Fama and French factors to be significant in explaining the cross-section of corporate bonds. Fourth, the recent literature studying determinants of corporate credit spreads emphasizes the role of liquidity risk. This literature is large and one of the debates is about the most appropriate measure of liquidity for corporate bond and equity pricing; see Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008) for a discussion. We apply two different proxies of liquidity. For the corporate bond spreads, we follow Fontaine and Garcia (2008) and use their

31The minimum ticksize equals USD 0.05 for options trading below USD 3 and USD 0.1 in any other case.
32Chacko (2006) and Downing, Underwood, and Xing (2007) study the pricing of liquidity risk in credit markets by constructing direct measures from the bond market. These studies focus on the impact of the liquidity level per se. de Jong and Driessen (2006) build liquidity risk factors, which represent systematic liquidity shocks in equity and government bond markets, similar to Acharya and Pedersen (2005), and show that corporate bond prices carry a substantial liquidity risk premium. Fontaine and Garcia (2008) extract an aggregate liquidity measure from the cross-section of on-the-run premia and show that this measure has a significant impact on risk premia for on-the-run and off-the-run bonds, LIBOR loans, swap contracts, and corporate bonds.
measure of aggregate liquidity, which is extracted from U.S. Treasuries. For equity returns, we apply the Pástor and Stambaugh (2003) liquidity measure.33

IV. Empirical Analysis

A. Proxies of Firm-Specific and Common Components in the Heterogeneity of Beliefs

In our model, belief disagreement of firms future earnings is defined as \( \frac{m^1_x - m^2_x}{\sigma^x} \), i.e., the difference of the subjective expected growth of cash flows, scaled by the volatility of cash flows. For each firm, we can proxy disagreement about future cash flows by the mean absolute difference of the available earnings forecasts for this firm, scaled by an indicator of firm earnings uncertainty. Since direct data on subjective earning uncertainty of individual analyst forecasts are not available, we proxy earnings uncertainty by the standard deviation of earnings forecasts. Therefore, we proxy belief disagreement about future firm earnings by the ratio of the mean absolute difference and the standard deviation of earnings forecasts.34

In the theoretical model, disagreement about the market-wide signal \( z(t) \) represents belief heterogeneity about common information of firm-specific and market-wide growth \( \mu_A(t) \) and \( \mu_z(t) \). The common disagreement component implied by the heterogeneity in beliefs about signal \( z(t) \) is given by:

\[
\frac{1}{\sigma_z} \left( E^1 \left( d_z(t) | F_t^{A,z} \right) - E^2 \left( d_z(t) | F_t^{A,z} \right) \right) = \frac{\sigma_A}{\sigma_z} \Psi_A(t) + \beta \Psi_z(t) ,
\]

and is a weighted sum of disagreement indices about individual firm and market-wide economic growth, with weights dependent on the relative signal-precision and the market-wide content of information provided by signal \( z(t) \) (i.e. weights \( \alpha \) and \( \beta \)). This expression motivates a number of potentially successful approaches to compute an empirical proxy for the common disagreement component in our model.

In principle, one could construct the common disagreement proxy either (i) from a cross-section of forecasts about an aggregate economic index or (ii) by working directly with firm-specific data and compiling a metrics from the whole cross-section of firms. In this paper, we follow the second approach for a number of reasons. First, even if analysts may agree on the general market movements, which would imply a small disagreement proxy computed from the aggregate index, it is possible that they might strongly disagree about a sector or a firm that systematically lags or leads the overall market. Neglecting this information can generate disagreement proxies with a too low time-series variability, disregarding an important dimension of the belief heterogeneity for asset pricing purposes. Second, a disagreement proxy computed from an aggregate index is likely to have a low signal-to-noise ratio, because it is

33We thank René Garcia for providing us their data. Pástor and Stambaugh (2003) find that during months with low liquidity, the correlation between their liquidity proxy and the return on corporate bonds is found to be as large as -27%. However, in our data, we find a very weak relationship between their measure and corporate credit spreads. We therefore prefer the liquidity measure by Fontaine and Garcia (2008), which they show has a significant impact on corporate credit spreads, using the same data as we do. Vice versa, their measure has a marginal impact on the equity market. We therefore rely on the Pástor and Stambaugh (2003) measure in this case.

34We considered also other proxies of firm-specific disagreement proposed in the literature, but we found our proxy to dominate in term of both cross-sectional and time series explanatory power. Results are available upon request from the authors.
computed from a low number of forecasts, e.g., 2 to 20, depending on the time period. In contrast, an aggregate proxy computed from the information of a large cross-section of firms or sectors can be based on thousands of forecasts each month. Third, proxies based on a large number of forecasts can better mitigate the effect of behavioral biases in analyst forecasts; see e.g., De Bondt and Thaler (1990), and Chan, Karceski, and Lakonishok (2003).

We construct our common Uncertainty-DiB proxy by estimating with dynamic factor analysis a common dynamic factor from the cross-section and the time series of individual disagreement proxies $\Psi_i(t)$ extracted from analyst earning forecasts. This approach allows us to split in a dynamically coherent way each individual disagreement proxy $\Psi_i(t)$ into a common and an idiosyncratic component that are mutually orthogonal. This feature simplifies the interpretation of the effect of each disagreement component on asset prices.

Let $\Psi_i(t)$ be the disagreement proxy computed from the cross-section of earning forecast of firm $i$ at time $t$ and suppose the following dynamic factor structure:

$$\Psi_i(t) = \sum_{k=1}^{q} b_{ki}(L)u_k(t) + \xi_i(t) := \chi_i(t) + \xi_i(t) \quad ; \quad i = 1, \ldots, n,$$

where $u_1(t), \ldots, u_q(t)$ is a set of $q$ orthonormal common white noise shocks, $b_{i1}(L), \ldots, b_{iq}(L)$ are firm-specific infinite-order lag polynomials, and $\xi(t) = (\xi_1(t), \ldots, \xi_n(t))^\prime$ is a possibly cross-correlated zero-mean stationary process, orthogonal to all common shock processes, which models the idiosyncratic component of the vector of individual belief disagreement proxies. Forni, Hallin, Lippi, and Reichlin (2000), show that the individual common components $\chi_i(t)$ can be consistently estimated by the projection $\hat{\chi}_i(t)$ of $\Psi_i(t)$ on all leads and lags of the first $q$ dynamic principal components extracted from the spectral density of the multivariate vector $(\Psi_1(t), \ldots, \Psi_n(t))^\prime$.

By inspecting the dynamic eigenvalues of this spectral density, we find that $q = 2$ common factors are plausible in our context. We then obtain a single proxy $\hat{\chi}(t)$ for the common disagreement across firms by averaging the estimated individual common components $\hat{\chi}_i(t)$ over the cross-section of firms, using as weight the firm’s market-capitalization: $\hat{\chi}(t) := \frac{1}{n} \sum_{i=1}^{n} w_i(t) \hat{\chi}_i(t)$, where $w_i(t)$ is the market-capitalization weight of firm $i$.

Given the estimated common factor $\hat{\chi}(t)$, we isolate the individual firm components of $\Psi_i(t)$ for any firm $i$ in our cross-section by computing the time-series residuals $\hat{\xi}_i(t)$ from a regression of the individual disagreement proxy $\Psi_i(t)$ on the common factor $\hat{\chi}(t)$: $\hat{\xi}_i(t)$ is our proxy of firm-specific disagreement for firm $i = 1, \ldots, n$ in all our estimations. In this way, we are able to consistently disentangle in our empirical study common from firm-specific disagreement.

We explicitly make use of a dynamic factor model and a dynamic principal component analysis, instead of a static one, in order to estimate the common and the firm-specific disagreement proxies. We find that this an important issue in order to account properly for (i) the heterogeneity in lag-lead relations across firm-specific analyst forecasts over the business cycle and (ii) the different persistence properties of individual disagreement proxies in the large cross-section of firms. The dynamic approach has also the advantage of embedding several alternative approaches as special cases. By construction, dynamic principal components collapse to static principal components when the
common belief components $\chi_i(t)$, $i = 1, \ldots, n$, do not contain any dynamic effects. Similarly, if the factor structure is of the simple single-factor form:

$$\Psi_i(t) = u(t) + \zeta_i(t) \quad ; \quad i = 1, \ldots, n,$$

with $u(t)$ a white noise sequence, then $\hat{\chi}_i(t) = \frac{1}{n} \sum_{i=1}^{n} \Psi_i(t)$: The estimated common component of any individual disagreement proxy $\Psi_i(t)$ is the cross-sectional average of the individual proxies.

In order to understand the potential implications of different proxies for the common disagreement in our context, it is useful to compare in Figure 8 the time series of common disagreement proxies estimated by different methods:

- Dynamic factor analysis and principal components of individual disagreement proxies
- Static factor analysis and principal components of individual disagreement proxies
- Value-weighted average of individual disagreement proxies
- Common disagreement proxy computed using industrial production forecasts from BlueChip Economic Indicators.

The time series in Figure 8 display a strikingly different behavior, reflecting the very different way in which they account for latent dynamic effects in the supposed factor structure.

[Insert Figure 8 approximately here.]

The proxy implied by dynamic factor analysis has a low negative unconditional correlation with all other proxies, is the most persistent one, and it is the only one showing a counter-cyclical behavior around all crisis periods in our sample. The proxy based on forecasts of a macro aggregate, namely industrial production, has a low signal-to-noise ratio that generates very little explanatory power for credit spreads. Proxies computed from static principal components and value-weighted averages have a high correlation with the proxy computed from dynamic factor analysis after the second half of 2002, even if with a less pronounced counter-cyclical pattern. Before 2002, however, these proxies grossly fail to reproduce an economically reasonable pattern of counter-cyclical economic uncertainty, suggesting that measures of Uncertainty-DiB derived from aggregate macro measures are less informative than measures based on firm-specific and sector information.

B. The Dynamics of Earnings Uncertainty

We start by investigating the cross-sectional and time-series properties of our proxies of earning uncertainty. A first result is as much interesting as striking: A single common component estimated using dynamic factor analysis can explain more than 87% of the time-series variation of the cross-section of individual firm disagreement proxies.

In a different context, Yu (2009) suggests the value-weighted average of individual disagreement proxies as a proxy for a common disagreement component.
This is indeed remarkable given that we are considering a cross-section of more than 337 firms, thus suggesting a large systematic component driving difference in beliefs on firms’ growth opportunities. The common disagreement component is highly time varying and it exhibits a strong counter-cyclical behavior. It has an average of 0.38, with a minimum (maximum) value of 0.12 (0.78), and a standard deviation of 0.13. The average firm-specific disagreement component is 0.22. The firm-specific disagreement is also highly volatile and it exhibits a substantial cross-sectional dispersion: The minimum (maximum) firm-specific disagreement is 0.01 (0.82), and its average time-series standard deviation is 0.14.

A second feature of the common disagreement component is that it typically rises in the six months before crisis periods and decreases shortly afterwards: The average increase of the common disagreement proxy in the six months before a crisis period is 41% and the average decrease six month after the crisis is around 34%. To illustrate the counter-cyclicality of the common disagreement more systematically, Table 1 summarizes its dynamics during all economic and financial crises since 1990, together with the average increase six months before and after each crisis. Figure 1 plots this time-series alongside an indicator of financial or economic crises (area shaded in blue) and the VIX index, and clearly shows that recessions and financial crises are periods of higher uncertainty. Interestingly, this relationship is stronger for the common disagreement proxy than for the VIX index, which is often used as a proxy for fear. The notable spikes in the graph are the ERM crisis in 1992 and the DotCom bubble burst in 2000. With regards to the first crisis, the increase in the systematic disagreement is 50% and for the latter it is 125%. Six months after the crisis, the decrease is 40% in 1992 and 65% in 2001. Both events generated a large increase in the disagreement proxy, without a substantial effect on the VIX, suggesting that earning uncertainty and the VIX have different empirical properties.

Finally, the common disagreement proxy exhibits a strong co-movement with the default spread (black dotted line in Figure 1: difference between Moody’s Baa and Aaa bond yields) and its unconditional correlation with the average corporate credit spread in the whole sample is 0.52. For instance, in 1992 the default spread increased from 50 basis points. One could argue that the VIX and the disagreement proxy have a similar economic denominator: They both allegorize a forward-looking perspective, in that they capture perceptions of risks contained in investors’ expectations. Yet, these two measures are conceptually very different. The VIX is calculated from financial prices itself. The disagreement proxy is constructed from forecast data, which is intimately linked to investors’ expectations.
points to 90 basis points, and it sharply dropped after the crisis to revert back to its initial level. Before the DotCom bubble burst, the default spread almost increased threefold and later dropped back to 20 basis points.\footnote{It may be not completely surprising to find a positive correlation between our common difference in beliefs proxy and default spreads, given the counter-cyclical nature of default spreads. What is surprising, however, is the size of the correlation: When we stratify the sample and focus on periods of financial and economic crises, the correlation between default spreads and the common component in difference in beliefs increases to 0.69.}

In what follows, we study more systematically the empirical links between uncertainty and asset prices suggested by our theoretical model. Our empirical study is articulated around two independent sets of testable implications. First, we use pooled panel regressions to investigate the impact of both individual and common disagreement proxies on corporate credit spreads, after controlling for other explanatory factors. Second, we study a number of testable implications in terms of capital structure arbitrage restrictions. This second line of investigation provides an important independent set of information on the role played by Uncertainty-DiB in credit markets.

C. The Dynamics of Credit Spreads

In our model, belief disagreement unambiguously increases credit spreads. Therefore, in panel regressions of credit spreads on differences in beliefs we expect a positive slope coefficient for the disagreement, independent of other controlling factors. We investigate the relevance of disagreement proxies with respect to several empirical reduced-form models in the literature. Accordingly, we consider the following empirical specifications, which embody specific sets of control variables previously studied in this literature: (1) Implied volatility and option-related factors; (2) Macro-financial factors; (3) Firm-specific factors, (4) Fama and French, liquidity, and volatility factors. Model (5) includes all determinants, while model (6) includes only statistically significant regressors.

In model (1), we control for the equity implied volatility and other option-related variables. This aspect is important as Cremers, Driessen, Maenhout, and Weinbaum (2006) and Cao, Yu, and Zhong (2007) find that the option-implied volatility and skewness are powerful explanatory factors of corporate credit spreads, both in the cross-section and in the time-series. They interpret these variables as proxies for a volatility and jump risk premium component in credit spreads. In our model, the option implied volatility and skewness are indeed important and are correlated with credit spreads. However, both option implied volatility and credit spreads are endogenously driven by heterogeneity in beliefs, so that the information contained in option-implied volatility should be subsumed by heterogeneity in beliefs. Table \ref{table:results} summarizes the results for model (1). Indeed we find that, after controlling for the difference in beliefs, the option-implied volatility, which is significant in univariate regressions, is no longer statistically significant. This is an important result since it suggests that option-implied (risk neutral) volatility is highly correlated with uncertainty, rather than being a pure proxy for measurable and uncertainty-free jump risk. The two disagreement proxies and the option-related variables explain 58% of the variation in corporate credit spreads. Both the individual uncertainty and common uncertainty proxies are highly statistically significant and the estimated coefficient has the expected positive sign. We also find that the marginal impact of changes in Uncertainty-DiB on credit spreads is economically important. Given that the cross-firm average of the standard deviation of a monthly change in belief disagreement is 0.18, the slope parameter estimates imply that a one-standard deviation change in the firm-specific
belief disagreement leads to an increase of approximately 18 basis points in corporate credit spreads. The effect of the common disagreement is slightly smaller. The standard deviation of the common disagreement is 0.13, hence, a one standard deviation change in the common disagreement leads to an increase of approximately 10 basis points. The adjusted $R^2$ of the regression is 0.54. This means that the disagreement proxies together with the option implied variables explain half of the time-series and cross-sectional variation of corporate credit spreads.

In model (2), we include macro-financial variables as controls. Controlling for these variables is relevant for three reasons. First, Collin-Dufresne, Goldstein, and Martin (2001) show that macro-financial variables such as the risk-free rate level and the slope of the yield curve are correlated with credit spreads. Thus, in addition to these variables, we also consider a NBER dummy. Second, Huang and Kong (2007) show that macroeconomic announcements of business-cycle related variables have a significant effect on corporate credit spreads. Among many possible announcement variables, we use non-farm pay-roll as a further control for the state of the economy. These variables are clearly potentially important, as macroeconomic conditions are related to both the probability of default and the recovery rate. Non-farm pay-roll is labeled by Andersen and Bollerslev (1998) the “king” of announcements. Moreover, Beber and Brandt (2007) document that it is the most influential macro announcement variable. Third, given the relative importance of a single market-wide factor in explaining the dynamics of differences in beliefs, it is interesting to measure the extent to which the role of the differences in beliefs is subsumed by the realizations of macro-financial and macro-economics variables. Does earning uncertainty play an independent role? The results in Table 4 (second column) show that, in addition to the firm-specific and common uncertainty proxy, the risk-free rate and non-farm pay-roll are highly significant. The NBER dummy is significant and has an expected negative sign. The sign of the coefficient for the other macro-financial variables is consistent with the findings in Collin-Dufresne, Goldstein, and Martin (2001). We find that, even after controlling for macroeconomic factors, the Uncertainty-DiB measures are both statistically and economic significant. Interestingly, however, when we control for these factors the size of the slope coefficient on the common component of the difference in beliefs declines from 0.718 to 0.476, supporting the conjecture that market-wide Uncertainty-DiB interacts with macroeconomic announcements (non-farm payroll and NBER recessions). The intuition is inline with Figure 1 which documents that the periods with the largest difference in beliefs coincide with the beginning of financial and economic crisis. However, the statistical and economic importance of the difference in beliefs is substantially larger than the one of any other explanatory variable, thus supporting the interpretation that Uncertainty-DiB, although clearly affected by the information flows on economic fundamentals, plays a role in explaining credit spreads.

Model (3) controls for firm-specific features. Leverage is an obvious control variable as it is positively related to the probability of default in structural models of credit risk, and it is found to be an important explanatory variable of credit spreads, as documented – among others – by Avramov, Jostova, and Philipov (2007). We also control for firm size, to proxy for the higher sensitivity of smaller firms to business-cycle factors (Fama and French, 1993). In the third column of Table 4, the regression results show that both the individual and common disagreement proxies are highly significant, despite the significance of leverage and firm size. Consistent with economic intuition, these

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38The negative coefficient of the risk-less rate is consistent with the intuition that a higher risk-neutral drift of the firm value process reduces the risk-neutral probability of default; see, e.g., Longstaff and Schwartz (1995).
variables have a positive estimated coefficient. Moreover, their significance is robust to the inclusion of additional control variables in model (6). If we compare their coefficients with the size of the disagreement slope coefficients, we find that given a standard deviation of 0.08, a one standard deviation change in leverage leads to a 3 basis points increase in corporate credit spreads, which is six times smaller than the contribution of the systematic disagreement, for instance. Firm size contributes to approximately 4 basis points. Even in this specification, Uncertainty-DiB is the factor with the highest statistical and economic significance with respect to any other control variable.

In model (4), we control for the Fama and French, liquidity, and volatility factors. Schaefer and Strebulaev (2008) find that corporate bond prices are significantly influenced by two Fama-French factors and the VIX implied volatility index. In our regressions, we use implied volatilities from individual stock options, rather than the aggregate index option implied volatility, to improve the granularity of the information provided by the risk neutral implied volatility. Longstaff, Mithal, and Neis (2005) find that a large fraction of the non-default component of corporate credit spreads can be related to illiquidity, and Fontaine and Garcia (2008) show that their aggregate measure of liquidity extracted from on-the-run premia is a good predictor of the default spread. The fourth column of Table 4 shows that even after controlling for these factors, both the individual and common disagreement measures are highly significant with t-statistics well above 5. Some of the additional explanatory variables, which are significant in univariate regressions, such as the market and Fama-French factors, are no longer significant after controlling for the two Uncertainty-DiB measures. There are three important exceptions: earning volatility, SMB size factor, and aggregate liquidity. Earnings volatility and the size factor have the expected positive sign and the liquidity factor has the expected negative sign. The result on the earning volatility is interesting since this variable plays a key role in any Merton-type structural model of credit spreads. Our regressions confirm this link but add a potentially interesting element to our understanding of it. When we regress credit spreads on both earning volatility and differences in beliefs, we find that a one standard deviation change in earnings volatility accounts for an approximate increase of 4 basis points in credit spreads. On the other hand, the effect of Uncertainty-DiB is statistically more significant and economically seven times larger. Our results regarding the liquidity factor are in line with those in Fontaine and Garcia (2008). For corporate credit spreads of higher credit quality, they find a highly significant and negative impact of liquidity on the spreads. They also argue that higher aggregate illiquidity valuation is associated with higher aggregate uncertainty and use the VIX to show that the aggregate uncertainty indeed impacts on aggregate liquidity. In contrast, we study liquidity and uncertainty jointly and show that the effect of Uncertainty-DiB is beyond the one of liquidity in terms of statistical power and economic importance.

In model (5), we run a regression including all explanatory factors. The statistical significance of the individual and common disagreement proxies remain remarkably high. Quite surprisingly, the economic significance remains stable even when we include all other variables. In terms of adjusted $R^2$, we find that all determinants together explain approximately 80% of the time series and cross-sectional variation of corporate credit spreads.

\footnote{We use a one-year moving average to calculate the volatility. Moreover, the earning volatility is scaled so that it has the same time-series standard deviation as the corresponding average implied volatility.}

\footnote{Avramov, Jostova, and Philipov (2007) also find that Fama and French factors lose their significance for credit spreads when combined with other control variables.}
In model (6), finally, we run the regression with only the explanatory factors that were found significant in the previous specifications (1)-(5). The main result do not change. Overall, our results show that the explanatory power of both the individual and common disagreement for credit spreads is high and robust with respect to several common control variables. These findings are remarkably robust also with respect to a stratification of the sample with respect to firm leverage.

[Insert Table 4 approximately here.]

D. The 2008 Credit Crisis: An Out-of-Sample Case Study

When in September 2008 the former U.S. Treasury Secretary Paulson announced the plan to setup an entity akin to the Resolution Trust Corporation (RTC), memories about the bygone savings and loan (S&L) crisis of 1990 aroused. Similar to the current crisis, the S&L crisis propagated after a housing boom bust and the failure of thousands of U.S. saving and loans associations. As a response, the U.S. government formed the RTC to help to liquidate “toxic” assets that it inherited from insolvent thrifts with a bailout package of USD 150 billion. The bailout compounded the large U.S. budget deficits of the early 1990s and contributed to the 1990-1991 recession. We remember from Table 1 that this economic slump came with a large surge in uncertainty. The question of whether we descry a similar pattern also in the recent credit crisis begs to be answered, in particular, as this offers an additional out-of-sample test of our hypotheses.

The main driver for the recent crisis was an increase in subprime mortgage defaults, which was first noted in February 2007; even if, to some extent, defaults on subprime mortgages were likely expected. The subprime market is the riskiest segment of the mortgage market, so it is hardly surprising that some borrowers default on their loans. Yet the incidences of defaults have been the catalyst for the crisis, which has ensnared not only housing markets, but also commodity, stock, and bond markets. How could this happen? A critical issue has been the difficulty of valuing structured credit products. As argued by Brunnermeier (2009), a possible trigger was the extent of securitization. For years, the asset-backed securitization markets fueled the explosion in consumer borrowing, allowing lenders to easily spread their risk to other investors like pension funds, hedge funds, and insurers. Securitization not only made the exposure of institutions to credit counter-party risk more opaque, increasing systemic leverage, but it also made these products more difficult to value. This, however, has direct implications on the valuations of asset prices. In a fair value accounting framework and with liquid markets, it is straightforward to value standardized instruments.

There are three levels used for classifying the type of fair valuation employed: Level 1 – quoted price in an active market; Level 2 – valuation using prices of related instruments; Level 3 – prices cannot be observed and model prices

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41 See e.g., “Subprime Defaults to Soar, Hurt Lenders, Funds Say”. Bloomberg, March 15, 2007.
42 One example of the gravity of the valuation problem was highlighted when in August 2008 BNP Paribas froze three hedge funds, stating that it was impossible to value the assets (nota bene, assets rated AA or higher). The asset values are reported to have fallen from USD 3.47 billion to USD 1.6 billion. In the third week of August, BNP Paribas announced that it had found a way to value the assets.
or management guesses need to be used. Model prices are used for marking-to-model third level assets. Inferring the parameters necessary to use the model becomes problematic in turbulent markets as observed prices might be well below their “true” value. This, however, increases the uncertainty associated with the valuation of instruments held in portfolios, which feeds back into the market turmoil: Lenders want collateral for their loans, but trepidation in the markets increases the potential for disagreement between borrowers and lenders over the valuation of the collateral. The heightened economic uncertainty manifests itself in Figure 2 (lower panel) where all sectors have witnessed a clear surge not only in default risk but also in uncertainty since mid 2007.

The origins of the recent crisis, which choked off the arteries of finance across all markets, are found in the financial sector. It started in 2007 when HSBC, then the world largest bank, wrote down subprime related mortgage backed securities by USD 10.5 billion. What happened to the uncertainty in the financial sector at this time? A bird’s eye view on Figure 2 (upper panel) reveals that at the end of 2007 and most notably in March 2008, the Uncertainty-DiB for both the financial and banking sector spiked. March 2008 was also the month when Bear and Stearns collapsed and the Dow Jones Industrial Average hit its lowest level since 2006. A second notable spike in the banking sector occurred in late summer 2008, which coincides with the collapse of Lehman Brothers in September 2008. Thereafter, in November 2008, the Uncertainty-DiB drops considerably to less than one fourth. One interpretation of this sudden drop could be the temporary quiet before the next storm, which was caused by mainly two events: First, the remaining investment banks like Goldman Sachs and Morgan Stanley converted to bank holding companies. At the same time, the U.S. government agreed on rescuing Citigroup with an additional injection of USD 25 billion. Second, in October 2008, the U.S. president signed the Emergency Economic Stabilization Act into law which, after being first rejected in September by the House of Representatives, was meant to “create liquidity and promote price discovery in the markets for these assets, while reducing investor uncertainty about the current value and prospects of financial institutions.” Interestingly, the surge in the uncertainty in the financial sector is followed by an increase of uncertainty in the real sector. For instance, in Figure 2 (lower panel), we see that the energy sector Uncertainty-DiB increased right after the ascent of the uncertainty in the financial sector. To nail it down with some numbers: From March 2007 to April 2008, the Uncertainty-DiB in the banking sector increased by a factor of 10 while in the financial sector the increase was fourfold. The increase in the energy sector, however, was slightly lagged: The peak in the Uncertainty-DiB was in July 2008. By this time, the energy Uncertainty-DiB more than doubled. This finding is intuitive, as the largest investment banks such as Goldman Sachs or Morgan Stanley were the major players in the

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44 In the first quarter of 2008, level 3 assets have increased in U.S. banks. Goldman Sachs reported an increase of 40% of these assets to reach a total of USD 96.4 billion of which USD 25 billion are asset backed securities. Level 3 assets were USD 78.2 billion and USD 42.5 billion for Morgan Stanley and Lehman Brothers, respectively. In Bear Stearns High Grade Structured Credit Strategies Enhanced Leveraged fund, over 63 percent were valued using models, and this is said to be one of the causes of the collapse of Bear Stearns (see Goldstein and Henry, 2007).


46 On April 2, 2009, the Financial Accounting Standards Board has relaxed the mark-to-market accounting rules. The new guidance allows banks to ignore prices achieved in competitors’ asset sales to help determine the market value of similar securities held. In essence, banks are now allowed to ignore transactions in which the seller is near bankruptcy. By shifting toxic and impaired securities from level 2 to level 3 and therefore letting banks use internal models instead of market prices, companies weighed down by mortgage-backed securities, such as Citigroup, could cut their losses by 50 percent to 70 percent (see, Bloomberg, Mark-to-Market Lobby Buys Bank Profits 20% as FASB May Say Yes, March 30, 2009).

47 Testimony before the U.S. Senate on September 23, 2008, by Federal Reserve Chairman Ben Bernanke.
commodity market. What was the impact of this increase of uncertainty on asset valuation? The general picture in Figure 2 (lower panel) reveals two interesting points: First, an increase in uncertainty is shortly followed by a rise in the asset swap spread. Second, the effect in the crisis period seems to be more pronounced. Is this a general pattern across different sectors? To answer this question, we estimate the relationship between asset swap spreads and uncertainty using simple linear regressions. We run predictive regressions to examine whether Uncertainty-DiB indeed predicts asset swap spreads and study two different periods (Pre-Crisis: March 1997 to March 2007 and Crisis: March 2007 to December 2008), in order to examine whether the impact of uncertainty is larger in crisis periods.

Table 5 (Panel A) reports estimated coefficients for the predictive regressions at different horizons. The results are striking. Contemporaneously, all estimated coefficients are highly significant. Across all sectors, a one standard deviation shock to Uncertainty-DiB increases on average the asset swap spread by 57 basis points. Up to a horizon of three months, estimated coefficients remain significantly different from zero and estimated coefficients remain remarkably stable at different horizons. For the information technology, services, financial, and banking sector, the Uncertainty-DiB predicts asset swap spreads even at a horizon of one year. In Panel B, we run contemporaneous regressions from asset swap spreads on Uncertainty-DiB for each of the two periods. Clearly, the much smaller sample size for the crisis period causes a loss of statistical power. Nevertheless, it is interesting to consider the coefficient estimates, which are consistently positive, as in the pre-crisis sample regressions. The estimated slope coefficients tend to be larger in the crisis period. Moreover, they are also more significant in half of the cases, despite the larger standard errors.

From a cross-sectional perspective there are several notable points. First, the largest (smallest) increase in the asset swap spread came with the largest (smallest) surge in the Uncertainty-DiB. From March 2007 to December 2008, the asset swap spread in the banking sector surged by a factor of 15. At the same time, the Uncertainty-DiB, which peaked in April 2008, increased threefold. The smallest ascent in default risk was witnessed in the services sector: During the crisis, the asset swap spread increased by a factor of 6. However, this sector also had the smallest increase in Uncertainty-DiB: During this period, the increase in uncertainty was less than double. Second, the cross-sectional dispersion of estimated coefficients is larger in the pre-crisis period than in the crisis period. In the pre-crisis period, the smallest coefficients is 0.14 and the largest 0.67, while in months of economic crisis the difference between the smallest and largest estimated coefficients is only 0.42. This is intuitive, as one would expect that in times of distress idiosyncratic and sector-wide uncertainty cluster, due to prevalent systematic uncertainty. Overall, the results for the credit crisis case study suggests a clear positive relation between Uncertainty-DiB and corporate credit spreads, which might be even stronger during the credit crisis than in the pre-crisis sample period. These findings are consistent with our model and make the link between these two components apparent, notwithstanding the different properties of the two time periods considered in our mini-case study.

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48 We report Newey and West (1987) standard errors. We also applied Hansen and Hodrick (1980) standard errors. The results remain quantitatively the same.

49 A principal component analysis yields that in the pre-crisis period the first principal component explains 74% of the variance in the Uncertainty-DiB, while in the crisis period the fraction explained is 92%.
Capital structure arbitrage has become increasingly popular among long/short, multi-strategy, event driven hedge funds. The success of these strategies depends on the empirical realism of the key assumptions on the joint behavior of the value of debt and equity, such as the sensitivities of corporate bond prices to changes in the price of equity. Anecdotal evidence suggests that this relationship often fails. However, although it is very relevant from a practical point of view, we know very little about this link both at an empirical and theoretical level. Nonetheless, the joint behavior of the value of debt and equity offers powerful additional information about alternative models of credit spreads.

While much of the literature has focused on predicting corporate bond price levels, second moment predictions like hedge ratios have so far been mostly neglected. The hedge ratio of standard single-factor models takes the form $(1/\Delta_S - 1)S/D$, where $\Delta_S$ is the sensitivity of the price of equity to the underlying price of the corporate bond and $S/D$ is the inverse leverage ratio. In contrast to single-factor models such as the Merton model, our theory implies that the sign of $\Delta_S$ might be both positive or negative, depending on the leverage of the firm, and that Uncertainty-DiB could play a role in explaining some of the violations.\footnote{A prominent example of a failure of capital structure arbitrage occurred in May 2005, when General Motors (GM) and Ford got downgraded to junk status. Before May 2005, many hedge funds sold CDS on GM and hedged their exposure by shorting the equity (or by creating a long volatility position in GM options). The rationale for this strategy was that, consistent with the structural Merton model, wider credit spreads would be accompanied by a drop in the share price (or an increase in the option implied volatility). After the downgrade of GM to junk status by Standard & Poor’s, credit spreads on a 10 year CDS increased by almost 200 basis points in one month. The share price, however, rose almost 25% to 32.75 USD, and the implied volatility of short-term at-the-money options on GM increased by 50% to reach 62.73%. Many widely known hedge funds engaging in capital structure arbitrage posted large losses and the state of the hedge fund industry obtained center stage in the financial press.}

To simplify our discussion, we first specify the main object of our analysis.

**Definition 2.** We define a violation event when $\Delta CS \cdot \Delta S > 0$, where $\Delta CS$ is the change in the credit spread and $\Delta S$ the change in the corresponding individual stock price.

The different co-movement of stock returns and credit spreads for different leverage regions in our model suggests that a violation according to Definition 2 is more likely to arise for low leverage firms and when disagreement is large. This gives rise to the following testable implication related to question Q4:

- Arbitrage violations according to Definition 2 are more likely to arise for moderately levered firms and when Uncertainty-DiB is high.

In the sequel, first we compare the empirical and model-implied frequency at which arbitrage violations of single-factor models occur. Then, we use panel Logit techniques to learn additional conditional properties of the data.

**E.1. Unconditional Violations and the Model**

We use the calibrated parameters in Table 2 to simulate our model and calculate the occurrence frequencies of this violation. The results are reported in Table 5 Panel A.
The unconditional average frequency of a violation in the data is approximately 13.9% (see Table 6, Panel B). This is a large number, considerably higher than other no-arbitrage restriction violations studied in index option markets. For instance, Bakshi, Cao, and Chen (2000) study violations of the one factor Black and Scholes (1973) model in index option markets and find that the probability that the delta of a call (put) is negative (positive) is between 1% and 4%, depending on the moneyness level. The frequency of occurrence of capital structure violations is larger by a factor of almost 5.

When we simulate the model with Uncertainty-DiB using the same calibrated structural parameters as in previous sections (see in Table 2) and allowing the $\Psi(t)$ to be time-varying, we find that the model can generate endogenous capital structure violations: The model-implied frequency is equal to 16.2%, which is quite close to what is observed empirically. Even more interestingly, after we stratify the sample with respect to firm’s leverage, we find that the empirical violation frequency is substantially higher (18.9%) for firms with low leverage than for firms with high leverage (14.3%). This result is consistent with the results obtained from the simulation of the model, where we find that the violations are 15.3% for low leverage firms and 12.2% for high leverage firms. Thus, the model helps to explain another feature of the data that traditional models cannot explain. This last finding is relevant since the way in which the model succeeds in generating an additional component in the default spread is by introducing an additional priced risk factor, Uncertainty-DiB, in the pricing kernel. This feature decreases firm value, increases equity return volatility and credit spreads, which could have been generated in other ways, but it also implies a co-movement of different parts of the capital structure which is consistent with the role of Uncertainty-DiB, after taking into account cross-sectional differences in leverage.

E.2. Conditional Violations and Uncertainty-DiB

Obviously, the previous unconditional results do not necessarily imply that Uncertainty-DiB is the only significant factor explaining no-arbitrage violations, since they might be explained, e.g., by either a misspecification of the one factor Merton (1974) model or market frictions.

Acharya, Schaefer, and Zhang (2008) study in much detail the GM and Ford downgrade of 2005. They find empirical evidence that institutional frictions and liquidity are responsible for a segmentation of equity and credit markets at this time. Capital structure arbitrage strategies can be set up as a convergence trade and illiquidity of a market increases transaction costs as well as risks of convergence trades. More generally, we expect the liquidity of the underlying securities to impact arbitrage activities in these markets. Greater liquidity would therefore imply a higher integration of both credit and stock markets. Even though the results in Acharya, Schaefer, and Zhang (2008) focus on two particular firms, their evidence is suggestive of the potential importance of running a joint study of liquidity.

\[51\] Convergence trading strategies are popular among hedge funds. A typical convergence trading strategy is to bet that the price difference between two assets with similar characteristics will narrow in the future. The collapse of Long-Term Capital Management (LTCM) is often cited as a chatoyant example illustrating the interplay of convergence trades and a deterioration of liquidity, together with its impact on asset prices and volatility (see Xiong, 2001).
factors and disagreement. We add two different liquidity factors to our Logit regressions: The Fontaine and Garcia (2008) liquidity measure, which is extracted from T-Bill markets, and the Pastor and Stambaugh (2003) measure, which is constructed using equity markets information. As capital structure arbitrage requires both trading in the corporate bond and the stock, both the liquidity in the credit and equity market might be relevant. We also add the Fama and French size and book-to-market factors to our regressions as they turned out to be significantly related to the corporate bond spreads. We also include the VIX index of implied volatility from index options (see Collin-Dufresne, Goldstein, and Martin, 2001).

In the following, we study how both individual and common belief disagreement plus some other determinants influence the conditional probability of a violation in credit markets. To this end, we estimate a set of panel Logit regressions, in which the binary variable $y(it)$, denoting the occurrence of a violation at time $t$ for firm $i$, is regressed onto a set of variables that include both disagreement proxies. More precisely, the probability that a violation occurs at time $t$ for firm $i$ is specified as:

$$P (y(it) = 1) = F(\beta_0 + \beta_1 \log \Psi_i(t) + \beta_2 \log \Psi_z(t) + \sum_{j=1}^{2} \delta_j F_{ij}(t) + \sum_{k=1}^{7} \gamma_k T_k(t)),$$

where $F$ is the cumulative distribution function of a logistic distribution, $\beta_1$ and $\beta_2$ are the loadings on the individual and common disagreement proxies, $\delta_j$ the loading of implied volatility and leverage, and $\gamma_k$ the loading of the VIX, the equity market liquidity, the credit market liquidity, market, size, book-to-market mimicking factors, and earnings volatility. The model is estimated by Maximum-Likelihood. The results are given in Table 7.

We find that both individual and common disagreement increase the conditional probability of a violation, with an estimated coefficient that is highly significant and stable across the different leverage levels. Leverage positively impacts the conditional probability of a violation and the estimated coefficients are significant. The implied volatility of individual options increases the probability of an arbitrage violation in credit markets. However, the estimated coefficients are significant at the 10% level only. The estimated coefficients for the equity market liquidity proxy (PS liquidity) are negative and marginally significant for the highest leverage bin. They are not distinguishable from zero for the other leverage ratios. In contrast, the estimated coefficients for the credit market liquidity proxy (FG liquidity) are significant across all leverage bins. The coefficients are negative and the size increases in absolute terms with a higher leverage, implying (i) that a higher liquidity reduces the probability of an arbitrage violation and (ii) that liquidity becomes more important in explaining these violations for firms in more distress. This finding is similar to Kapadia and Pu (2008), who find that liquidity of the credit market is significant in linking equity and credit markets, while equity market liquidity has no effect. At the same time, the option volatility index itself (VIX) has significant coefficients at the 10% level, only. The market factor is not significant at all and the size factor has little significance for the lowest and highest leverage firms.

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52 The unconditional correlation between the two liquidity proxies is fairly low: In the period from December 1985 to December 2007 the unconditional correlation is only -10%.
Overall, we obtain corroborating evidence that belief disagreement is a missing factor in structural models, explaining part of the empirical no-arbitrage violations of single-factor models in credit markets. These results are important for a number of reasons. First, the distinction between our and other credit risk models is the role played by beliefs heterogeneity in determining firm expected cash flows and the equilibrium pricing kernel, thus affecting both absolute and relative prices of contingent claims on the capital structure, such as corporate bonds and equity. This provides independent supporting evidence on the importance of Uncertainty-DiB in asset pricing. Second, these results are also of broader interest and relevance, as capital structure arbitrage strategies have become very popular among many hedge funds, and their performance depends on the relative value of different parts of the capital structure.

F. Stock Returns

An additional testable implication suggested by our calibrated model in Section II.D. can be obtained by studying the differences of the slope coefficients in a regression of stock returns on Uncertainty-DiB across firms with different leverage. As shown by the calibrated structural model, leverage plays an important and revealing role, since while credit spreads are always increasing in the difference in beliefs, the relationship between stock returns and Uncertainty-DiB can be non-monotonic. A positive (negative) relation between disagreement and future equity returns is more likely for higher (lower) levels of leverage, since the skewness effect of the firm value tends to vanish for increasing leverage levels. Thus, we investigate in further details this testable implication of the model. We stratify by leverage by introducing a dummy variables according to three different, equally weighted, leverage bins: The low/medium/high bins corresponds to the first/second/third leverage terciles.

Table 8 summarizes the results.

We find two important regularities. First, in the credit spread regression the significance and the size of the estimated coefficients for disagreement are monotone cross-sectionally, with a sign independent of the leverage level. Second, in equity return regressions (last column), the estimated coefficient of disagreement is statistically significant across all leverage bins, but the sign of the estimated coefficient for the low leverage firms is negative. This finding could prove to be interesting for two reasons. First, it provides further supporting evidence of the importance of credit risk in the context of a structural model of a levered firm, in which skewness effects generated by an increases in the difference in beliefs tends to vanish for high leverage. Second, it helps to explain the contradicting result found by previous empirical reduced-form equity return literature.

The three terciles correspond to leverage ratios below 0.045, between 0.045 and 0.35, and above 0.35, respectively.

Diether, Malloy, and Scherbina (2002) find a negative coefficient and interpret the result as supporting evidence for the behavioral style model; Anderson, Ghysels, and Juergens (2005) run a similar regression using a different dataset of firms and find a positive slope coefficient. They interpret the result as supporting evidence of a neoclassical model.
V. Robustness

Our results support the hypothesis that belief disagreement is a priced risk factor for credit spreads and stock returns. In this section, we assess the robustness of our results by studying (i) the extent to which our disagreement proxies capture other sources of risk and (ii) a setting with time dummies and firm fixed effects, in order to explore to what extent our disagreement proxies measure cross-sectional versus time-series variation.

A. Idiosyncratic Volatility

Idiosyncratic volatility is a potentially important risk factor for stock returns and credit spreads. Johnson (2004), for example, studies a model, in which stock returns of a levered firm are decreasing in the asset’s idiosyncratic risk. Mei, Scheinkman, and Xiong (2005) use the idiosyncratic volatility of stock returns as a proxy for firm uncertainty in the Chinese stock market. Chen, Collin-Dufresne, and Goldstein (2008) emphasize that the credit spread puzzle is closely related to the ratio of idiosyncratic and total volatility of stock returns. Campbell and Taksler (2003) empirically document that idiosyncratic stock return volatility is an important explanatory factor for the cross-section of credit spreads.

Even if belief disagreement is not itself a measure of pure idiosyncratic risk, it is a natural robustness check to investigate the extent to which it proxies for idiosyncratic volatility. To this end, we calculate the time-series standard deviation of daily market adjusted stock returns 180 days preceding each observation, and use it as a further explanatory variable in our regressions, leading to the results in Table 9.

Confirming the results in Campbell and Taksler (2003), idiosyncratic risk significantly and positively affects corporate credit spreads. However, it does not have an impact on either the economic or statistical significance of our belief disagreement proxy, which is the most significant variable in the model. The adjusted $R^2$ of the regressions with idiosyncratic risk without disagreement are slightly lower than those of our benchmark regressions without idiosyncratic risk. The estimated coefficient for disagreement in the aggregated regression for stock returns is highly significant. The one of idiosyncratic volatility is negative and significant, but only at the 10 percent significance level. This last finding is consistent with the results in Ang, Hodrick, Xing, and Zhang (2006) and Guo and Savickas (2006), even if the empirical literature also finds opposite results in some cases.\footnote{In a time-series analysis Goyal and Santa-Clara (2003) find that the average stock variance has explanatory power for market returns, where the average stock variance is mainly idiosyncratic risk. Malkiel and Xu (2006) find a positive link between stock returns and idiosyncratic risk. Bali, Cakici, Yan, and Zhang (2005) find no significant link between idiosyncratic risk and market returns.}

Interestingly, in the regression for stock returns with dummy variables for leverage, our proxy for disagreement consistently maintains a significant explanatory power, but the idiosyncratic volatility does not.

[Insert Table 9 approximately here.]
B. Time and Firm Fixed Effects

To prevent potential biases due to a spurious time series correlation, we add time dummies to our baseline regressions. The results are summarized in Table 10. We note that the time dummies have very little effect on the coefficients of disagreement. For the idiosyncratic disagreement, the coefficients remain at the same level as in the regressions without time effects and the t-statistics remain essentially the same. The coefficient of the common disagreement proxy is lower and significant at the 10% level. This is not surprising, since the systematic disagreement picks up time variation only. Similar findings apply to the other time-series variables, for example, non-farm payroll and the slope of the risk-free rate lose almost all their explanatory power. The adjusted $R^2$ remains almost unchanged which means that our determinants already account for low frequency time variation. To gauge more intuition about the cross-sectional variation, we run a firm fixed effects regression. The coefficients of the idiosyncratic disagreement remain almost unchanged and their estimates remain highly statistically significant, with t-statistics of 7.4 for credit spreads and 5.2 for expected stock returns. The largest effect can be observed for the coefficient of leverage. For the credit spreads regression, the coefficient drops from a 1% significance level to a 5% significance level. This means that leverage is more closely related to individual time-series variation in credit spreads, and less related to cross-sectional variation, the reason being that introducing firm fixed effects allows the variables to focus on individual time-series variation, since the firm dummies take care of (part of) the cross-sectional variation.

[Insert Table 10 approximately here.]

VI. Conclusion

In this paper, we investigate the economic relation between uncertainty, belief disagreement, and credit markets. In order to rigorously motivate a set of testable implications for the role of common and firm-specific uncertainty in the determination of asset prices, we develop a structural equilibrium model of credit risk with heterogeneous beliefs. In the model, uncertainty about firm-specific and market wide growth opportunities induces agents to disagree about the future earnings and the solvency of a levered firm. These features endogenize the firm value process and make the market price of default risk dependent on the degree of belief disagreement among investors: A higher disagreement lowers the equilibrium firm value, increases the firm value volatility and strengthens the firm value negative skewness in a way that is more pronounced if economic uncertainty is higher. In the context of our economy, we obtain: (i) a positive relation between economic uncertainty and disagreement, (ii) a positive relation between belief heterogeneity, credit spreads, and stock volatility, (iii) a positive relation between disagreement and the frequency of arbitrage free violations and (iv) an ambiguous relation between disagreement and stock returns, which depends on the degree of firm leverage. It follows that heterogeneity in beliefs is a priced risk factor for any claim on the firm capital structure, which yields a positive belief-driven co-movement of credit spread and stock volatility, as well as an ambiguous leverage-dependent sign for the co-movement of credit spread and stock returns.
Using a merged data-set of individual firm earning forecasts, credit spreads, and stock returns, we test the model predictions using a set of panel and Logit regressions. We first construct proxies of individual firm disagreement for a large cross-section of about 330 firms, using one year ahead earnings forecasts of financial analysts. In order to extract a common belief component linked to market wide uncertainty, we use dynamic factor analysis to estimate a dynamic factor model for the cross section and time series of individual firm disagreement proxies. We find that the dynamic common component estimated from the factor model can explain more than 87% of the variation of the individual disagreement proxies in the large cross-section of firms. This common component is highly counter-cyclical and strongly linked to increases and decreases of economic uncertainty associated with economic recessions or financial crises. It is also strongly related to the dynamics of the average level of corporate credit spreads.

Our empirical study produces a number of novel results for the empirical credit risk literature. First, systematic and idiosyncratic disagreement both unambiguously widen corporate credit spreads in the time series and the cross-section. This result is significant, both economically and statistically, and robust to the inclusion of a variety of commonly used control variables. It is well-known that standard structural models tend to predict credit spreads that are on average too low, especially for highly rated firms. Our result adds an element to the understanding of the credit spread puzzle, by providing direct empirical evidence that disagreement is a priced risk factor in credit markets. It also provides an explicit empirical link between counter-cyclical economic uncertainty, our counter-cyclical proxy for the common disagreement and the counter-cyclical features of credit spreads and stock volatilities.

Second, disagreement helps to explain the large frequencies of violations of capital structure no-arbitrage restrictions of single-factor credit risk models. These models imply a negative relation between credit spreads and the price of equity. In our model, this monotonic relation can be violated for some regions of leverage, due to a time–varying risk-neutral skewness endogenously driven by the degree of heterogeneity in beliefs. The percentage of no–arbitrage violations in our data for credit spreads is substantial and is comparable to the one predicted by our calibrated model. We investigate the extent to which belief disagreement can explain these violations in a set of Logit regressions. In all regressions, we find that the slope coefficient of both individual and common disagreement is positive and highly significant.

Third, while credit spreads are monotonic in belief dispersion, equity returns are not: The empirical analysis yields a significant positive relation between stock returns and disagreement using aggregated data, but this relation is reversed and significant for low leverage firms when we stratify our panel with respect to leverage. This result is interesting for at least two reasons. First, it corroborates an empirical prediction of the structural model with heterogenous beliefs when leverage is introduced. Second, the recent empirical asset pricing literature has debated on the sign of the relation between stock returns and divergence of opinions. Our analysis offers a structural explanation for these mixed results, because we show that an increase in disagreement can raise the price of equity in some cases. In our frictionless economy with heterogenous beliefs, this feature can emerge because when leverage is sufficiently low the stronger negative skewness of the firm value can have a dominating impact on the price of equity, which contains a long put option on the firm value.
Fourth, we find that the recent 2008 credit crisis provides further supporting evidence to the results obtained using the pre-crisis large panel data set. Regressions of asset swap spreads on difference in beliefs proxies for the crisis period produce an even stronger economic and statistical significance than in the pre-crisis period. This finding further highlights the major role of counter-cyclical uncertainty in asset pricing, as well as the strong link between differences in beliefs and credit markets.

Our results rise some potentially interesting questions. A first important issue is, e.g., the link between heterogeneity in beliefs and liquidity. For instance, when corporate credit spreads began to surge in mid 2007, funding liquidity fell quite substantially; See, e.g., Brunnermeier (2009). Such increases in illiquidity were not confined to the 2008 credit crisis. Routledge and Zin (2004) propose a model to study the impact of Knightian uncertainty on liquidity risk in times of economic crises, and it is natural to expect that Uncertainty-DiB and liquidity might interact in interesting ways within a setting with heterogeneous beliefs and market frictions. A surge in uncertainty might rise the incentives to trade for symmetrically informed disagreeing investors, but it might also make it more difficult to distinguish informed from uninformed traders, and thus reduce the incentive of uninformed agents to trade. Empirically, the interaction of Uncertainty-DiB and liquidity is supported by the data. In preliminary results, we find that (i) sector-wide Uncertainty-DiB and illiquidity proxies alone can predict a large portion of the variation of the asset swap spread across all sectors and (ii) the economic significance of Uncertainty-DiB is larger than the one of the illiquidity proxy. These findings indicate an interesting empirical link that could constitute an important topic of future research. Finally, our results from the 2008 credit crisis in Section IV suggest that economic uncertainty and heterogeneity in beliefs might spread slowly across contiguous sectors. The diffusion of economic uncertainty across different industries and the way it can generate waves of systemic disagreement across sectors is a second interesting avenue of future research.

\[^{56}\text{For instance, Acharya and Pedersen (2005) find that their proxy of illiquidity was particularly high during the Iraqi invasion in 1990, the Asian crisis in 1997, and the Russian default in 1998. Bao, Pan, and Wang (2008) obtain similar findings with a different liquidity proxy.}\]
References


Appendix

To save space, details of most calculations are presented in a technical Appendix to this paper, which is available on the authors' webpage.

Appendix A. Proof of Lemma 2. (Security Prices)

Lemma 2. Let

\[ G(t, T, x; \Psi_A, \Psi_z) \equiv \int_0^\infty \left( \frac{1 + \lambda(T)^{1/\gamma}}{1 + \lambda(t)^{1/\gamma}} \right)^\gamma \left[ \frac{1}{2\pi} \int_{-\infty}^{\infty} \left( \frac{\lambda(T)}{\lambda(t)} \right)^{-ix} F_{\Psi_A, \Psi_z}(\Psi_A, \Psi_z, t, x; i\chi) d\chi \right] d\lambda(T) \lambda(t). \]

1. The equilibrium firm value is:

\[ V(t) := V(A, m_A, \Psi_A, \Psi_z) = A(t) \int_t^\infty e^{-\rho(u-t)} F_{m_A^1}(m_A^1, t, u; 1 - \gamma) G(t, u, 1 - \gamma; \Psi_A, \Psi_z) du. \]

2. The equilibrium price of the corporate zero-coupon bond is:

\[ B(t, T) := B(t, T; m_A, \Psi_A, \Psi_z) = e^{-\rho(T-t)} F_{m_A^1}(m_A^1, t, T; -\gamma) G(t, T, -\gamma; \Psi_A, \Psi_z). \]

3. The equilibrium price of the senior defualtable bond is:

\[ B_s^*(t, T) := B_s^*(t, T; A, m_A, \Psi_A, \Psi_z) = B(t, T) - \frac{1}{A(t)} \left( e^{-\rho(T-t)} \left( \frac{A(t)}{A(T)} \right)^{\gamma} (K_1 - V(T))^+ \right). \]

4. The equilibrium price of the junior defualtable bond is:

\[ B^j(t, T) := B^j(t, T; A, m_A, \Psi_A, \Psi_z), \]

\[ \quad = E_1^1 \left( e^{-\rho(T-t)} \left( \frac{A(t)}{A(T)} \right)^{\gamma} (V(T) - K_1)^+ - (V(T) - (K_1 + K_2))^+ \right). \]

5. The equilibrium price of equity is:

\[ S(t) := S(t; A, m_A, \Psi_A, \Psi_z) = V(t) - B^*(t, T) - B^j(t, T). \]

By definition, the risk-less zero coupon bond price is given by:

\[ B(t, T) = \frac{1}{\xi(t)} E_1^1 \left( e^{-\rho(T-t)} \xi^1(T) \right). \]

Using the expression for \( \xi^1(t) \), we get:

\[ B(t, T) = \frac{1}{\xi(t)} E_1^1 \left( e^{-\rho(T-t)} \left( \frac{A(T)}{A(t)} \right)^{\gamma} \left( \frac{1 + \lambda(T)^{1/\gamma}}{1 + \lambda(t)^{1/\gamma}} \right)^{\gamma} \right). \]  \hspace{1cm} (A-1)

Let

\[ G(t, T, x; \Psi_A, \Psi_z) \equiv \int_0^\infty \left( \frac{1 + \lambda(T)^{1/\gamma}}{1 + \lambda(t)^{1/\gamma}} \right)^\gamma \left[ \frac{1}{2\pi} \int_{-\infty}^{\infty} \left( \frac{\lambda(T)}{\lambda(t)} \right)^{-ix} F_{\Psi_A, \Psi_z}(\Psi_A, \Psi_z, t; -\gamma; i\chi) d\chi \right] d\lambda(T) / \lambda(t). \]

By Fourier inversion, it then follows:

\[ B(t, T) = e^{-\rho(T-t)} F_{m_A^1}(m_A^1, t, T; -\gamma) G(t, T, -\gamma; \Psi_A, \Psi_z). \]

In a similar way, the firm value is:

\[ V(t) = E_1^1 \left( \int_t^\infty e^{-\rho(u-t)} \xi^1(u) A(u) du \right), \]

\[ = A(t) E_1^1 \left( \int_t^\infty e^{-\rho(u-t)} \left( \frac{1 + \lambda(t)^{1/\gamma}}{1 + \lambda(u)^{1/\gamma}} \right)^\gamma \left( \frac{A(u)}{A(t)} \right)^{1-\gamma} du \right), \]

\[ = A(t) \int_t^\infty \left( e^{-\rho(u-t)} F_{m_A^1}(m_A^1, t, u; 1 - \gamma) G(u, T, 1 - \gamma; \Psi_A, \Psi_z) \right) du. \]
The price of the senior bond is:

\[ B^s(t, T) = K_1 B(t, T) - E_1^1 \left( e^{-\rho(T-t)} \frac{\xi^1(T)}{\xi^1(t)} (K_1 - V(T))^+ \right), \]

\[ = K_1 B(t, T) - E_1^1 \left( e^{-\rho(T-t)} \left( \frac{A(T)}{A(t)} \right)^{-\gamma} \left( \frac{1 + \lambda(T)^{1/\gamma}}{1 + \lambda(t)^{1/\gamma}} \right)^{\gamma} (K_1 - V(T))^+ \right), \]

\[ = K_1 B(t, T) - P(t, T, K_1), \]

where \( P(t, T, K_1) \) is the price of the put option on the firm value. The price of the junior bond is:

\[ B^j(t, T) = E_1^1 \left( e^{-\rho(T-t)} \frac{\xi^1(T)}{\xi^1(t)} (V(T) - K_1^+) \right) - E_1^2 \left( e^{-\rho(T-t)} \frac{\xi^1(T)}{\xi^1(t)} (V(T) - (K_1 + K_2))^+ \right), \]

\[ = C(t, T, K_1) - C(t, T, K_1 + K_2), \]

where \( C(t, T, K_1) \) and \( C(t, T, K_1 + K_2) \) are call options on the firm value with strikes \( K_1 \) and \( K_1 + K_2 \), respectively. Equity in our economy is a call option on the firm value with strike price \( K_1 + K_2 \). Therefore:

\[ S(t) = E_1^1 \left( e^{-\rho(T-t)} \frac{\xi^1(T)}{\xi^1(t)} (V(T) - (K_1 + K_2))^+ \right) = C(t, T, K_1 + K_2). \]

A European call option on the equity value is derived in the following way:

\[ O(t, T) = E_1^1 \left( e^{-\rho(T-t)} \frac{\xi^1(T)}{\xi^1(t)} (S(T) - K_e)^+ \right). \]

This concludes the proof.
<table>
<thead>
<tr>
<th>Date</th>
<th>Crisis Description</th>
<th>% Up</th>
<th>% Down</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990-1991</td>
<td><strong>S&amp;L Crisis:</strong> Failure of thousands of U.S. thrifts due to high risk loans in the real estate sector. The S&amp;L crisis is said to be the contributing cause of the 1990-1991 economic recession.</td>
<td>+96%</td>
<td>-66%</td>
</tr>
<tr>
<td>1992-1993</td>
<td><strong>ERM Crisis:</strong> World interest rates rise following the German reunification. There is an outflow of money from Europe and ERM currencies as the lira and the peseta towards the bottom of their target zones.</td>
<td>+50%</td>
<td>-39%</td>
</tr>
<tr>
<td>1994</td>
<td><strong>Mexican Crisis:</strong> The high Mexican budget deficit was financed by debt instruments on the Mexican Peso, indexed to the US Dollar. Political wrangling and economic downturn led people to sell these debt instruments and cause a decline in the Mexican central banks dollar reserves.</td>
<td>+ 40%</td>
<td>-10%</td>
</tr>
<tr>
<td>1997-1998</td>
<td><strong>Asian &amp; Russian Crisis:</strong> The Asian crisis started with the collapse of the Thai Baht due to a decision of the government to float the currency. The crisis spread to Southeast Asia and Japan with slumping currencies. Russia defaulted in August 1998 on GKO debt.</td>
<td>+37.5%</td>
<td>-24%</td>
</tr>
<tr>
<td>2000-2001</td>
<td><strong>DotCom Bubble:</strong> Soaring of I.T. stock prices until the burst of the NASDAQ bubble in March 2000, after a massive sell order batch on major tech firms triggered a chain reaction of selling.</td>
<td>+125%</td>
<td>-65%</td>
</tr>
</tbody>
</table>
This table lists the parameter values used for all figures in the paper. We calibrate the model parameters to the mean and volatility of the time-series average of operating cash flow for all firms present in our database. Operating cash flow is earnings before extraordinary items (Compustat item 18) minus total accruals, scaled by average total assets (Compustat item 6), where total accruals are equal to changes in current assets (Compustat item 4) minus changes in cash (Compustat item 1), changes in current liabilities (Compustat item 5), and depreciation expense (Compustat item 14) plus changes in short-term debt (Compustat item 34). The initial values for the conditional variances are set to their steady-state variances. Agent specific values are consistent with estimated values from Brennan and Xia (2001).

<table>
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<tr>
<td>Mean-reversion parameter of cash flow growth</td>
<td>( a_{1t} )</td>
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<tr>
<td>Volatility of cash flow</td>
<td>( \sigma_A )</td>
</tr>
<tr>
<td>Initial level of cash flow</td>
<td>( A )</td>
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<tr>
<td>Initial level of cash flow growth</td>
<td>( m_{A} )</td>
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<table>
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<th>Parameters for Signal</th>
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<table>
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<th>Agent specific Parameters</th>
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<td>Relative risk aversion for both agents</td>
<td>( \gamma )</td>
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<tr>
<td>Time Preference Parameter</td>
<td>( \rho )</td>
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Table 3
Corporate Credit Spreads, Volatility, and Probability of Default

This table reports the calibrated credit spreads (in basis points), the volatility of credit spreads, and the cumulative default probability as a function of risk aversion, $\gamma$, and the agent perceived difference in uncertainty, $\Delta \sigma_{\mu_z}$. Economic uncertainty, $\sigma_{\mu_z}$, is set equal to 0.008. The parameter values used are given in Table 2.

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
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<th>Merton $\Delta \sigma_{\mu_z} = 0.0015$</th>
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<td></td>
<td>$\gamma = 2$</td>
<td>$\gamma = 4$</td>
<td>$\gamma = 2$</td>
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<td>123</td>
<td>129</td>
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<td>Volatility of CS</td>
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<td>Probability of Default</td>
<td>0.043</td>
<td>0.032</td>
<td>0.039</td>
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Table 4
OLS Panel Regression Results for Credit Spreads

Using data running from January 1996 to December 2004, we regress credit spreads on corporate bonds on a set of variables listed below. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level. Model (1) corresponds to the regression model with option-impli ed determinants (see Cremers, Driessen, and Maenhout (2008)). Model (2) corresponds to macro determinants. Model (3) corresponds to firm specific variables, Model (4) corresponds to the regression model with systematic risk factors and Model (5) includes all determinants. Model (6) is the regression with significant values only. All estimations use autocorrelation and heteroscedasticity-consistent t-statistics.

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<th>(6)</th>
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<td>Constant</td>
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<td>0.613***</td>
<td>0.594***</td>
<td>0.420***</td>
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<td>Individual DiB</td>
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<td>0.837***</td>
<td>0.837***</td>
<td>0.880***</td>
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<td>[8.93]</td>
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<td>Adjusted $R^2$</td>
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<td>0.68</td>
<td>0.70</td>
<td>0.68</td>
<td>0.80</td>
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</table>
Table 5
Predictive Pre-Crisis and Crisis Regressions Across Sectors

This table reports standardized (zero mean and unit variance) beta estimations when regressing asset swap spreads onto the different sector Uncertainty-DiB proxies at different horizons (Panel A). We run the following regressions:

\[ \text{spread}_i(t) = \beta \text{DiB}_i(t-h) + \epsilon_i(t), \]

where \( \text{spread}_i(t) \) is the asset swap spread of sector \( i \) at time \( t \), \( \text{DiB}_i(t-h) \) is the Uncertainty-DiB for sector \( i \) at time \( t - h \) and \( h = 0, 1, 3, 6, 9, 12 \) months. In Panel B, we report standardized beta coefficients of contemporaneous regressions from sector-wide asset swap spreads on sector-wide Uncertainty-DiB. Pre Credit Crisis indicates a regression from July 2002 to March 2007. Credit Crisis indicates a regression from March 2007 to December 2008. Average adjusted \( R^2 \) is the average of all adjusted \( R^2 \) across different sectors. \* denotes significance at the 10% level, ** at the 5% level, and *** denotes significance at the 1% level.

### Panel A: Predictive Regressions:

<table>
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<th>Horizon</th>
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<td>0.37</td>
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<td>0.491*</td>
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<td>[2.36]</td>
<td>[1.88]</td>
<td>[1.44]</td>
<td>[1.24]</td>
<td>[1.09]</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.23</td>
<td>0.20</td>
<td>0.23</td>
<td>0.16</td>
<td>0.12</td>
<td>0.07</td>
</tr>
</tbody>
</table>

### Panel B: Pre and Crisis Regressions:

<table>
<thead>
<tr>
<th>Description</th>
<th>Pre Credit Crisis</th>
<th>Credit Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Information Technology</strong></td>
<td>0.671***</td>
<td>0.709***</td>
</tr>
<tr>
<td><strong>Services</strong></td>
<td>0.148***</td>
<td>0.691***</td>
</tr>
<tr>
<td><strong>Financials</strong></td>
<td>0.428**</td>
<td>0.437**</td>
</tr>
<tr>
<td><strong>Banks</strong></td>
<td>0.525**</td>
<td>0.580**</td>
</tr>
<tr>
<td><strong>Capital Goods</strong></td>
<td>0.564***</td>
<td>0.758***</td>
</tr>
<tr>
<td><strong>Energy</strong></td>
<td>0.482**</td>
<td>0.857***</td>
</tr>
<tr>
<td><strong>Average adjusted ( R^2 )</strong></td>
<td>0.27</td>
<td>0.30</td>
</tr>
</tbody>
</table>
This table shows the violation frequencies implied by the Monte Carlo simulation of our model (Panel A). The reported numbers are the simulated fractions of the violation occurrence across 10,000 simulation trials of the model. Panel B summarizes the empirical frequency arbitrage violations of a percentage of total observations at a given leverage. Low, Average, and High refer to the leverage ratios.

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Average</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Simulated Violations</td>
<td>15.3</td>
<td>14.2</td>
<td>12.2</td>
</tr>
<tr>
<td>Panel B: Empirical Violations</td>
<td>18.9</td>
<td>15.4</td>
<td>14.3</td>
</tr>
</tbody>
</table>
Table 7
Logit Regression of Arbitrage Violations on Credit Markets

This table summarizes the Logit regression results for the violation frequency in credit markets. The probability that a violation event occurs is specified as:

\[ P(y(t) = 1) = F(\beta_0 + \beta_1 \log \Psi_i(t) + \beta_2 \log \Psi_c(t) + \sum_{j=1}^{2} \delta_j F_j(t) + \sum_{k=1}^{7} \gamma_k T_k(t)), \]

where \( \Psi_i \) is the firm-specific disagreement, \( \Psi_c \) is the common disagreement, \( F_j \) the implied volatility and leverage, and \( T_k \) indicate the VIX, Pástor and Stambaugh Liquidity proxy (PS Liquidity), Fontaine and Garcia Liquidity (FG Liquidity) proxy, Fama and French factors (market, size, and book-to-market), and earnings volatility. t-values are in brackets. ★ denotes significance at the 10% level, ★★ denotes significance at the 5% level and ★★★ denotes significance at the 1% level, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Leverage Average</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.21**</td>
<td>-0.32**</td>
<td>-0.37**</td>
</tr>
<tr>
<td></td>
<td>[-2.39]</td>
<td>[-2.19]</td>
<td>[-2.43]</td>
</tr>
<tr>
<td>Individual DiB</td>
<td>0.17***</td>
<td>0.18***</td>
<td>0.23***</td>
</tr>
<tr>
<td></td>
<td>[3.32]</td>
<td>[3.83]</td>
<td>[4.27]</td>
</tr>
<tr>
<td>Common DiB</td>
<td>0.12**</td>
<td>0.18**</td>
<td>0.13**</td>
</tr>
<tr>
<td></td>
<td>[2.40]</td>
<td>[2.36]</td>
<td>[2.43]</td>
</tr>
<tr>
<td>Implied Volatility</td>
<td>0.19*</td>
<td>0.26*</td>
<td>0.18*</td>
</tr>
<tr>
<td></td>
<td>[1.68]</td>
<td>[1.75]</td>
<td>[1.90]</td>
</tr>
<tr>
<td>VIX</td>
<td>0.05*</td>
<td>0.04*</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>[1.67]</td>
<td>[1.66]</td>
<td>[1.38]</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.13**</td>
<td>0.18**</td>
<td>0.21*</td>
</tr>
<tr>
<td></td>
<td>[2.02]</td>
<td>[2.30]</td>
<td>[1.71]</td>
</tr>
<tr>
<td>PS Liquidity</td>
<td>-0.16</td>
<td>-0.12</td>
<td>-0.11*</td>
</tr>
<tr>
<td></td>
<td>[-1.22]</td>
<td>[-1.58]</td>
<td>[-1.73]</td>
</tr>
<tr>
<td>FG Liquidity</td>
<td>-0.17</td>
<td>-0.20**</td>
<td>-0.21**</td>
</tr>
<tr>
<td></td>
<td>[-1.88]</td>
<td>[-2.01]</td>
<td>[-2.29]</td>
</tr>
<tr>
<td>( R_m - R_f )</td>
<td>0.05</td>
<td>0.10</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>[1.32]</td>
<td>[1.57]</td>
<td>[1.63]</td>
</tr>
<tr>
<td>SMB</td>
<td>0.24*</td>
<td>0.17</td>
<td>1.28*</td>
</tr>
<tr>
<td></td>
<td>[1.90]</td>
<td>[1.43]</td>
<td>[1.91]</td>
</tr>
<tr>
<td>HML</td>
<td>0.18</td>
<td>0.23</td>
<td>0.48**</td>
</tr>
<tr>
<td></td>
<td>[1.47]</td>
<td>[1.62]</td>
<td>[2.52]</td>
</tr>
<tr>
<td>Earnings Volatility</td>
<td>0.40*</td>
<td>0.49*</td>
<td>0.42*</td>
</tr>
<tr>
<td></td>
<td>[1.69]</td>
<td>[1.91]</td>
<td>[1.75]</td>
</tr>
<tr>
<td>Pseudo ( R^2 )</td>
<td>0.19</td>
<td>0.19</td>
<td>0.22</td>
</tr>
</tbody>
</table>
Using data running from January 1996 to December 2004, we regress credit spreads of corporate bonds and firm stock returns on a set of variables listed below. The coefficients for Dispersion (HL), Dispersion (AL), and Dispersion (LL) are obtained by multiplying the coefficient with a dummy variable that takes the value 1 if the firm is in the high, average, and low leverage bin and zero otherwise. The same applies to the variables Implied Volatility, Implied Volatility Skewness, and Leverage. ★ denotes significance at the 10% level, ★★ denotes significance at the 5% level and ★★★ denotes significance at the 1% level. All estimations use autocorrelation and heteroskedasticity-consistent t-statistics.

<table>
<thead>
<tr>
<th>Credit Spreads</th>
<th>Stock Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>0.0653***</td>
</tr>
<tr>
<td><strong>Individual DiB (LL)</strong></td>
<td>0.736***</td>
</tr>
<tr>
<td><strong>Individual DiB (AL)</strong></td>
<td>0.786**</td>
</tr>
<tr>
<td><strong>Individual DiB (HL)</strong></td>
<td>0.859**</td>
</tr>
<tr>
<td><strong>Common DiB</strong></td>
<td>0.721***</td>
</tr>
<tr>
<td><strong>Implied Volatility (LL)</strong></td>
<td>0.625*</td>
</tr>
<tr>
<td><strong>Implied Volatility (AL)</strong></td>
<td>0.520</td>
</tr>
<tr>
<td><strong>Implied Volatility (HL)</strong></td>
<td>0.492</td>
</tr>
<tr>
<td><strong>Implied Volatility Skew (LL)</strong></td>
<td>-0.261</td>
</tr>
<tr>
<td><strong>Implied Volatility Skew (AL)</strong></td>
<td>-0.324</td>
</tr>
<tr>
<td><strong>Implied Volatility Skew (HL)</strong></td>
<td>-0.529</td>
</tr>
<tr>
<td><strong>Slope of Term Structure</strong></td>
<td>-0.377</td>
</tr>
<tr>
<td><strong>Risk-free Rate</strong></td>
<td>-0.506***</td>
</tr>
<tr>
<td><strong>Non-Farm Payroll</strong></td>
<td>-0.597***</td>
</tr>
<tr>
<td><strong>NBER Dummy</strong></td>
<td>-1.657</td>
</tr>
<tr>
<td><strong>Leverage (LL)</strong></td>
<td>0.427***</td>
</tr>
<tr>
<td><strong>Leverage (AL)</strong></td>
<td>0.287***</td>
</tr>
<tr>
<td><strong>Leverage (HL)</strong></td>
<td>0.265***</td>
</tr>
<tr>
<td><strong>Liquidity</strong></td>
<td>-0.129**</td>
</tr>
<tr>
<td><strong>Rm - Rf</strong></td>
<td>-0.532</td>
</tr>
<tr>
<td><strong>SMB</strong></td>
<td>0.417**</td>
</tr>
<tr>
<td><strong>HML</strong></td>
<td>0.313*</td>
</tr>
<tr>
<td><strong>Earnings Volatility</strong></td>
<td>0.373*</td>
</tr>
<tr>
<td><strong>Adjusted R²</strong></td>
<td>0.75</td>
</tr>
</tbody>
</table>
Using data running from January 1996 to December 2004, we regress credit spreads of corporate bonds and firm stock returns on a set of variables listed below. The variable Idiosyncratic Volatility is the time-series sample standard deviation of daily stock returns 180 days preceding the observation. For better comparison, we standardize this variable to have the same standard deviation as the option implied volatility. ★ denotes significance at the 10% level, ★★ denotes significance at the 5% level and ★★★ denotes significance at the 1% level. All estimations use autocorrelation and heteroskedasticity-consistent t-statistics.

### Table 9

**OLS Panel Regressions with Idiosyncratic Volatility**

<table>
<thead>
<tr>
<th>Credit Spreads</th>
<th>Stock Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>0.283***</td>
</tr>
<tr>
<td></td>
<td>[4.82]</td>
</tr>
<tr>
<td><strong>Individual DiB</strong></td>
<td>0.762***</td>
</tr>
<tr>
<td></td>
<td>[7.48]</td>
</tr>
<tr>
<td><strong>Common DiB</strong></td>
<td>0.432**</td>
</tr>
<tr>
<td></td>
<td>[2.34]</td>
</tr>
<tr>
<td><strong>Implied Volatility</strong></td>
<td>0.329*</td>
</tr>
<tr>
<td></td>
<td>[1.78]</td>
</tr>
<tr>
<td><strong>Implied Volatility Skew</strong></td>
<td>−0.233</td>
</tr>
<tr>
<td></td>
<td>[−1.47]</td>
</tr>
<tr>
<td><strong>Idiosyncratic Volatility</strong></td>
<td>0.332**</td>
</tr>
<tr>
<td></td>
<td>[2.27]</td>
</tr>
<tr>
<td><strong>Slope of Term Structure</strong></td>
<td>−0.210</td>
</tr>
<tr>
<td></td>
<td>[−1.29]</td>
</tr>
<tr>
<td><strong>Risk-free Rate</strong></td>
<td>−0.220*</td>
</tr>
<tr>
<td></td>
<td>[−1.95]</td>
</tr>
<tr>
<td><strong>Non-Farm Payroll</strong></td>
<td>−0.492**</td>
</tr>
<tr>
<td></td>
<td>[−2.01]</td>
</tr>
<tr>
<td><strong>Leverage</strong></td>
<td>0.372***</td>
</tr>
<tr>
<td></td>
<td>[3.93]</td>
</tr>
<tr>
<td><strong>Liquidity</strong></td>
<td>−0.113**</td>
</tr>
<tr>
<td></td>
<td>[−2.18]</td>
</tr>
<tr>
<td><strong>R_m – R_f</strong></td>
<td>−0.219</td>
</tr>
<tr>
<td></td>
<td>[−1.00]</td>
</tr>
<tr>
<td><strong>SMB</strong></td>
<td>0.126</td>
</tr>
<tr>
<td></td>
<td>[1.58]</td>
</tr>
<tr>
<td><strong>HML</strong></td>
<td>0.124*</td>
</tr>
<tr>
<td></td>
<td>[1.66]</td>
</tr>
<tr>
<td><strong>Adjusted R^2</strong></td>
<td>0.75</td>
</tr>
</tbody>
</table>
Using data running from January 1996 to December 2004, we regress credit spreads and stock returns on a set of variables listed below including either year dummies or firm fixed effects. Their coefficients are not reported. ★ denotes significance at the 10% level, ★★ denotes significance at the 5% level and ★★★ denotes significance at the 1% level. All estimations use autocorrelation and heteroskedasticity-consistent t-statistics.

<table>
<thead>
<tr>
<th></th>
<th>Credit Spreads</th>
<th>Stock Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.582***</td>
<td>0.529***</td>
</tr>
<tr>
<td></td>
<td>[3.28]</td>
<td>[4.49]</td>
</tr>
<tr>
<td>Individual DiB</td>
<td>0.739***</td>
<td>0.787**</td>
</tr>
<tr>
<td></td>
<td>[6.99]</td>
<td>[7.43]</td>
</tr>
<tr>
<td>Common DiB</td>
<td>0.323**</td>
<td>0.312**</td>
</tr>
<tr>
<td></td>
<td>[1.99]</td>
<td>[2.01]</td>
</tr>
<tr>
<td>Implied Volatility</td>
<td>0.626*</td>
<td>0.642*</td>
</tr>
<tr>
<td></td>
<td>[1.75]</td>
<td>[1.86]</td>
</tr>
<tr>
<td>Implied Volatility Skew</td>
<td>-0.213</td>
<td>-0.218</td>
</tr>
<tr>
<td>Slope of Term Structure</td>
<td>-0.134</td>
<td>-0.198</td>
</tr>
<tr>
<td>Risk-free Rate</td>
<td>-0.315**</td>
<td>-0.372**</td>
</tr>
<tr>
<td></td>
<td>[-1.99]</td>
<td>[-2.01]</td>
</tr>
<tr>
<td>Non-Farm Payroll</td>
<td>-0.355*</td>
<td>-0.365*</td>
</tr>
<tr>
<td></td>
<td>[-1.85]</td>
<td>[-1.78]</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.426***</td>
<td>0.389**</td>
</tr>
<tr>
<td></td>
<td>[3.31]</td>
<td>[2.03]</td>
</tr>
<tr>
<td>Liquidity</td>
<td>-0.183**</td>
<td>-0.121**</td>
</tr>
<tr>
<td></td>
<td>[-2.19]</td>
<td>[-2.18]</td>
</tr>
<tr>
<td>$R_m - R_f$</td>
<td>-0.212</td>
<td>-0.272</td>
</tr>
<tr>
<td></td>
<td>[-1.00]</td>
<td>[-1.04]</td>
</tr>
<tr>
<td>SMB</td>
<td>0.124*</td>
<td>0.120*</td>
</tr>
<tr>
<td></td>
<td>[1.69]</td>
<td>[1.94]</td>
</tr>
<tr>
<td>HML</td>
<td>0.124*</td>
<td>0.120*</td>
</tr>
<tr>
<td></td>
<td>[1.63]</td>
<td>[1.71]</td>
</tr>
<tr>
<td>Earnings Volatility</td>
<td>0.203*</td>
<td>0.201*</td>
</tr>
<tr>
<td></td>
<td>[1.67]</td>
<td>[1.68]</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.69</td>
<td>0.69</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Firm Dummies</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 1. Co-Movement of Assets

In the left panel, we plot the common dynamic principal component of Uncertainty-DiB estimated by dynamic factor analysis (left axis red solid line) and the VIX (left axis blue dashed line), together with the default spread (right axis black line), which is defined as the difference between Moody’s Baa and Aaa bond yield. We de-trend the common DiB and the VIX index by applying a Hodrick-Prescott filter. In the right panel, we plot monthly averages of these quantities from t-12 to t+12. 0 indicates the peak of the crisis.
Financials & Banks: Asset Swap Spreads, Stock Index and DiBs

Figure 2. Asset Swap Spreads and DiBs Across Sectors

The upper panel plots the asset swap spreads and Uncertainty-DiBs for the financial and banking sectors. The lower panel plots the asset swap spreads together with the Uncertainty-DiBs for different sectors. Sectors are defined according to the Standard & Poors four digit global industry classification standard. $\beta$ indicates the (standardized) estimated beta from a regression of the asset swap spread series on the sector DiB:

$$\text{spread}(t) = \beta_1 \text{DiB}(t) + \epsilon(t).$$

t-values are in brackets below the estimate. The data is monthly and runs from March 1997 to December 2008.
Figure 3. Disagreement as a Function of Average Uncertainty and Difference in Uncertainty

We plot the first and second moment of the steady state distribution of $\Psi_z$ as a function of the average uncertainty, i.e. $\bar{\sigma}_{\mu z} \equiv \frac{1}{2}(\sigma_{\mu z}^1 + \sigma_{\mu z}^2)$ and the agent perceived difference in uncertainty, i.e. $\Delta \sigma_{\mu z} \equiv \sigma_{\mu z}^1 - \sigma_{\mu z}^2$. 
Figure 4. Equity Volatility and Senior Bond Credit Spreads for High Leverage Ratio

These figures plot the equity volatility (left panel) and senior bond credit spreads (right panel) for a high leverage ratio as a function of difference in beliefs $\Psi_A(t)$ and the common disagreement, $\Psi_z(t)$. The parameter values used are given in Table 2.
Figure 5. Firm Value, Firm Value Volatility, and Risk-Neutral Skewness

These figures plot the firm value, the firm value volatility, and the firm value risk-neutral skewness as a function of belief disagreement about cash flow $\Psi_A(t)$ and the common disagreement, $\Psi_d(t)$. The parameter values used are given in Table 2.
Figure 6. Firm Equity Price for High and Low Leverage Ratio

The price of equity with high leverage ratio (left panel) and low leverage ratio (right panel) is plotted as a function of the difference in beliefs $\Psi_A(t)$ and the common disagreement, $\Psi_2(t)$. The parameter values used are given in Table 2.
Figure 7. Change in the Equity Price

This figure plots the change in the equity price as a function of the bonds face values. We split up the total variation of equity, into four main effects: The Delta effect, which is due to a change in the firm value, the Vega effect, which is due to a change in the firm value volatility, a Skew effect, which is due to a change in the risk-neutral skewness, and a bond effect.
Figure 8. Comparison Common DiB

In the upper panel, we plot the common Uncertainty-DiB factor estimated using a dynamic factor analysis from the cross-section of individual disagreement measures (left axis, solid line) and as the value weighted average from the same cross-section (right axis). The lower panel plots the static principal component (left axis, solid line) and the disagreement factor computed from macro-economic aggregates (right axis). The disagreement factor from macro-economic aggregates is calculated using one year ahead forecasts on industrial production from the BlueChip Economic Indicator. All series have been de-trended for comparison reasons.
Figure 9. Spectral Density of Common DiB

The panel plots the non-parametric estimate of the spectral density of the common disagreement proxy based on the Bartlett kernel.