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Abstract

We explore the implications of ambiguity—Knightian uncertainty—for the pricing of credit default swaps (CDS). A stylized model with heterogeneous investors predicts that the net exposure of the marginal investor determines the sign of the impact of ambiguity on the price of CDS contracts, because they are assets in zero-net-supply. Empirically, we find strong evidence that the marginal investor is a net buyer of credit protection, as ambiguity has a negative impact on spreads. The economic significance of ambiguity is similar to that of risk, given a six percent decrease in spreads for a one standard deviation change in ambiguity.

Keywords: Derivatives, Equilibrium, Heterogeneous Agents, Insurance, Risk aversion

JEL Classification: C65, D81, D83, G13, G22

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I Introduction

Option payoffs are non-linear in the outcomes of the underlying asset. As a consequence, option values are *increasing* in the volatility of the underlying asset outcomes. This statement, however, implicitly presumes perfect information about the probabilities of all future outcomes. In contrast, when the probabilities of outcomes are not perfectly known, our willingness to pay for any gamble may also depend upon our preferences for such uncertainty about the likelihoods of future outcomes. In other words, as (financial) decision makers, we face ambiguity—the uncertainty about the *probabilities* of future outcomes—in addition to risk—the uncertainty about the realization of future *states*. In particular, when investors are averse to ambiguity, the certainty equivalent of an uncertain gamble will be lower, effectively *decreasing* the option value. While the effect of risk on asset prices has been well studied, the impact of ambiguity has hitherto been little explored from an empirical perspective. The key objective of this paper is to address this gap by investigating the implications of ambiguity for the pricing of credit default swaps (CDS).

We empirically assess the role of ambiguity, also known as *Knightian uncertainty*, in the pricing of CDS. The focus is on the distinct impact of ambiguity on the pricing of corporate credit spreads independently from that of risk, typically measured by equity volatility. To generate testable predictions, we develop a stylized model for the CDS market with heterogeneous investors, who feature both risk and ambiguity aversion. The model suggests that the impact of risk on spreads is unambiguously positive, while the impact of ambiguity on spreads depends on the net exposure of the marginal investor in the CDS market. Our results show that ambiguity and risk capture two different dimensions of uncertainty that significantly explain the cross-sectional variation and the dynamics of CDS spreads. In particular, we find strong evidence that ambiguity has a negative effect on CDS spreads, as apposed to the positive effect of risk. This suggests that the marginal investor in the CDS market is a net buyer of credit protection.

The CDS market is a natural environment for testing the impact of ambiguity in conjunction with risk on the prices of financial insurance products, as the payoffs from CDS are linked to the (uncertain) likelihood of a firm-specific credit event, i.e., default. In this view, the CDS of two similar companies might trade at different prices because of differences in the uncertainty about their default probabilities (different degree of ambiguity), despite similar *expected* default probabilities. Even though CDS represent a particular type of insurance contract, our insights are more broadly applicable to the pricing of other (financial) insurance products as well as of (stock) options.

We focus on two main hypotheses. Namely, we conjecture that credit spreads are *lower* (*higher*) for firms with higher *ambiguity*, if the marginal investor in the CDS market is net short (long) credit risk. In addition, we test whether credit spreads are *higher* for firms with higher *risk*. To draw these hypotheses, we develop a static equilibrium model with heterogeneous investors in the CDS market, underpinned by a decision theory framework that allows for the explicit separation of risk and ambiguity. Endowed with equal wealth, investors decide whether to optimally buy or sell credit protection on some underlying debt. The decision depends on the investors' differences in sensitivities towards risk and ambiguity. One key driver of the model is that, in the presence of ambiguity, agents overweight (underweight) the probabilities of the unfavorable (favorable) outcome. Thus, whether a greater probability is assigned to the default or solvency outcome depends on the net exposure to default risk, as CDS buyers (sellers) face a positive payoff in case of default (solvency). The market clearing condition for assets in zero net supply yields the equilibrium price for CDS contracts.

The framework delivers two predictions. First, risk unambiguously has a positive effect on spreads, irrespective of the preferences of investors. Intuitively, this arises because the demand effect tends to outweigh the supply effect when risk or ambiguity increases. Second, the impact of ambiguity on spreads depends on the net exposure of the marginal investor in the CDS market. Everything else equal, the marginal investor is determined either by lower risk aversion (greater risk-bearing capacity), or greater sensitivity to ambiguity. Thus, if the buyer is less risk averse or more ambiguity averse, credit spreads are decreasing in the amount of ambiguity. The testable predictions are illustrated analytically using constant absolute risk aversion, and constant absolute ambiguity aversion, as well as numerically using constant relative risk aversion, and constant relative ambiguity aversion.

We further develop the intuition behind these predictions by introducing the framework into a simple binomial option pricing model. We relate the value of credit spreads to that of option values, as proposed by the Merton (1974) model, which is the basic starting point for most valuations of defaultable corporate debt. The key insight of the Merton model is that risky debt is equivalent to a portfolio that consists of risk-free debt and a short position in a put option written on the assets of that same firm. A higher volatility implies a greater default-contingent compensation (i.e., lower bond prices) due to the non-linearity in the option payoff function, and thus credit spreads are increasing in the volatility of the firm's assets. By a similar reasoning, the hypothesis that credit spreads are decreasing in the ambiguity of future outcomes is derived from the fact that higher ambiguity about the likelihood of a default event reduces the willingness of an ambiguity-averse investor to pay for a put option on the assets of a firm.

Our key findings show that ambiguity and risk have opposite effects on CDS spreads, and that the economic impact of ambiguity is as important as that of risk. The fact that higher ambiguity is associated with *lower* levels of CDS spreads suggest that the marginal investor in the CDS market is net short credit risk, i.e., a CDS buyer. To reach this conclusion, we use a sample of 491 U.S. CDS firms with 53,356 monthly observations from January 2001 until October 2014. In *univariate* regression tests with firm fixed effects, we find that a one standard deviation increase in ambiguity leads to a decrease in CDS spreads of approximately 24 percent, which translates into a 39 basis points (bps) *decrease* for the average firm in our sample. On its own, ambiguity explains about 20 percent of the cross-sectional variation in the level of CDS spreads. Risk, on the other hand, explains only about 9 percent, and its economic significance is similar to that of ambiguity, although with the opposite sign. Multivariate regressions demonstrate that a one standard deviation change in ambiguity or risk, respectively, decreases or increases the level of CDS spreads by at least six percent, corresponding to a magnitude of at least ten basis points for the average firm. Subject to the empirical model specification, the explanatory power of the level regressions is up to 75%, in terms of adjusted R^2, and up to 33% for regressions using spread changes. We find qualitatively similar results for regression specifications with CDS percentage changes or natural logarithms of CDS spread levels.

The empirical proxies for risk and ambiguity are measured independently of each other, and are rooted in a theoretical decision theory framework of expected utility with uncertain probabilities (EUUP), applied in Izhakian and Yermack (2017). In that framework, the degree of ambiguity can be measured by the volatility of the probabilities of future outcomes, just as the degree of risk can be measured by the volatility of the realized outcomes. The explicit separation of risk and ambiguity is an essential prerequisite for the empirical assessment of the impact of ambiguity on asset prices, which is challenging based on frameworks that cannot explicitly distinguish ambiguity from risk. Most importantly, the measure of ambiguity extracted from EUUP can be estimated using high frequency stock price data, and therefore used in empirical studies to test the implications of ambiguity for asset pricing. For example, Izhakian and Yermack (2017) show that ambiguity influences the employees' decision to exercise their executive stock options.

In addition to the contemporaneous relationship between ambiguity and credit risk, we examine the predictability of ambiguity and risk on the level of CDS spreads and their changes, using lags of up to three months. Both lagged measures of ambiguity and risk help predict the level of CDS spreads. This mitigates concerns that firms with higher CDS spreads endogenously have lower degrees of ambiguity. We also examine whether aggregate market risk and ambiguity, measured using the return information on the S&P 500, impact credit spreads in addition to firm-specific ambiguity. While aggregate ambiguity has weaker explanatory power and lower economic impact than firm-specific ambiguity on the level of spreads, aggregate risk has greater explanatory power and similar economic impact than firm-specific risk.

We test the two additional hypotheses that greater ambiguity leads to a flatter slope of the term structure of CDS spreads, and that greater risk results in a steeper slope of the term structure of spreads. These two hypotheses are drawn by static scenario analysis based on a simple binomial option pricing model, which suggests that the impact of risk and ambiguity is greater for longer contract maturities. Our findings indeed confirm that ambiguity and risk have greater impact for longer horizon contracts, which in turn confirms our hypotheses concerning the term structure of CDS spreads.

All findings are robust against the inclusion of firm-specific control variables including leverage, Standard and Poor's (S&P's) long-term credit ratings, CDS liquidity, and firm size. This also holds while controlling for observable and unobservable macroeconomic risk factors, and (unobservable) time invariant firm heterogeneity. In addition, we control for other aggregate market risk factors including the CBOE option-implied volatility index, high-yield and investment-grade credit spreads, and the return on the S&P 500 stock index. All in all, the empirical analysis strongly supports the view that ambiguity captures a dimension of uncertainty that is different from risk.

Last, we present a long battery of robustness tests, verifying that our findings are consistent with the previous literature, yet showing that alternative explanations cannot drive out the negative relationship between ambiguity and credit spreads. In particular, we verify that our results hold if we control for the probability of default implied by the Merton distance-to-default measure, equity volatility, jump risk measures constructed using high frequency stock price returns, and various accounting and balance sheet information. Furthermore, we show that the magnitude of the negative regression coefficient attributed to ambiguity does not change when controlling for the contemporaneous stock return. We also examine several industries separately using industry fixed effects to show that the direction of the effect of ambiguity on credit spreads depends on the net economic exposure of the marginal investor to the risks of the firm. As ambiguity-averse investors assign lower probabilities to high utility states, the findings of a negative relationship between credit spreads and ambiguity is consistent with the anecdotal evidence that banks and broker-dealers, who dominate the heavily concentrated market, are net buyers of CDS (Bongaerts et al.; 2011; Duffie et al.; 2015; Peltonen et al.; 2014).

The current paper combines two strands of literature. First, it relates to the previous studies that examine the determinants of credit spreads and their changes. Second, it assimilates with the theoretical literature that introduces ambiguity into decision-making processes and its associated implications for asset prices. With respect to the former, structural credit risk models suggest that asset volatility and leverage are key determinants of credit spreads (Black and Scholes; 1973; Merton; 1974). More recently, Collin-Dufresne et al. (2001) empirically test these predictions using corporate bond spreads and conclude that the structural factors have limited ability to explain credit spread changes, based on low explanatory power of the regressions. In contrast, Ericsson et al. (2009) find that structural variables, including volatility and leverage, do explain a great fraction of the level and changes of CDS spreads. Other studies of the determinants of credit spreads highlight the significant explanatory power of both total and idiosyncratic firm-specific volatility for the level of yield spreads (Campbell and Taksler; 2003), or of the information captured by option-implied and historical volatility of CDS and bond spreads (Cremers et al.; 2008; Cao et al.; 2010). Zhang et al. (2009) explain the level of CDS spreads using high-frequency return-based volatility and jump risk measures, computed from high-frequency equity returns. The role of firm fundamentals and the Merton (1974) distance-to-default measure for credit spreads is confirmed by Bharath and Shumway (2008) and Bai and Wu (2016). A visual summary of the main suggested determinants of CDS spreads, proposed by the prior major studies in recent years, is provided in Table 1.[1] With

[1]See also Blanco et al. (2005), and Das et al. (2009) for the role of accounting information in CDS spreads. For an exhaustive review of the determinants of CDS spreads, see Augustin et al. (2014). Other market frictions

respect to this literature, the novel contribution of the current paper is the empirical test of the relationship between credit spreads and ambiguity, which allows to infer the net exposure of the marginal investors in the CDS market.

The theoretical success of preferences concerning ambiguity to match asset prices (Chen and Epstein; 2002; Cao et al.; 2005; Epstein and Schneider; 2008; Illeditsch; 2011; Boyarchenko; 2012) has motivated more direct empirical tests of the role of ambiguity for equity returns (Anderson et al.; 2009; Ulrich; 2013; Antoniou et al.; 2014; Williams; 2014; Brenner and Izhakian; 2016). Only a few studies, however, have attempted to deal with the implications of ambiguity for options, and those studies tend to focus on theoretical aspects (Faria and Correia-da Silva; 2014). Izhakian and Yermack (2017) empirically show that expected ambiguity has a significant positive impact on employees' decision to exercise their vested stock options, as future option values are expected to be lower. Our contribution relative to the previous literature is that we empirically assess the independent impacts of risk and ambiguity on the pricing of credit insurance contracts. Such an assessment provides valuable feedback for the theoretical success of models with ambiguity-averse preferences in matching asset and option prices.

The remainder of this paper is organized as follows. Section II presents a theoretical discussion of ambiguity and develops the hypotheses. Section III describes the sample selection and data construction, including the estimates of the ambiguity and volatility variables that are central to our investigation. Section IV presents the main regression analysis of CDS spreads, while section V discusses several robustness tests. Section VI concludes the paper.

II Ambiguity

II.1 The decision theoretic framework of ambiguity

Knight (1921) distinguishes the concept of uncertainty (ambiguity) from risk through the conditions under which the odds of future events are either not unique or unknown.[2] *Knightian uncertainty*,

that have been shown to affect credit spreads reflect, for example, liquidity and liquidity risk in CDS (Longstaff et al.; 2005; Tang and Yan; 2007; Bongaerts et al.; 2011; Qiu and Yu; 2012) and bonds (Acharya et al.; 2013; Chen et al.; 2007), counterparty risk (Arora et al.; 2012), recovery risk (Pan and Singleton; 2008; Elkamhi et al.; 2014), cheapest-to-deliver options (Jankowitsch et al.; 2008; Ammer and Cai; 2011), and restructuring risk (Berndt et al.; 2007).

[2]Knight (1921) defines the concept of Knightian uncertainty as distinct from risk. The distinction is made through the conditions under which the set of events that may occur is *a priori* unknown, and the odds of these events are also either not unique or unknown. Roughly speaking, the concept of ambiguity can be viewed as underpinning two

which has provided the basis for a rich literature in economic decision theory, has been stimulated by Ellsberg (1961), who demonstrates that, in the presence of ambiguity, individuals tend to violate the basic axiom of expected utility theory. We distinguish the concepts of risk and ambiguity using the theoretical framework of EUUP (Izhakian; 2017). This ambiguity framework formally separates tastes from beliefs, and risk from ambiguity. Importantly, these separations enable the risk-independent measurement of the extent of ambiguity in the data, a challenge faced by the previous literature. More importantly, the measurability feature enables the empirical validation of testable predictions derived from the theoretical framework.[3]

The main idea of EUUP is that, in the presence of ambiguity, i.e., when there exists uncertainty about the probabilities of future state outcomes, preferences concerning ambiguity are applied exclusively to these probabilities. Thus, aversion to ambiguity is defined as aversion to mean-preserving spreads in probabilities. As such, the Rothschild and Stiglitz (1970) approach, which is typically applied to state outcomes for the measurement of risk, can also be applied to probabilities for the measurement of ambiguity, independently from the measurement of risk. In particular, the degree of ambiguity can be measured by the volatility of probabilities, just as the degree of risk can be measured by the volatility of outcomes. The resulting measure is risk-independent and accounts for the variance of all the moments of the outcome distribution. This represents a significant departure from other measures of ambiguity, which are risk-dependent and consider only the variance of a single moment of the outcome distribution, i.e., the variance of the mean or the variance of the variance.

Financial decision makers (investors) face ambiguity about the probabilities of future payoffs. This means that the future realizations of outcomes are unknown, and that the probabilities associated with these realizations are also not uniquely assigned or not known. We formally define the uncertain payoff X in a probability space $(\mathcal{S}, \mathcal{E}, \mathrm{P})$, with a state space $\mathcal{S}$, a σ-algebra of subsets

strands of literature. The first is the literature relating to "unawareness," which assumes that decision makers may not be aware of a subset of events (e.g., Karni and Vierø (2013)). The second is the literature relating to ambiguity, which assumes that the set of events is perfectly known, but the outcome probabilities are either not unique, or unknown (e.g., Gilboa and Schmeidler (1989) and Schmeidler (1989)). These two strands of literature can be viewed as overlapping when dealing with monetary outcomes (real numbers). In this case, the "uncertain", i.e., risky and ambiguous, variable is defined by a measurable function from states into real numbers such that there exists no real monetary outcome the decision maker is unaware of. It is possible that the decision maker is unaware of some events (the so-called black swans), which may affect the uncertainty about the probabilities of some outcomes. However, this uncertainty is already accounted for by ambiguity.

[3] Other models do not permit such derivations since either ambiguity is not distinguished from aversion to ambiguity (Schmeidler; 1989; Gilboa and Schmeidler; 1989) or aversion to ambiguity is defined as aversion to mean-preserving spreads in certainty equivalent utilities, which are subject to risk and preferences for risk (Chew and Sagi; 2008).

of the state space (i.e., a set of events) $\mathcal{E}$, and a probability measure $\mathrm{P} \in \mathcal{P}$ that belongs to a (convex) set of probability measures $\mathcal{P}$. An algebra Π of measurable subsets of $\mathcal{P}$ is equipped with a probability measure ξ. The uncertain real (monetary) outcome is then given by the "uncertain" variable $X : \mathcal{S} \to \mathbb{R}$, mapping from the set of possible states into the real numbers. Denote by $\varphi(x)$ the marginal probability (density or probability-mass function) associated with the cumulative probability $\mathrm{P} \in \mathcal{P}$ of x. The expected marginal and cumulative probability of x, taken using the second-order probability measure ξ, are then defined by

$$\mathrm{E}[\varphi(x)] \equiv \int_{\mathcal{P}} \varphi(x)\, d\xi \qquad \text{and} \qquad \mathrm{E}[\mathrm{P}(x)] \equiv \int_{\mathcal{P}} \mathrm{P}(x)\, d\xi \tag{1}$$

respectively, and the variance of the marginal probability is defined by

$$\mathrm{Var}[\varphi(x)] \equiv \int_{\mathcal{P}} \big(\varphi(x) - \mathrm{E}[\varphi(x)]\big)^2 d\xi. \tag{2}$$

With these definitions in place, the expected outcome and the variance of outcomes are computed using the expected probabilities. That is,

$$\mathbb{E}[X] \equiv \int \mathrm{E}[\varphi(x)]\, x dx \qquad \text{and} \qquad \mathbb{V}\mathrm{ar}[X] \equiv \int \mathrm{E}[\varphi(x)] \big(x - \mathbb{E}[x]\big)^2 dx. \tag{3}$$

Since every $\mathrm{P} \in \mathcal{P}$ is additive, and the variance is computed using expected probabilities, the expectation and the variance of outcomes can be viewed as if they are computed using linear compounded probabilities. That is, no element of ambiguity (or aversion to ambiguity) is involved.

Investors have distinct preferences concerning risk and ambiguity. As usual, preferences concerning risk are modeled by a bounded, strictly-increasing and continuously twice-differentiable utility function $\mathrm{U} : \mathbb{R} \to \mathbb{R}$. We assume risk-averse investors, which implies that $\mathrm{U}(\cdot)$ is a concave function. Similar to cumulative prospect theory of Tversky and Kahneman (1992), we assume a reference point, k, relative to which outcomes are classified as either unfavorable (a loss) or as favorable (a gain).[4] Without loss of generality, we normalize the utility function to $\mathrm{U}(k) = 0$.

As investors are sensitive to ambiguity, they do not compound the set of priors $\mathcal{P}$ and the prior ξ over $\mathcal{P}$ in a linear way (compounded lotteries). Instead, they aggregate these probabilities in a non-linear way, reflecting their aversion to ambiguity. Preferences concerning ambiguity are modeled by a strictly-increasing and continuously twice-differentiable function over probabilities, $\Upsilon : [0, 1] \to \mathbb{R}$. Similarly to risk, ambiguity aversion takes the form of a concave function $\Upsilon(\cdot)$.

[4]Unlike cumulative prospect theory, we do not assume asymmetric utility from losses over gains (i.e., loss aversion), although this could be included in the EUUP framework.

In the EUUP framework, ambiguity aversion is reflected in the preference of an investor for the expectation of an uncertain payoff probability over the uncertain probability itself.[5]

Suppose that a decision to save one unit of wealth is made at the beginning of the period, and its outcome, which is the only source of wealth, occurs at the end of the period. The expected utility of this investment opportunity can be approximated by[6]

$$\begin{aligned} \mathrm{W}(X) \approx & \int_{x \leq k} \mathrm{U}(x) \underbrace{\mathrm{E}[\varphi(x)]\left(1-\frac{\Upsilon''(1-\mathrm{E}[\mathrm{P}(x)])}{\Upsilon'(1-\mathrm{E}[\mathrm{P}(x)])} \mathrm{Var}[\varphi(x)]\right)}_{\text{Perceived Probability of Unfavorable Outcome}} dx + \\ & \int_{x \geq k} \mathrm{U}(x) \underbrace{\mathrm{E}[\varphi(x)]\left(1+\frac{\Upsilon''(1-\mathrm{E}[\mathrm{P}(x)])}{\Upsilon'(1-\mathrm{E}[\mathrm{P}(x)])} \mathrm{Var}[\varphi(x)]\right)}_{\text{Perceived Probability of Favorable Outcome}} dx, \end{aligned} \tag{4}$$

where X is the investment payoff and $-\frac{\Upsilon''(1-\mathrm{E}[\mathrm{P}(x)])}{\Upsilon'(1-\mathrm{E}[\mathrm{P}(x)])}$ defines the intensity of ambiguity aversion.[7] Notice that when investors are ambiguity neutral, i.e., $\Upsilon(\cdot)$ is linear, this equation collapses to standard expected utility.

Using the notion of the volatility of probabilities, a measure of the extent of ambiguity derived by Equation (4) is

$$\mho^2[X] \equiv \int \mathrm{E}[\varphi(x)] \mathrm{Var}[\varphi(x)] \, dx. \tag{5}$$

The measure $\mho^2$ can be computed both in the general case of a space with infinitely many outcomes, or in a discrete state space with finitely many outcomes. The measure $\mho^2$ is risk-independent. Moreover, this measure allows for the comparison of two assets with different degrees of ambiguity and equal volatility, or two assets with different degrees of volatility and equal ambiguity. This is not possible when ambiguity is approximated by, for example, the volatility of volatility.[8]

To observe the distinct impact of ambiguity and attitude toward it on the value of an asset, consider a security with a binomial payoff, which can either be high (H) or low (L) in the "good" and "bad" states of nature, respectively. Suppose that the reference point k satisfies $L \leq k \leq$

[5]Recall that risk aversion is exhibited when an investor prefers the expected outcome of the uncertain outcome over the uncertain outcome itself.

[6]See (Izhakian; 2016, Theorem 2).

[7]The EUUP representation also supports subjective distortions of perceived probabilities, derived by mental accounting. However, for simplicity, we assume no distortions of these probabilities.

[8]The earlier literature suggested the volatility of the volatility or the volatility of the mean as measures of ambiguity. The measure of ambiguity $\mho^2$ accounts for both, as well as for the volatility of all higher moments of the probability distribution (i.e., skewness, kurtosis, etc.) through the variance of probabilities. As opposed to the volatility of the volatility and to the volatility of the mean, $\mho^2$ is risk-independent, as it does not depend upon the magnitudes of outcomes, but only upon their probabilities.

$\mathbb{E}[X] < H$.[9] By Equation (4), the value of this asset in terms of expected utility is

$$\begin{aligned} \mathrm{W}(X) \;\approx\; & \mathrm{U}(L)\,\mathrm{E}[\varphi(L)]\left(1 - \frac{\Upsilon''(\mathrm{E}[\mathrm{P}(H)])}{\Upsilon'(\mathrm{E}[\mathrm{P}(H)])}\mathrm{Var}[\varphi(L)]\right) + \\ & \mathrm{U}(H)\,\mathrm{E}[\varphi(H)]\left(1 + \frac{\Upsilon''(\mathrm{E}[\mathrm{P}(H)])}{\Upsilon'(\mathrm{E}[\mathrm{P}(H)])}\mathrm{Var}[\varphi(H)]\right). \end{aligned} \tag{6}$$

Note that, since every $\mathrm{P} \in \mathcal{P}$ is additive, $1 - \mathrm{E}[\mathrm{P}(L)] = \mathrm{E}[\mathrm{P}(H)]$. In addition, in this case, the variance of the probabilities of an event is equal to the variance of the probabilities of its complementary event; that is, $\mathrm{Var}[\varphi(L)] = \mathrm{Var}[\varphi(H)]$. Expected utility in our framework is assessed using the investor's perceived probabilities. Ambiguity and related aversion are modeled in Equation (6) through the investor's marginal perceived probabilities. Consider, for example, the "good" payoff H. The expression

$$\mathrm{Q}(H) \;\approx\; \mathrm{E}[\varphi(H)]\left(1 + \frac{\Upsilon''(\mathrm{E}[\mathrm{P}(H)])}{\Upsilon'(\mathrm{E}[\mathrm{P}(H)])}\mathrm{Var}[\varphi(H)]\right) \tag{7}$$

is the marginal perceived probability of this outcome occurring. This probability is a function of the extent of ambiguity, measured by $\mathrm{Var}[\varphi(H)]$, and the investor's attitude toward ambiguity, captured by $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)}$. Therefore, for an ambiguity-averse investor (i.e., $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)} > 0$), a higher aversion to ambiguity, or a higher extent of ambiguity, results in lower marginal perceived probabilities of the "good" states, and higher marginal perceived probabilities of the "bad" states. This, in turn, implies a lower expected utility. In other words, an ambiguity-averse investor overweights the probabilities of unfavorable outcomes and underweights those of favorable outcomes.

II.2 Implications of ambiguity and risk for credit spreads

To derive testable predictions about the effect of ambiguity and risk on CDS spreads, we now turn to develop a stylized equilibrium model that accommodates risk, ambiguity, and heterogeneous investors for the pricing of CDS spreads. Assume a closed economy with one single defaultable reference entity (firm) for which investors can buy or sell CDS, i.e., credit default protection. The firm is leveraged with the face value of debt denoted N. This firm faces only two possible events, it can default (DF) on its outstanding debt commitments, or it can remain solvent (SL). In case of default, investors recover a fraction R of the face value of debt.

Suppose that there are two types of investors with the same initial wealth, w. Both investors

[9] It is assumed that the reference point is lower than the expected outcome. Otherwise, a rational decision maker will not consider the investment opportunity.

face the same level of ambiguity about the probabilities of these events, and the same level of risk. However, investors may differ in their aversion to risk and to ambiguity.[10] Both investors exhibit a neutral time preference, implying a zero risk-free rate. Each of the investors can purchase or sell h units of the CDS, i.e., they can buy or sell credit protection. The amount h can be interpreted as the fraction of the face value of debt that the buyer of insurance would like to insure. Thus, $h = 1$ means full coverage, $h > 1$ means over-insurance, and $h < 1$ means partial insurance. The amount h an investor can buy is subject to his budget constraint.

The unfavorable outcome depends on the net exposure to the payoff derived from the CDS contract. A long investor prefers default, as it results in a non-negative payoff. A short investor, who sells insurance, on the other hand, has a preference for the firm to remain solvent. Thus, in the presence of shorting and assets in zero net supply, an investor needs to solve two different optimization problems in order to determine the optimal holdings of credit protection. In particular, each investor decides whether to buy or sell the CDS by solving the following two maximization problems

$$\begin{aligned} \max_{h} \quad & \mathrm{Q}(DF)\mathrm{U}\left(w - hp + h\left(N - R\right)\right) + \left[1 - \mathrm{Q}(DF)\right]\mathrm{U}\left(w - hp\right) \\ \text{s.t.} \quad & 0 \leq h \leq \tfrac{w}{p} \qquad \text{and} \qquad 0 < p < N - R \end{aligned} \tag{8}$$

and

$$\begin{aligned} \max_{h} \quad & \left[1 - \mathrm{Q}(SL)\right]\mathrm{U}\left(w + hp - h\left(N - R\right)\right) + \mathrm{Q}(SL)\mathrm{U}\left(w + hp\right) \\ \text{s.t.} \quad & 0 \leq h \leq \tfrac{w}{N-R-p} \qquad \text{and} \qquad 0 < p < N - R \end{aligned} \tag{9}$$

where p is the market price of the CDS. When the utility of the maximization problem (8) is higher than that of (9), then the investor optimally buys the CDS. In this case, the investor's initial wealth is denoted w_B, and the purchased amount is denoted h_B. On the other hand, when the utility of the maximization problem (9) is higher than that of (8), the investor optimally sells the CDS. In this case, the investor's initial wealth is denoted w_S, and the sold amount is denoted h_S. The main motivation for *selling* a CDS is that the seller's perceived probability of default is low relatively to the perceived probability of solvency. In contrast, the main motivation for *buying* a CDS is that the buyer's perceived probability of default is high relatively to the probability of solvency.

[10] Equilibrium prices are determined by the difference in marginal utility, which is a function of risk-bearing capacity. In turn, risk-bearing capacity is subject to wealth and innate risk aversion. For simplicity, we assume homogeneous wealth and focus on heterogeneity in risk aversion.

The optimal decision of an investor to buy or to sell is made base upon the attitude toward risk, captured by U, and toward ambiguity, captured by Υ. In equilibrium, the market clearing condition

$$h_B = h_S \qquad (10)$$

enforces that one type of investors buys CDS, while the other sells. The agent with the higher risk/ambiguity tolerance will be the seller of credit protection and engage in risk and ambiguity sharing with the more risk and/or ambiguity averse investor.

The boundary condition $0 < p < N - R$ characterizes the CDS price as the present value of all the expected future insurance payments implied by the credit protection.[11] The boundary conditions on h in the maximization problems (8) and (9) are dictated by the budget constraint. We focus exclusively on interior solutions to the maximization problems (8) and (9), for which the market clearing condition (10) holds. Since U and Υ are strictly concave, this assumption implies a unique solution for both maximization problems and, therefore, by the market clearing condition, a unique equilibrium price. Corner solutions, such as $h = 0$, do not guaranty a unique equilibrium price.

In equilibrium, the price p of the CDS contract is determined by the market clearing condition, and, therefore, depends on the intensities of aversion to risk and ambiguity, and the initial wealth of both investors. To illustrate the pricing impacts of differences in the intensities of aversion to risk and ambiguity, we consider for simplicity a one-period model. We derive testable predictions by assuming that the buyers and sellers exhibit a constant absolute risk aversion (CARA) as well as a constant absolute ambiguity aversion (CAAA). Namely, $\mathrm{U}(x) = \frac{1-e^{-\gamma_j x}}{\gamma_j}$ and $\Upsilon(x) = \frac{1-e^{-\eta_j x}}{\eta_j}$, for $j = \{B, S\}$, such that buyers and sellers may have different intensities of aversion to risk $\{\gamma_B, \gamma_S\}$ and to ambiguity $\{\eta_B, \eta_S\}$. The assumption of CARA and CAAA is by no means restrictive, and for simplicity only, as it allows us to derive analytical solutions to the optimization problem. We further show, using numerical solutions, that the same implications for the impact of ambiguity and risk on the pricing of CDS also hold for investors with constant relative risk aversion (CRRA) and constant relative ambiguity aversion (CRAA).

[11] For simplicity, we refer to the CDS price as the present value of all the expected future insurance payments implied by the credit protection. By convention, CDS contracts are quoted in running spreads. Since the implementation of the Big Bang protocol in 2009, CDS contracts are traded with fixed coupons and upfront payments. Thus, the price p can be interpreted as a contract that its entirely settled upfront with a zero bps coupon.

As in Rothschild and Stiglitz (1970), an underlying security is said to become risker if its new payoffs can be written as a mean-preserving spread of the old payoffs. Accordingly, the next proposition assumes neither that risk is measured by the variance of payoffs, nor that returns are normally distributed or that the utility is quadratic.

Proposition 1 *Suppose that the buyers and the sellers are characterized by CARA and CAAA preferences, possibly with different intensity of aversion to ambiguity and to risk, such that the boundary conditions in* (8) *and* (9) *are slack. The higher the risk, the higher is the CDS spread.*[12]

In the model, risk is captured implicitly by varying rates of recovery. A lower recovery rate widens the outcome gap between the default and solvency states, and thus implies greater risk. Proposition 1 suggests that the effect of risk on CDS spreads is independent of the type of the marginal investor (net buyer or net seller). Thus, regardless of the marginal investor's degree of risk aversion, risk positively affects the price of the CDS. In general equilibrium, an increase in risk affects both the buyer and the seller. The buyer's demand for the CDS increases due to greater demand for risk sharing. The buyer will also attribute additional value to each unit of insurance, which increases the CDS spread. The seller, on the other hand, will increase the supply of the CDS, given the increased profit opportunities from risk sharing, which reduces the value of the spread. Proposition 1 highlights that, with respect to risk, the demand effect always supersedes the supply effect, and so risk impacts CDS spreads always positively in equilibrium.

Proposition 2 *Suppose that the buyers and the sellers are characterized by CARA and CAAA, with an identical intensity of aversion to risk, such that the boundary conditions in* (8) *and* (9) *are slack. When*

$$\eta_B \frac{\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]}{\mathrm{Q}(DF)\left[1-\mathrm{Q}(DF)\right]} \quad > \quad \eta_S \frac{\mathrm{E}\left[\mathrm{P}\left(SL\right)\right]}{\mathrm{Q}(SL)\left[1-\mathrm{Q}(SL)\right]} \tag{11}$$

the higher the ambiguity the lower the CDS spread. When

$$\eta_B \frac{\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]}{\mathrm{Q}(DF)\left[1-\mathrm{Q}(DF)\right]} \quad < \quad \eta_S \frac{\mathrm{E}\left[\mathrm{P}\left(SL\right)\right]}{\mathrm{Q}(SL)\left[1-\mathrm{Q}(SL)\right]} \tag{12}$$

the higher the ambiguity the higher the CDS spread.

Proposition 2 suggests that the sign of the impact of ambiguity on CDS spreads depends upon the intensity of the aversion to ambiguity of the marginal investor. A CDS buyer is willing to pay

[12]Proof: See Appendix.

a higher price when the perceived probability of default is high. However, as the buyer underweights the probability of default (and overweights the probability of solvency), higher ambiguity reduces the perceived probability of default, such that the value of the credit protection is reduced. Therefore, the buyer's demand for CDS decreases. At the same time, as the seller underweights the probability of solvency (and overweights the probability of default), higher ambiguity reduces the perceived probability of solvency, such that the seller reduces the supply. The overall effect of higher ambiguity is, therefore, determined by the relative sensitivity to ambiguity between the buyer and the seller. When the buyer is more sensitive, i.e., more averse, to ambiguity than the seller, such that inequality (11) holds, then an increase in ambiguity should result in a lower spread. On the other hand, when the seller is more sensitive, i.e., more averse, to ambiguity than the buyer, such that inequality (12) holds, then an increase in ambiguity will result in a higher spread.

Propositions 1 and 2 are based on the assumption that investors exhibit CARA and CAAA preferences. This assumption allows us to analyze the impact of risk and ambiguity on CDS spreads using analytical solutions, but it is by no means restrictive. Figure 1 shows numerically that similar predictions arise for investors with CRRA and CRAA preferences. The upper two panels in Figure 1 describe the relationship between risk and the price of credit protection, illustrating the cases of investors with equal ambiguity aversion, but heterogeneity in risk aversion (upper left), as well as equal risk aversion, but heterogeneity in ambiguity aversion (upper right). Similar to the conclusions of Proposition 1, the figures illustrate that the impact of risk on spreads is always positive, irrespective of the preferences with respect to ambiguity and risk. The lower two panels, on the other hand, describe the relationship between ambiguity and CDS spreads. Again, we illustrate the relationship separately for heterogeneous investors with respect to either ambiguity (lower right) or risk preferences (lower left). If the buyer has greater (lower) risk-bearing capacity, characterized through a lower (higher) degree of risk aversion than the seller, the relationship between ambiguity and CDS spreads is predicted to be negative (positive). Moreover, as analytically shown in Proposition 2, the impact of ambiguity on CDS spreads will be negative (positive) if the buyer has a greater (lower) aversion to ambiguity.

II.3 Hypotheses

It is helpful to provide additional intuition about the impact of risk and ambiguity on credit spreads by drawing an analogy with the Merton (1974) model. In this model, debt values are equivalent to a portfolio made up of the present value of the face value of the firm's debt and a short position in a put option on the assets of the firm, with strike price equal to the face value of debt. Thus, the higher the value of the put option, the lower the price of the risky bond, and the greater the credit spread. Consider, for example, a put option on the assets of a firm. In case of default, the holder of the put option receives the payout $N-R$. Suppose that the exercise price is the reference point k, satisfying $0 \leq k \leq N-R$. By Equation (6), the value of this option (in terms of expected utility) is

$$p \quad \approx \quad \mathrm{E}\left[\varphi\left(DF\right)\right]\left(1+\frac{\Upsilon''\left(\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]\right)}{\Upsilon'\left(\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]\right)}\mathrm{Var}\left[\varphi\left(DF\right)\right]\right)\mathrm{U}\left(N-R\right). \qquad (13)$$

Equation (13) suggests that the option value is increasing in the risk of the underlying asset, since the option payoff is convex in the state outcomes. To see this more clearly, consider a firm with a recovery of R in case of default. Assume that the risk of the underlying asset increases (while the expected outcome remains unchanged), such that the recovery in case of default is $R-\Delta$. Since the reference point satisfies $k \leq N-R$, the expected utility from this put option is positively affected by the magnitude of Δ, as derived from the volatility of the underlying assets. Therefore, by Equation (13), the value of the put option and the credit spread increase in the risk of the underlying debt.[13] Thus, as supported by Proposition 1, we conjecture the following hypothesis.[14]

Hypothesis 1 *Credit spreads are higher for higher degrees of firm-specific risk.*

In addition to the effect of risk, a higher ambiguity implies lower perceived probabilities of the good states from the perspective of the CDS buyer, and therefore a lower value of the put option (and hence the CDS). To see this, in Equation (13), consider for example an ambiguity attitude of the CAAA type. In this case $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)}=\eta$, where η is the coefficient of absolute ambiguity aversion. Since aversion to ambiguity implies a positive $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)}$, a higher ambiguity of the underlying debt, measured by $\mho^2$ (which in this case is equal to $\mathrm{Var}\left[\varphi\left(DF\right)\right]$), implies lower perceived probabil-

[13] Note that, assuming normally distributed returns, a quadratic utility function or an exponential utility function (all imply a mean-variance-ambiguity preference), risk can be measured by the variance of returns, computed using expected probabilities (Izhakian and Yermack; 2017).

[14] This is a well documented result that we aim to confirm empirically.

ities (Equation (7)) and therefore a lower value of the put option or the CDS, from the buyers' perspective. Overall, as supported by Proposition 2, we formulate our main hypothesis.

Hypothesis 2 *Assuming that the marginal investor is a CDS buyer, credit spreads are lower for higher degrees of firm-specific ambiguity.*

Using static equilibrium analysis, we also show in Figure 2 that the impact of risk and ambiguity is greater for longer contract maturities. This leads us to conjecture that a greater risk leads to a steepening of the slope of the term structure of CDS spreads.

Hypothesis 3 *The slope of the term structure of CDS spreads is increasing in the amount of firm-specific risk.*

On the other hand, a greater ambiguity leads to a flattering of the slope of the term structure of CDS spreads, as is illustrated in the left panel. This allows us to formulate a second hypothesis regarding the slope of the term structure of CDS spreads.

Hypothesis 4 *The slope of the term structure of CDS spreads is decreasing in the degree of firm-specific ambiguity.*

We note that this last hypothesis is closely related to Duffie and Lando (2001), who illustrate how a lack of accounting transparency can lead to a flatter slope of the term structure of credit spreads. In a similar way, the greater the uncertainty about the probabilities of future state outcomes (or the greater the aversion towards this uncertainty), the flatter is the slope of the term structure of credit spreads. It is important to emphasize that these hypotheses are written subject to the assumption that the marginal investor is a CDS buyer. However, Proposition 2 clearly emphasizes that the sign of the impact of ambiguity on CDS spreads remains an empirical question. Empirically, we may find a positive or negative relationship between CDS spreads and ambiguity, depending on the net exposure of the marginal investor. For risk, however, we expect to find unambiguously a positive relationship with CDS spreads.

II.4 Binomial example

To further deepen the intuition about our hypotheses, we illustrate the impact of ambiguity and risk on CDS spreads using a simple one-period binomial example for an investor who is long credit risk. As in the previous section, we borrow from Merton (1974) and examine the impact on credit spreads through the lens of put option values. Consider a company with face value of debt equal to \$100 and assets worth \$100. After one period, the value of the assets may either go up to $H = \$120$ or down to $L = \$80$, i.e., corresponding to up and down returns of 20%, respectively. In the case of default, i.e., $L < 100$, the put option pays the difference between the strike price K (which is \$100) and the underlying asset value, i.e., $100 - L$. For simplicity, we assume that the investor is risk neutral and we normalize interest rates to zero.

When the probabilities of both the bad and the good returns are exactly 50% (no ambiguity), the variance of the probabilities is 0. Therefore, by substituting into Equation (13), the value of the put option (in terms of expected utility) is $P = 0.5 \times (100 - 80) = 10$. If the risk of the underlying equity increases, such that the returns in the up and down states are +30% or -30%, respectively, then the value of the option increases to $P = 0.5 \times (100 - 70) = 15$. Thus, the increase in risk is associated with an increase in the value of the put option, and therefore credit spreads.

To examine the impact of ambiguity, assume instead that the probabilities of the future return of the underlying equity are ambiguous. Up and down returns occur with probability distributions $(0.4, 0.6)$ or $(0.6, 0.4)$. The investor, who does not have any information regarding the precision of these probability estimates, acts as if he assigns an equal weight to each state probability. In this case, the expected probability of the up state is $\mathrm{E}[\varphi(H)] = 0.5 \times 0.4 + 0.5 \times 0.6 = 0.5$ and its variance is $\mathrm{Var}[\varphi(H)] = 0.5 \times (0.4 - 0.5)^2 + 0.5 \times (0.6 - 0.5)^2 = 0.01$. The same values apply for the down state. This implies that the degree of ambiguity is $\mho^2 = 0.5 \times 0.01 + 0.5 \times 0.01 = 0.01$.

Assume first an ambiguity-neutral investor. The ambiguity preference of this investor is characterized by a linear function $\Upsilon(\cdot)$, implying that perceived probabilities are formed through expected probabilities to assess expected utility. Accordingly, by Equation (13), the value of the option (in terms of expected utility) remains the same and equal to $P = 0.5 \times (100 - 80) = 10$. For comparison, assume instead an ambiguity-averse investor of a constant absolute ambiguity aversion type with coefficient of ambiguity aversion $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)} = \eta = 2$. Due to aversion to ambiguity, this investor does not form perceived probabilities through a linear compounding of probabilities, but aggregates probabilities in a non-linear way as described in Equation (7). Substituting into Equation (13), the value of the option (in terms of expected utility) becomes $P \approx 0.5 \times (1 - 2 \times 0.01) \times (100 - 80) = 9.8$.[15]

[15] Note that given these parameter values, the value of the call option is also equal to 9.8. Thus, put-call parity holds, and a self-financing strategy does not permit arbitrage opportunities.

For an investor with higher aversion to ambiguity, say $\eta = 4$, the value of the option (in terms of expected utility) drops to $P \approx 0.5 \times (1 - 4 \times 0.01) \times (100 - 80) = 9.6$. Thus, an increase in aversion to ambiguity *decreases* put option values and therefore credit spreads. The reason is that with a long exposure, the investor puts more weight on the "bad" outcome, which depends on the net exposure, the no-payoff (no-default) state in this case.

A similar effect is noticeable if, instead of the intensity of aversion to ambiguity, the extent of ambiguity of the underlying equity increases. For example, if future returns are distributed either $(0.3, 0.7)$ or $(0.7, 0.3)$ with equal likelihoods, then the expected probability of the state H remains unchanged: $\mathrm{E}[\varphi(H)] = 0.5 \times 0.3 + 0.5 \times 0.7 = 0.5$, but the variance of its probability increases to $\mathrm{Var}[\varphi(H)] = 0.5 \times (0.3 - 0.5)^2 + 0.5 \times (0.7 - 0.5)^2 = 0.04$, implying a degree of ambiguity of $\mho^2 = 0.04$. Substituting into Equation (13), the value of the put option drops to $P \approx 0.5 \times (1 - 2 \times 0.04)(100 - 80) = 9.2$.

In Figure 2, we depict the sensitivity of credit spreads to ambiguity and risk using the intuition of the above one-period binomial model. More specifically, we treat credit spreads as the spreads of risky yields over risk-free debt for a risky bond that is equivalent to a portfolio of riskless debt with face value $K = 100$, and a short position in a put option on the assets of the firm with strike price K. We plot the credit spread as a function of ambiguity and risk for three different maturities equal to one, two, and five time periods. The value of the put option is computed using a symmetric one-period binomial model of Equation (13) as explained above, assuming a risk-free rate of zero percent, initial debt value of 100, a coefficient of ambiguity aversion η equal to 1, and a risk neutral investor. The left panel depicts the sensitivity to ambiguity keeping risk constant at a level of 10 percent, i.e., implying equal up and down movements of 10 percent. Everything else equal, the credit spread is decreasing in the degree of ambiguity, with higher impacts for longer maturities. The right panel depicts the sensitivity to risk, keeping ambiguity at a level of 10 percent, i.e., implying a deviation up and down from expected probabilities equal to 10 percent. Everything else equal, risk positively impacts credit spreads, with a greater impact on longer-term contracts. Thus, an increase in risk should lead to a steepening of the slope of the term structure of CDS spreads.

III Data

The primary data sources for the analysis are Markit for historical information on CDS spreads, intraday trade and quote (TAQ) data for the estimation of the firm-specific degree of ambiguity, and the Chicago center for research in security prices (CRSP) for the estimation of firm-specific risk. We further source company-specific balance sheet information from Compustat, and macroeconomic control variables from the St. Louis Federal Reserve Economic database. For a given firm, we require a minimum of 24 months of monthly information on both CDS and stock price information in TAQ and CRSP, leaving us with a sample of 491 CDS firms with 53,356 observations, from January 2001 until October 2014, for which we can extract joint information on CDS, ambiguity, and risk.

III.1 Credit default swaps

We proxy the return on a company's debt over a risk-free benchmark with the CDS spread, as it is less contaminated than bonds by covenants and contractual differences, improving a direct comparison across companies. CDS spreads are indicative mid-market dealer quotes and represent constant-maturity spreads, thereby further facilitating the cross-firm price comparison. The data source Markit, one of the major data providers on CDS, makes information available for over 3,000 international firms. We rely on the 1,259 unique U.S. parent company identifiers for which we can match a corresponding identifier in CRSP, excluding all CDS written on subsidiaries and private firms.[16] For CDS, we retain the USD denominated contracts written on senior debt with the modified restructuring credit event clause, which was the contract by convention until the introduction of the Big Bang Protocol in 2009, following which the no restructuring credit event clause became the standard.[17] Our benchmark results are based on monthly averages of daily CDS spreads. All results are, however, robust against the use of end-of-month spreads.

III.2 Estimating ambiguity

To proxy for the ambiguity associated with a firm, we estimate the ambiguity of its equity. Intuitively, ambiguity represents the uncertainty in future outcome *probabilities*, as opposed to risk,

[16]To match the Markit and CRSP databases, we manually verify all possible pairs of company name and ticker.
[17]All our results are unaffected by the use of the CDS contract with the no restructuring credit event clause.

which measures the uncertainty in future *outcomes*. We employ the empirical method used by Izhakian and Yermack (2017) to estimate the degree of ambiguity using intraday stock trading data from the TAQ database. We compute the degree of ambiguity, given in Equation (5), for each stock and for each month, by applying the following procedure.[18]

We suppose the existence of a representative agent with a set of priors over the intraday return distributions. The observed intraday returns on the underlying asset are assumed to be a realization of one specific prior. That is, every day is characterized by a different distribution of returns, and the set of these distributions over a month represents the agent's set of priors.[19] Assuming that stock returns are normally distributed, the degree of ambiguity of the return r_j on the underlying equity j can be measured by

$$\mho^2 [r_j] = \int \mathrm{E}[\phi(r_j; \mu_j, \sigma_j)] \,\mathrm{Var}[\phi(r_j; \mu_j, \sigma_j)] \, dr_j, \tag{14}$$

where $\phi(r_j; \mu_j, \sigma_j)$ stands for the normal probability density function of r_j, conditional upon the mean μ_j and the variance σ_j^2. It is important to recall that the degree of ambiguity, measured by $\mho^2$, accounts for the uncertainty (ambiguity) about the mean and the variance (volatility), as well as for the uncertainty about all higher moments of the probability distribution (i.e., skewness, kurtosis, etc.) through the variance of probabilities.

To estimate the set of possible probability distributions of returns using the TAQ data, we sample the price of the stock every five minutes starting from 9:30 until 16:00. The decision to use five-minute time intervals is motivated in part by Andersen et al. (2001), who show that this time interval is sufficient to eliminate microstructure effects. In cases in which there is no trade at a specific time interval, we take the volume-weighted average of the closest trading price. Using these prices, we compute five-minute returns, resulting in a maximum of 78 intraday returns on any given day. We ignore returns between closing and next-day opening prices, thereby eliminating the impact of overnight price changes and dividend distributions. For each stock, we drop all trading days with less than 15 different five-minute time intervals, and we drop all trading months with less than 15 intra-daily return distributions. In addition, we drop extreme returns based on extreme price movements (plus or minus 10 percent log returns) within five minutes, as many of them are

[18]We emphasize that our empirical tests use a measure of the degree of ambiguity, defined by Equation (5), which is distinct from aversion to ambiguity. The former, which is a matter of beliefs (or information), is estimated from the data, while the latter, which is a matter of tastes, is endogenously determined by the empirical estimations.

[19]The set of priors of the representative agent reflects the aggregation of all agents' identical sets of priors.

due to mistaken orders that were cancelled by the stock exchange.[20]

For a given stock, for each day, we compute the normalized (by the number of intraday observations) mean μ_j and variance σ_j^2 of the returns. As in French et al. (1987), the variance of the returns is computed by applying the adjustment for non-synchronous trading, proposed by Scholes and Williams (1977).[21] Based upon the assumption that the intraday returns are normally distributed, for each stock j we construct the set of priors $\mathcal{P}_j$, where each prior P_j within the set $\mathcal{P}_j$ is defined by a pair of μ_j and σ_j.

The set $\mathcal{P}_j$ of (normal) probability distributions of each stock j for a given month consists of 15 to 22 different probability distributions. To compute the monthly degree of ambiguity of a given asset, specified in Equation (14), we represent each daily return distribution by a histogram. To this end, we divide the range of daily returns, from -40% to 40%, into 160 intervals (bins), each of width 0.5%. For each day, we compute the probability of the return being in each bin. In addition, we compute the probability of the return being lower than -40% and the probability of the return being higher than 40%. Using these probabilities, we compute the mean and the variance of probabilities for each of the 162 bins separately, assigning equal weights to each probability distribution in the set $\mathcal{P}_j$ (i.e., all histograms are equally likely). This is equivalent to assuming that the daily ratios $\frac{\mu_j}{\sigma_j}$ are student's-t distributed.[22] Then, we estimate the degree of ambiguity of each stock j for each month by the discrete form

$$\mho^2[r_j] = \frac{1}{w\ln\left(\frac{1}{w}\right)} \times \left(\begin{array}{l} \mathrm{E}\big[\Phi(r_{j,0};\mu_j,\sigma_j)\big]\mathrm{Var}\big[\Phi(r_{j,0};\mu_j,\sigma_j)\big] + \\ \sum_{i=1}^{160} \mathrm{E}\big[\Phi(r_{j,i};\mu_j,\sigma_j) - \Phi(r_{j,i-1};\mu_j,\sigma_J)\big]\mathrm{Var}\big[\Phi(r_{j,i};\mu_j,\sigma_j) - \Phi(r_{j,i-1};\mu_j,\sigma_j)\big] + \\ \mathrm{E}\big[1 - \Phi(r_{j,160};\mu_j,\sigma_j)\big]\mathrm{Var}\big[1 - \Phi(r_{j,160};\mu_j,\sigma_j)\big] \end{array} \right),$$

where $\Phi(\cdot)$ stands for the cumulative normal probability distribution, $r_{j,0} = -0.40$, $w = r_{j,i} -$

[20] Testing our hypotheses while including observations with extreme price changes shows that the effect of ambiguity is even more significant than while excluding these observations.

[21] The Scholes and Williams (1977) adjustment for non-synchronous trading suggests that the volatility of returns takes the form $\sigma_t^2 = \frac{1}{N_t}\sum_{i=1}^{N_t}(r_{t,i} - \mathrm{E}[r_{t,i}])^2 + 2\frac{1}{N_t - 1}\sum_{i=2}^{N_t}(r_{t,i} - \mathrm{E}[r_{t,i}])(r_{t,i-1} - \mathrm{E}[r_{t,i-1}])$. We also test our model without the Scholes-Williams correction for non-synchronous trading. The results are essentially the same.

[22] When $\frac{\mu}{\sigma}$ is Student's t-distributed, cumulative probabilities are uniformly distributed. See, for example, Proposition 1.27 on p.21 in Kendall and Stuart (2010). This is consistent with the idea that the representative investor does not have any information indicating which of the possible probability distributions is more likely, and thus he acts as if he assigns an equal weight to each possibility.

$r_{j,i-1} = 0.005$, and $\frac{1}{w \ln\left(\frac{1}{w}\right)}$ scales the weighted-average volatilities of probabilities to the bins' size. This scaling, which is analogous to Sheppard's correction, has been tested to verify that it minimizes the effect of the selected bin size on the values of $\mho^2$.[23]

III.3 Estimating risk

Along with ambiguity, volatility serves as the most important explanatory variable in our analysis. We compute volatility with standard methods, using daily returns adjusted for dividends obtained from the CRSP database. Since probabilities are uncertain, volatilities can be viewed as computed using the expected probabilities of outcomes. For each individual stock j in a given month t, we calculate the standard deviation, $\mathbb{S}\mathrm{td}_{j,t}$, of the stock's daily returns over that month, again applying the Scholes and Williams (1977) correction for non-synchronous trading and a correction for heteroscedasticity.[24]

III.4 Other explanatory variables

In addition to ambiguity and risk, our empirical model includes a number of control variables, such as the standard predictive state variables from the Merton model, and many other variables based on the prior studies listed in Table 1. We use Compustat for balance sheet information and the St. Louis Federal Reserve Economic database for common macroeconomic aggregates.

The Merton model suggests that the key state variables beyond volatility are firm leverage and the risk-free interest rate. Accordingly, we introduce firm leverage, defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), and the two-year constant-maturity treasury yield (*r2*). Other firm-specific controls include firm size in million USD, measured as the number of shares outstanding times the stock price at the end of the month (*Size*), CDS depth defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), and the S&P's long-term issuer credit rating, which we map into a numerical scale ranging from 1 for AAA to 21 for C (*Rating*).

We also control for several aggregate market variables, including the aggregate risk, return, and

[23] Brenner and Izhakian (2016) formally rule out the concern that $\mho^2$ may capture other well-known "uncertainty" factors including skwness, kurtosis, variance of variance, variance of mean, downside risk, mixed data sampling measure of forecasted volatility (MIDAS), investors' sentiment, among several others. Their tests also rule out the concern that observed returns are generated by a single (additive) probability distribution. This is confirmed in Table 3, which shows a weak correlation of negative twenty percent between ambiguity and risk.

[24] See, for example, French et al. (1987).

ambiguity based on the S&P500 stock market index (*SP500Risk*, *SP500Ret*, and *SP500Ambiguity*), the CBOE S&P500 implied volatility index (*VIX*), the difference between the 10-year and 2-year constant-maturity treasury yields (*TSSlope*), and the difference between the BofA Merrill Lynch US High Yield BBB (BB) and AAA (BBB) Effective Yields (*BBB_AAA* and *BB_BBB*). A detailed description of the data sources and construction is available in Data Appendix Table A-1.

III.5 Summary statistics

Table 2 reports summary statistics of all variables. For the 491 CDS firms with 53,356 monthly observations between January 2001 and October 2014, the average CDS spread is 162bps, while the median is 79bps. The average (median) monthly degree of firm ambiguity, measured by the standard deviation of the return probabilities, is 33.50% (32.09%), while the average monthly (median) volatility of stock returns is 8.24% (6.90%), implying positive skewness for both measures. Table 3 reports the average pairwise correlation coefficients between all explanatory variables. Focusing on the correlation between ambiguity and risk, our key variables of interest, it can be observed that they are weakly negatively correlated with a magnitude of twenty percent. This underscores the fact that both measures capture different aspects of uncertainty. Figure 3 describes two simple scatter plots of the natural logarithm of the five-year CDS spread against the natural logarithm of ambiguity and risk. These plots provide a first indication that risk is positively associated with the level of credit spreads, a well-known result, while ambiguity bears a negative relationship, a result that has hitherto not been explored.

Turning to the other firm-specific variables of interest, the average (median) firm in the sample has a leverage ratio of 21.59% (21.48%), a market capitalization of $26.81 billion ($9.69 billion), and a numerical rating of 8.55 (9.00), which corresponds to a long-term credit rating equivalent to a BBB firm. The CDS of the average firm is quoted by six to seven dealers, while the average risk-free borrowing rate is equal to 2.05% during our sample period. Overall, there is a fair amount of heterogeneity, which we will exploit in our analysis.

Table 2 further reports summary statistics on several macroeconomic aggregates. The square root of aggregate market ambiguity is higher and more volatile than the average firm-specific ambiguity, with a monthly mean (standard deviation) of 41.46% (40.40%). Aggregate market volatility, on the other hand, is lower than that of individual firms. The monthly average S&P500

volatility (standard deviation) is equal to 0.94% (0.64%). The average monthly return on the S&P500 index is equal to 0.59%. During our sample period, the VIX has been fluctuating between 10.82% and 62.64% on a monthly basis, with an average equal to 20.59%. The slope of the term structure of interest rates has on average been positive with a value of 1.59%, while the monthly investment-grade and high-yield bond indices were on average 1.50% and 1.73%, respectively. More granular unreported summary statistics by rating categories suggest that the average credit spread is increasing from 48bps for firms rated AA or higher to 592bps for companies rated B or lower. On average, less creditworthy firms have higher leverage, higher risk, and lower ambiguity.

IV Empirical Design and Analysis

IV.1 Contemporaneous regression tests

The main objective of this study is to investigate whether ambiguity is a significant determinant of credit risk, in addition to volatility, i.e., risk. To this end, we contemporaneously regress the natural logarithm of the level of five-year CDS spreads on both ambiguity and risk.[25] Proposition 2 suggests that the sign of the impact of ambiguity on CDS spreads should depend on the net exposure of the marginal investor. Then, we will subsequently introduce several control variables, captured by the vector $X_{j,t}$, firm fixed effects ζ_j for firm j, and time fixed effects β_t. Thus, we define the benchmark regression

$$\ln\left(CDS_{j,t}\right) = \alpha + \eta \cdot Ambiguity_{j,t} + \gamma \cdot Risk_{j,t} + \delta \cdot X_{j,t} + \zeta_j + \beta_t + \varepsilon_{j,t}, \qquad (15)$$

where $\varepsilon_{j,t}$ represents i.i.d. standard normal errors. The set of company-specific controls includes firm leverage, the S&P's long-term credit rating, CDS liquidity, and firm size. Time fixed effects account for unobservable macroeconomic factors that may affect credit spreads over time, while the firm fixed effects absorb unobserved and time-invariant firm-specific characteristics. All regressions are clustered on both the time and firm dimension to account for cross-sectional and serial correlation in the error terms. Though we do present the benchmark results using the natural logarithm of spreads, we confirm in the appendix that all findings are highly robust and qualitatively similar with a specification that uses percentage changes in spreads.

[25] We use the natural logarithm of CDS spreads to mitigate the influence of outliers, similar to Bharath and Shumway (2008) and Bai and Wu (2016).

The main findings are reported in Table 4. Column (1) indicates a significant negative relationship between credit spreads and ambiguity, which individually attains an explanatory power of twenty percent. The magnitude of the coefficient indicates that a one standard deviation increase in ambiguity results in a decrease of 37 percent in the credit spread, which is economically very meaningful. Given that the average firm has a spread of 162bps, this implies that a one standard deviation increase in ambiguity results in a spread that is lower by 60bps. The univariate regression in column (2) confirms the well-documented significant and positive relationship between credit spreads and risk. The explanatory power amounts to nine percent, somewhat lower than the explanatory power of ambiguity. The economic significance is, however, similar. A one standard deviation increase in risk results in an increase of about 58bps in CDS spreads, on average, or a proportional increase of 36 percent. While introducing both ambiguity and risk in the same regression, the magnitudes of the coefficients decrease slightly. Both remain significant at the one percent level, with a joint explanatory power of 24 percent. This formally underscores that risk and ambiguity capture different dimensions of uncertainty, and that they are both significant determinants of CDS spreads, confirming hypotheses H1 and H2.

In column (4), we introduce the aforementioned firm-specific control variables. The coefficients of all of them have the expected sign and are statistically significant. Namely, credit spreads are positively associated with leverage and deteriorating credit ratings, while companies covered by a greater amount of dealers tend to have lower spreads, on average. In columns (5) to (6), we successively introduce time and firm fixed effects. While the battery of fixed effects does absorb a significant amount of variation in CDS spreads, they do not reduce the explanatory power of risk and ambiguity. The magnitudes of the coefficients still suggest that a one standard deviation increase in ambiguity is associated with a 10bps (6%) decrease in CDS spreads for the average firm, while a one standard deviation in risk is associated likewise with an 11bps (7%) increase in spreads. The explanatory power of these regression tests ranges between 41% and 75%, depending on the specification. This compares well with recent empirical models applied in, for example, Zhang et al. (2009), Bharath and Shumway (2008), or Bai and Wu (2016).[26]

[26] We note that results using percentage changes in CDS spreads yield adjusted R^2s of up to 33%.

IV.2 Predictive regression tests

We now turn to examine whether lagged risk and ambiguity have a predictive ability for CDS spreads, both individually and jointly. More specifically, we run the following regression:

$$\ln\left(CDS_{j,t}\right) = \alpha + \sum_{i=1}^{3} \eta \cdot Ambiguity_{j,t-i} + \sum_{i=1}^{3} \gamma \cdot Risk_{j,t-i} + \delta \cdot X_{j,t} + \zeta_j + \beta_t + \varepsilon_{j,t}, \qquad (16)$$

where we include up to three-months lagged risk and ambiguity, all firm-specific controls, and firm and time fixed effects in each regression.

The results in Table 5 suggest that the economic significance of lagged risk and ambiguity is approximately equal to that of contemporaneous measures, with a six percent change in spreads for a one standard deviation increase for each variable. Benchmarking this result on the average firm, which has a mean spread of 162bps, this corresponds to a decrease (increase) of 10bps in spreads for a one standard deviation increase in ambiguity (risk). Columns (2) to (3) find that lagged variables of the predictors have individually the same statistical significance, and similar economic magnitudes and similar explanatory power, although the economic impact is slightly decreasing for more distant lags. The adjusted R^2 does increase by about one to two percent, and all variables remain highly significant when we pool all lags together in column (4). These findings indicate that both contemporaneous and past risk and ambiguity have economically meaningful predictive power for credit spreads, but they predict spread variations in opposite directions.

IV.3 Aggregate risk and ambiguity

In this section, we further examine whether aggregate measures of risk and ambiguity are relevant determinants of CDS spreads. We proxy the market risk and ambiguity by the monthly variance of returns and probabilities, respectively, of the S&P500 stock index. The estimation method is identical as for the firm-specific measures of risk and ambiguity. Then, we augment the empirical model in Equation (15) to account for aggregate risk and ambiguity of the S&P500, as well as multiple other macroeconomic factors. Namely, we include the constant maturity 2-year Treasury rate, i.e., one of the key state variables in the Merton model, the monthly return on the S&P500 index, the VIX index, the slope of the term structure of risk-free rates, measured as the difference between the 10-year and the 2-year constant-maturity treasury yields, and an investment-grade and high-yield corporate bond index. Our findings are reported in Table 6, where the standard errors are clustered by firm. We confirm, however, that the results are robust to explicit corrections for both serial and cross-sectional correlation in the residuals.

Columns (1) to (4) in Table 6 report univariate regressions for firm-specific and aggregate risk and ambiguity. For ambiguity, the firm-specific measure appears to have greater explanatory power in terms of the R^2 of the regression (12.8% vs. 1%), and greater economic significance than the aggregate market ambiguity. While the coefficient of -2.48 indicates a 24 percent decrease in the level of spreads for a one standard deviation change in firm-specific ambiguity, the coefficient -0.38 indicates a six percent decrease for a one standard deviation increase in market ambiguity. The benchmark of these findings to the average firm implies a decrease of 39bps and 10bps for a one standard deviation increase in firm-specific and market ambiguity, respectively. Concerning risk, on the other hand, firm-specific and market risk both have higher explanatory power (7.1% vs. 6.6%) and about equal economic impact, each of them being associated with a nineteen percent increase in the spreads for a one standard deviation change.

The horse race between all four variables in column (5) shows that none of the independent variables loses its significance, and both specific and aggregate market ambiguity dominate their corresponding risk measures in terms of economic significance. These results are qualitatively unchanged when we further control for all firm-specific controls in column (6), as well as for the other macroeconomic factors. The latter all have the expected sign. Namely, a higher risk-free rate, a steeper slope of the term structure of interest rates, and a positive performance of the aggregate stock market all lead to lower CDS spreads, while greater high-yield and investment-grade bond spreads are associated with higher CDS spreads, on average. The coefficient of the VIX is weakly negative, but statistically insignificant. The empirical model fits the data well with an R^2 of 61%, which is slightly lower than 67%, obtained in the specification with time fixed effects in Column (5) of Table 5. The coefficient on firm-specific ambiguity equals -0.73, which corresponds to an eight percent decrease in spreads for a one standard deviation change in ambiguity, or, alternatively, to a 13bps decrease in the perspective of the average firm in the sample. This is an economically meaningful impact, and very similar to previous alternative specifications that include all the controls. Overall, this underscores the robustness of the previous findings, confirming hypotheses H1 and H2.

IV.4 Slope regressions

Figure 2 shows that the marginal impact of ambiguity and risk on the level of credit spreads is greater for longer contract maturities. As a consequence, we expect to empirically observe that a rise in ambiguity flattens the slope of the term structure of CDS spreads (henceforth the slope), while a rise in risk steepens the slope. These conjectures, corresponding to hypotheses H3 and H4, are formally tested by regressing the slope, measured as the difference between the ten-year and one-year CDS spreads, on risk, ambiguity, and all previously used control factors:[27]

$$\ln\left(Slope_{j,t}\right) = \alpha + \eta \cdot Ambiguity_{j,t} + \gamma \cdot Risk_{j,t} + \delta \cdot X_{j,t} + \zeta_j + \beta_t + \varepsilon_{j,t}. \tag{17}$$

Table 7 reports the results using double clustered standard errors. The external appendix reports qualitatively similar results using percentage changes in the slope of the term structure of CDS spreads. Column (1) confirms our conjecture that a rise in ambiguity flattens the slope. Quantitatively, the magnitude of the univariate regression coefficient indicates a twelve percent decrease in the slope for a one standard deviation increase in ambiguity, corresponding to a 12bps flattening of the slope for a one standard deviation increase in ambiguity for the average firm, given a mean slope of 91bps. The explanatory power of this univariate result is 2%, which is weaker than for the level of spreads. The economic impact of volatility on the slope is similar, as a one standard deviation increase in risk is associated with a 14bps (15%) steepening of the slope in the univariate regression in column (2), although the fit of that model is weaker, i.e, approximately 1%. The horse race between risk and ambiguity in column (3) changes the magnitude of the regression coefficients only marginally, and both remain significant. In columns (4) to (5), we introduce firm-specific controls, time fixed effects to control for unobserved common macroeconomic factors, and firm fixed effects to absorb time-invariant heterogeneity. In the most stringent regression specification in column (5), the statistical significance of risk fades away, while ambiguity preserves its statistically significant negative impact on the slope, with a coefficient that represents a slightly weaker economic impact. Each one standard deviation increase in ambiguity is associated with a three percent decrease in the difference between the ten-year and one-year CDS spreads. Overall, these findings confirm hypotheses H3 and H4.

[27]Note that our specification uses the natural logarithm of the slope to avoid the impact of some extreme outliers in the sample. Thus, we only use the firm-months with a positive slope in our sample, which corresponds to approximately 96% of the 50,057 available observations for the slope.

IV.5 Ambiguity during the crisis

The 2007-2009 financial crisis was marked by increased market volatility and, especially, uncertainty about the growth of the world economy, future economic recovery, and the quantity of default risk in the financial system. Thus, ambiguity should have played a relatively greater role during the financial crisis. To test this conjecture, we interact risk and ambiguity with an indicator variable that takes on the value one during the 2007-2009 financial crisis, and zero otherwise, and add this interaction term to the empirical regression model. Results are reported in Table 8.

Irrespective of what specification we use, the interaction term between ambiguity and the financial crisis dummy turns out to be negative and statistically significant, suggesting that the impact of ambiguity on credit spreads was indeed amplified during the financial crisis. On the other hand, risk does not appear to play a role that is significantly different during than outside the crisis times in our sample.

V Robustness

All results thus far point towards a statistically significant negative (positive) impact of ambiguity (risk) on CDS spreads. In this section, we explore the sensitivity of our results to alternative explanations suggested in the literature. Conscious of space constraints, we only briefly discuss the key findings, which are reported in Table 9.

V.1 Distance-to-default

Bharath and Shumway (2008) examine the importance of the distance-to-default measure implied by the Merton model for the pricing of credit spreads. They compare the probability of default, computed using the model-implied distance-to-default, to a "naive" approximation and, using a horse race, confirm that the latter outperforms the formal Merton measure.[28] Therefore, in our test in column (1), we introduce the "naive" distance-to-default measure and compare it to the

[28] More specifically, the "naive" distance-to-default DD_{naive} measure is computed as $DD_{naive} = \frac{ln(E+F/F)+(r_{i,t-1}-0.5\ naive\ \sigma_V^2)T}{naive\ \sigma_V\sqrt{T}}$, where F stands for the sum of debt in current liabilities plus one-half of long-term debt, and E for the market value of the firm. Naive volatility ($naive\ \sigma_V$) is defined as $naive\ \sigma_V = \frac{E}{E+F}\sigma_E + \frac{naive\ D}{E+F}(0.05+0.25\times\sigma_E)$, and naive debt volatility is given by $naive_D = 0.05+0.25\times\sigma_E$. Equity volatility σ_E is given by the annualized percent standard deviation of returns estimated from the prior year stock return data for each month, and $r_{i,t-1}$ refers to the firm's stock return over the previous year. The naive probability of default is computed as $\pi_{naive} = \mathcal{N}(-DD_{naive})$. For further details, see Bharath and Shumway (2008).

measure of ambiguity. Even though the "naive" probability of default implied by the Merton model is positively associated with the level of credit spreads and statistically significant, it does not drive out the statistical significance of ambiguity, and it hardly changes the magnitude of the regression coefficient.

V.2 High frequency equity volatility and jump risk

Zhang et al. (2009) suggest that several different measures of uncertainty and jump risk, computed using high frequency stock price data, help to improve the explanatory power of the level of CDS spreads. In particular, they include the volatility premium, computed as the difference between the realized volatility and the average implied volatility in the preceding month, and the historical moments of firm-specific equity returns (mean, variance, skewness and kurtosis), computed for the one-year horizon from historical daily equity returns. In addition, those tests introduce different aspects of one-year jump risk measures, including the jump intensity (JI), the jump volatility (JV), and positive (JP) and negative (JN) jump sizes. For the data construction, we follow Zhang et al. (2009). Column (2) in Table 9 confirms the results in Table 4 of the work of the aforementioned authors. In particular, jump intensity, jump variance, and negative jumps are positively associated with the level of CDS spreads (although JN is not statistically significant), while positive jumps are negatively associated with the level of spreads. Furthermore, the historical mean and kurtosis (skewness) are positively (negatively) associated with the level of spreads. While these results are consistent with previous evidence on the relationship between CDS spreads and high frequency equity volatility and jump risk, none of these alternative sources of uncertainty explains our findings that ambiguity is negatively associated with the level of CDS spreads. The regression coefficient for ambiguity remains highly statistically significant and negative, with the same magnitude.

V.3 Accounting information

A large literature in accounting suggests that additional accounting variables can explain heterogeneity in the level and dynamics of CDS spreads.[29] We verify the findings from this literature by controlling for additional balance sheet information including the market to book ratio, measured as the market value of debt and equity divided by book assets; the return on equity, measured

[29]See Augustin et al. (2014) for a comprehensive survey.

as the net income divided by stock holders' equity; return on assets, measured as the net income divided by total assets; and the dividend payout ratio, measured as the total dividend distributed divided by total assets. All these variables are computed using Compustat data and measured at a quarterly frequency. The findings in column (3) of Table 9 suggest that a high market-to-book ratio and a high return on assets correlate positively with 5-year CDS spreads, while return on equity and the dividend payout ratio are statistically insignificant. Importantly, none of these lower frequency components is able to account for the explanatory power of risk and ambiguity.

V.4 Firm-specific equity returns

Debt and equity prices are jointly determined in the Merton (1974) model. Hence, the equity return should locally capture most of the variation in CDS spread returns. In other words, a finding that ambiguity significantly explains variation in the dynamics of CDS spreads, despite controlling for the equity return, would imply a strong robustness test for the empirical findings. Column (4) of Table 9 reports the results for a regression specification that includes the monthly firm-specific stock return. The magnitude and significance for the regression coefficient attributed to ambiguity does not change. As this specification relates the level of spreads to stock returns, we verify the results using contemporaneous percentage changes in CDS spreads. In that (unreported) specification, the equity return is positively and significantly related to CDS spread returns, but it cannot explain the relationship between the credit spreads and ambiguity.

V.5 Industry heterogeneity

Several previous authors have deployed industry fixed effects to absorb time-invariant heterogeneity in spreads specific to individual industries. We use the Fama and French (1997) 12-industry classification and generate indicator variables that take on the value one for a specific industry and zero otherwise. Column (5) of Table 9 confirms that absorbing time-invariant industry heterogeneity through fixed effects does not alter any of our previous conclusions about the economic significance and negative relationship between CDS spreads and ambiguity.

V.6 Investor heterogeneity

Ambiguity-averse agents assign higher probabilities to *lower* utility states. While this is true, it is important to emphasize that, for assets in zero net supply, the lower utility state depends on the net economic exposure of the marginal investor. In other words, the "bad" state depends on whether the marginal investor has a net long or a net short credit risk exposure. This, in turn, will depend on the total accumulated CDS positions, but also on the aggregate position (long and short) in the underlying, i.e., the corporate bond. An investor may hold CDS for two reasons. Either, she holds on to an uncovered position as she is betting on a payoff from a future default. Alternatively, she holds a fully covered position, i.e., both the CDS and the underlying, in which case the CDS serves as an insurance against default on the underlying asset. In each case, the low utility state is different and the perception of the unfavorable event depends on the net exposure of the marginal investor.

If the marginal investor is net short credit risk (i.e., in an uncovered-CDS holder's view), default is a favorable event as it results in a positive payoff. Therefore, an ambiguity-averse agent will attribute a lower probability to the default state (and a higher probability to the no-default state). If, on the other hand, the marginal investor is positively exposed to default risk, then default is considered to be the lower utility state, and the perceived probability of default is higher compared to an ambiguity-neutral investor. Hence, the effect of ambiguity on credit spreads will crucially depend on the aggregated net position of the marginal investor in financial markets. Thus, although we find that, on average, the effect of ambiguity on credit spreads is negative, it is conceivable to find evidence of a positive relationship in particular times, or for sub-segments of the market. Given that there exists no full disclosure of the net economic exposures of each investor in the economy, the equilibrium outcome is ultimately an empirical question. However, the existing (sparse) data is suggestive that banks and broker dealers, who hold the biggest market share, are, on average, net buyers of CDS protection, i.e., they are short credit risk (Bongaerts et al.; 2011; Duffie et al.; 2015; Peltonen et al.; 2014).

Focusing on nine *financial* firms, Boyarchenko (2012) suggests that ambiguity amplified CDS spreads during the financial crisis. These results are not at odds with our findings that, on average, ambiguity negatively affects the level of CDS spreads. As we have discussed, the sign of the impact of ambiguity on credit spreads crucially depends on the net economic exposure of the marginal investor. While we show in Table 8 that the negative effect of ambiguity is, on average, amplified during the financial crisis, this result is determined by the period prior to the Lehman default in September 2008. Column (6) in Table 9 shows that if we restrict the sample to September 2008 until December 2009, the average effect of ambiguity is positive and statistically significant. In addition, if we further restrict the sample to only financial firms in column (7), the coefficient remains positive, but statistically insignificant. However, this may be due to a power issue, given a similar weakening in the economic significance for risk. Results for different sub-periods and other industry segments consistently feature a negative impact of ambiguity on credit spreads.

VI Conclusion

We examine the impact of risk and ambiguity on the level and dynamics of CDS spreads. While risk represents uncertainty about the *realizations* of future outcomes, ambiguity reflects the uncertainty about the *probabilities* of these future outcomes. Motivated by economic decision theory, which incorporates preferences for risk and ambiguity, and which allows to separate the intensity of each dimension of uncertainty, we estimate ambiguity separately from risk using high frequency stock price information. Empirically, we find that higher ambiguity is negatively associated with the level of credit spreads, while higher risk is positively associated with the level of spreads. The finding of a negative relationship between ambiguity and spreads suggests that the price setters in the CDS market are net short credit risk, i.e., they are CDS buyers. We gain this intuition from a stylized model with heterogeneous investors in the CDS market and assets in zero net supply.

The impact of both dimensions of uncertainty are economically meaningful, as a one standard deviation increase in ambiguity (risk) leads to a six to seven percent decrease (increase) in the level of spreads. Using the average firm in the sample as a benchmark, this indicates a change of ten to twelve basis points for a one standard deviation move in the independent variable. The empirical models fit the data well compared with the previous literature, reaching an explanatory power of up to 75% for the level of spreads, and up to 33% for the dynamics of spreads.

Our analysis focuses on a particular type of insurance contracts, securities protecting against default risk. This focus is driven by data availability on CDS and the ability to rigorously measure ambiguity from stock prices, which allows for a comprehensive empirical examination of our conjectures. The results provide, however, insights that are more broadly applicable to the pricing of other types of insurance claims. We leave a detailed empirical analysis of such applications for future research.

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Appendix

Proof of Proposition 1. Denote $A = w_S + hp$, $B = w_S + hp - hY$, $C = w_B - hp$, and $D = w_B - hp + hY$, where $Y = N - R$ is the payoff of the CDS. The first order condition (FOC) of the maximization problem of the buyer in Equation (8) can be written

$$F^B(p,h,Y) = \frac{\mathrm{Q}(DF)\mathrm{U}'(D)\,Y}{\mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C)} - p = 0. \tag{18}$$

The first order condition of the maximization problem of the seller in Equation (9) can be written

$$F^S(p,h,Y) = \frac{[1-\mathrm{Q}(SL)]\,\mathrm{U}'(B)\,Y}{[1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A)} - p = 0. \tag{19}$$

The partial deferentials of the buyer's FOC in Equation (18) are

$$\begin{aligned}
\frac{\partial F^B}{\partial p} &= \mathrm{Q}(DF)\,[1-\mathrm{Q}(DF)]\,Yh\frac{\mathrm{U}'(D)\,\mathrm{U}''(C) - \mathrm{U}''(D)\,\mathrm{U}'(C)}{\left(\mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C)\right)^2} - 1,\\
\frac{\partial F^B}{\partial h} &= \mathrm{Q}(DF)\,[1-\mathrm{Q}(DF)]\,Y\frac{p\mathrm{U}'(D)\,\mathrm{U}''(C) + (Y-p)\,\mathrm{U}''(D)\,\mathrm{U}'(C)}{\left(\mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C)\right)^2},\\
\frac{\partial F^B}{\partial Y} &= \mathrm{Q}(DF)\,[1-\mathrm{Q}(DF)]\,Yh\frac{\mathrm{U}''(D)\,\mathrm{U}'(C)}{\left(\mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C)\right)^2}\\
&\quad + \mathrm{Q}(DF)\frac{\mathrm{U}'(D)}{\mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C)}.
\end{aligned}$$

The partial deferentials of the seller's FOC in Equation (19) are

$$\begin{aligned}
\frac{\partial F^S}{\partial p} &= \mathrm{Q}(SL)\,[1-\mathrm{Q}(SL)]\,Yh\frac{\mathrm{U}''(B)\,\mathrm{U}'(A) - \mathrm{U}'(B)\,\mathrm{U}''(A)}{\left([1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A)\right)^2} - 1\\
\frac{\partial F^S}{\partial h} &= -\mathrm{Q}(SL)\,[1-\mathrm{Q}(SL)]\,Y\frac{p\mathrm{U}'(B)\,\mathrm{U}''(A) + (Y-p)\,\mathrm{U}''(B)\,\mathrm{U}'(A)}{\left([1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A)\right)^2}\\
\frac{\partial F^S}{\partial Y} &= -\mathrm{Q}(SL)\,[1-\mathrm{Q}(SL)]\,Yh\frac{\mathrm{U}''(B)\,\mathrm{U}'(A)}{\left([1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A)\right)^2}\\
&\quad + [1-\mathrm{Q}(SL)]\,\frac{\mathrm{U}'(B)}{[1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A)}
\end{aligned}$$

Denote

$$\begin{aligned}
K &= \mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C),\\
L &= [1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A),\\
k &= \mathrm{Q}(DF)\,[1-\mathrm{Q}(DF)]\,Y,\\
l &= \mathrm{Q}(SL)\,[1-\mathrm{Q}(SL)]\,Y.
\end{aligned}$$

The total differential of the system in Equations (18) and (19) can then be written

$$J\begin{bmatrix} dp \\ dh \end{bmatrix} = -\begin{bmatrix} \frac{\partial F^B}{\partial Y} \\ \frac{\partial F^S}{\partial Y} \end{bmatrix} dY,$$

where

$$J = \begin{vmatrix} kh\frac{\mathrm{U}'(D)\mathrm{U}''(C) - \mathrm{U}''(D)\mathrm{U}'(C)}{K^2} - 1 & k\frac{p\mathrm{U}'(D)\mathrm{U}''(C) + (Y-p)\mathrm{U}''(D)\mathrm{U}'(C)}{K^2} \\ lh\frac{\mathrm{U}''(B)\mathrm{U}'(A) - \mathrm{U}'(B)\mathrm{U}''(A)}{L^2} - 1 & -l\frac{p\mathrm{U}'(B)\mathrm{U}''(A) + (Y-p)\mathrm{U}''(B)\mathrm{U}'(A)}{L^2} \end{vmatrix}.$$

When both buyers and sellers are CARA, $\mathrm{U}'(B)\,\mathrm{U}''(A) = \mathrm{U}''(B)\,\mathrm{U}'(A)$ and $\mathrm{U}'(D)\,\mathrm{U}''(C) = \mathrm{U}''(D)\,\mathrm{U}'(C)$. Thus,

$$J = lY\frac{\mathrm{U}'(B)\,\mathrm{U}''(A)}{L^2} + kY\frac{Y\mathrm{U}''(D)\,\mathrm{U}'(C)}{K^2} < 0,$$

where the strict inequality is obtained since by the boundary condition $0 < Y$, and since $\mathrm{U}' > 0$ and $\mathrm{U}'' < 0$. Let

$$H = \begin{vmatrix} -kh\frac{\mathrm{U}''(D)\mathrm{U}'(C)}{K^2} - \mathrm{Q}(DF)\frac{\mathrm{U}'(D)}{K} & k\frac{p\mathrm{U}'(D)\mathrm{U}''(C)+(Y-p)\mathrm{U}''(D)\mathrm{U}'(C)}{K^2} \\ lh\frac{\mathrm{U}''(B)\mathrm{U}'(A)}{L^2} - [1-\mathrm{Q}(SL)]\frac{\mathrm{U}'(B)}{L} & -l\frac{p\mathrm{U}'(B)\mathrm{U}''(A)+(Y-p)\mathrm{U}''(B)\mathrm{U}'(A)}{L^2} \end{vmatrix}.$$

Again, by CARA,

$$H = lY\mathrm{Q}(DF)\frac{\mathrm{U}'(D)}{K}\frac{\mathrm{U}''(B)\,\mathrm{U}'(A)}{L^2} + kY[1-\mathrm{Q}(SL)]\frac{\mathrm{U}'(B)}{L}\frac{\mathrm{U}''(D)\,\mathrm{U}'(C)}{K^2} < 0.$$

Finally, since $J \neq 0$, by Cramer's rule,

$$\frac{\partial p}{\partial Y} = \frac{H}{J} > 0.$$

■

Proof of Proposition 2. Using the notation of the proof of Proposition 1, the FOC of the maximization problem of the buyer in Equation (8) can be written

$$F^B\left(p,h,\mho^2\right) = \frac{\mathrm{Q}(DF)\mathrm{U}'(D)\,Y}{\mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C)} - p = 0. \tag{20}$$

The first order condition of the maximization problem of the seller in Equation (9) can be written

$$F^S\left(p,h,\mho^2\right) = \frac{[1-\mathrm{Q}(SL)]\,\mathrm{U}'(B)\,Y}{[1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A)} - p = 0. \tag{21}$$

The partial deferential of the buyer's FOC in Equation (20) with respect to $\mho^2$ is

$$\frac{\partial F^B}{\partial \mho^2} = \frac{\mathrm{U}'(D)\,\mathrm{U}'(C)\,Y}{\left(\mathrm{Q}(DF)\mathrm{U}'(D) + [1-\mathrm{Q}(DF)]\,\mathrm{U}'(C)\right)^2}\frac{\partial \mathrm{Q}}{\partial \mho^2}.$$

The partial deferential of the seller's FOC in Equation (21) with respect to $\mho^2$ is

$$\frac{\partial F^S}{\partial \mho^2} = -\frac{\mathrm{U}'(B)\,\mathrm{U}'(A)\,Y}{\left([1-\mathrm{Q}(SL)]\,\mathrm{U}'(B) + \mathrm{Q}(SL)\mathrm{U}'(A)\right)^2}\frac{\partial \mathrm{Q}}{\partial \mho^2}.$$

The total differential of the system in Equations (20) and (21) can then be written

$$J\begin{bmatrix} dp \\ dh \end{bmatrix} = -\begin{bmatrix} \frac{\partial F^B}{\partial \mho^2} \\ \frac{\partial F^S}{\partial \mho^2} \end{bmatrix} d\mho^2.$$

By Equation (20), $J < 0$. Let

$$H = \begin{bmatrix} -\frac{\partial F^B}{\partial \mho^2} & \frac{\partial F^B}{\partial h} \\ -\frac{\partial F^S}{\partial \mho^2} & \frac{\partial F^S}{\partial h} \end{bmatrix} = \begin{vmatrix} -\frac{\mathrm{U}'(D)\mathrm{U}'(C)Y}{K^2}\frac{\partial \mathrm{Q}}{\partial \mho^2} & k\frac{p\mathrm{U}'(D)\mathrm{U}''(C)+(Y-p)\mathrm{U}''(D)\mathrm{U}'(C)}{K^2} \\ \frac{\mathrm{U}'(B)\mathrm{U}'(A)Y}{L^2}\frac{\partial \mathrm{Q}}{\partial \mho^2} & -l\frac{p\mathrm{U}'(B)\mathrm{U}''(A)+(Y-p)\mathrm{U}''(B)\mathrm{U}'(A)}{L^2} \end{vmatrix}.$$

By CARA and CAAA,

$$H = Y^2\frac{\mathrm{U}'(A)\mathrm{U}'(B)\mathrm{U}'(C)\mathrm{U}'(D)}{K^2L^2}\left(l\frac{\mathrm{U}''(B)}{\mathrm{U}'(B)}\frac{\Upsilon''(DF)}{\Upsilon'(DF)}\mathrm{E}\left[\mathrm{P}(DF)\right] - k\frac{\mathrm{U}''(D)}{\mathrm{U}'(D)}\frac{\Upsilon''(SL)}{\Upsilon'(SL)}\mathrm{E}\left[\mathrm{P}(SL)\right]\right)$$

Since $J \neq 0$, by Cramer's rule,

$$\frac{\partial p}{\partial \mho^2} = \frac{H}{J} < 0,$$

when $l\frac{\mathrm{U}''(B)}{\mathrm{U}'(B)}\frac{\Upsilon''(DF)}{\Upsilon'(DF)}\mathrm{E}\left[\mathrm{P}(DF)\right] - k\frac{\mathrm{U}''(D)}{\mathrm{U}'(D)}\frac{\Upsilon''(SL)}{\Upsilon'(SL)}\mathrm{E}\left[\mathrm{P}(SL)\right] > 0$ and

$$\frac{\partial p}{\partial \mho^2} = \frac{H}{J} > 0,$$

when $l\frac{\mathrm{U}''(B)}{\mathrm{U}'(B)}\frac{\Upsilon''(DF)}{\Upsilon'(DF)}\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]-k\frac{\mathrm{U}''(D)}{\mathrm{U}'(D)}\frac{\Upsilon''(SL)}{\Upsilon'(SL)}\mathrm{E}\left[\mathrm{P}\left(SL\right)\right]<0.$ ■

Table 1: Previous Studies on the Determinants of Corporate Credit Spreads

This table summarizes the key literature on the determinants of credit spreads, proposed by the prior major studies in recent years, which have used regressions in levels, in changes, or both. We group previous determinants in thematic buckets. Campbell and Taksler (2003) also include idiosyncratic equity volatility. Aggregate controls include the return and volatility of the aggregate stock market, the implied volatility and volatility skew computed from options on the aggregate stock market, a measure of the aggregate credit spreads, inflation, sentiment, the level and volatility of aggregate GDP, and industrial production growth. The categorical dummies include, among others, indicator variables for sector and industry, maturity, the cheapest-to-deliver option, as well as restructuring clauses.

	Model		Determinants of Credit Spreads														
Study	Levels	Changes	ST Interest Rate	Yield Curve Slope	Leverage	Equity Volatility	IV, IV skew, VRP	Ratings	Distance-to-Default	Jump risk	VIX	Liquidity	Accounting Inform.	Size	Aggreg. Controls	Indicators	**Ambiguity**
Collin-Dufresne et al. (2001)		✓	✓	✓	✓	✓								✓			
Campbell and Taksler (2003)	✓		✓	✓	✓	✓		✓				✓			✓	✓	
Blanco et al. (2005)		✓	✓	✓						✓	✓			✓			
Tang and Yan (2007)	✓				✓	✓	✓	✓		✓	✓	✓		✓	✓		
Bharath and Shumway (2008)	✓		✓	✓	✓	✓		✓	✓			✓	✓	✓	✓	✓	
Cremers et al. (2008)	✓		✓		✓	✓	✓				✓	✓			✓		
Ericsson et al. (2009)	✓	✓	✓	✓	✓	✓		✓			✓				✓		
Zhang et al. (2009)	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓		
Das et al. (2009)	✓		✓		✓	✓		✓				✓	✓	✓	✓	✓	
Cao et al. (2010)	✓		✓	✓	✓	✓	✓	✓			✓	✓			✓		
Tang and Yan (2010)	✓		✓	✓	✓	✓	✓	✓			✓				✓		
Bai and Wu (2016)	✓	✓			✓	✓			✓		✓		✓	✓			
The current study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2: Summary Statistics

This table presents summary statistics for the key firm-specific and macroeconomic variables used in the analysis. The sample period is January 2001 until October 2014. The data sample includes in total 491 firms with a minimum of 24 months of continuous information on the 5-y senior unsecured CDS spread with the modified restructuring clause (*CDS5y*), the monthly standard deviation of the outcome probabilities, i.e., ($\sqrt{Ambiguity}$), the monthly standard deviation of daily equity returns, i.e., equity volatility ($\sqrt{Risk}$), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The table reports several aggregate market variables, including the aggregate market risk, return, and ambiguity based on the S&P500 stock market index ($\sqrt{SP500Risk}$, *SP500Ret*, and $\sqrt{SP500Ambiguity}$), the CBOE S&P 500 implied volatility index (*VIX*), the 2-year constant-maturity Treasury yield (*r2*), the difference between the 10-year and 2-year constant-maturity Treasury yields (*TSSlope*), the difference between the BofA Merrill Lynch US High Yield BBB (BB) and AAA (BBB) Effective Yields (*BBB_AAA* and *BB_BBB*). Risk, ambiguity and returns are measured at the monthly frequency, all other variables are annualized. All variables other than liquidity, rating, and size are expressed in percentages. We report the mean (*Mean*), standard deviation (*Std*), minimum (*Min*), median (*Med*), the maximum (*Max*), the number of observations (*Obs*), and the number of firms (*N*).

Variable	**Mean**	**Std**	**Min**	**Med**	**Max**	**Obs**	**N**
CDS5y	1.62	3.06	0.02	0.79	95.67	53,356	491
$\sqrt{Ambiguity}$	33.50	14.33	3.71	32.09	180.28	53,356	491
$\sqrt{Risk}$	8.24	6.90	0.04	6.49	172.04	53,356	491
r2	2.05	1.62	0.21	1.71	5.12	53,356	491
Leverage	21.59	9.19	0.00	21.48	57.80	53,356	491
Rating	8.55	3.00	1.00	9.00	23.00	53,356	491
Liquidity	6.62	4.20	2.00	5.39	29.18	53,356	491
Size	26.81	49.33	0.04	9.69	513.36	53,356	491
$\sqrt{SP500Ambiguity}$	41.46	15.51	15.77	40.40	130.38	53,356	491
$\sqrt{SP500Risk}$	0.94	0.64	0.12	0.82	5.10	53,356	491
SP500Return	0.59	4.28	-16.52	1.18	10.91	53,356	491
VIX	20.59	9.24	10.82	17.71	62.64	53,356	491
TSSlope	1.59	0.90	-0.14	1.83	2.83	53,356	491
BBB_AAA	1.50	0.77	0.54	1.40	4.42	53,356	491
BB_BBB	1.73	0.89	0.63	1.48	5.96	53,356	491

Table 3: Cross-correlations

This table presents pairwise pearson correlation coefficients between the variables used in the study: the 5-y senior unsecured CDS spread with the modified restructuring clause (*CDS5y*), the monthly variance of the outcome probabilities, i.e., (*Ambiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*Risk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*), aggregate ambiguity (*SP500Ambiguity*), aggregate risk (*SP500Risk*), the monthly return on the S&P500 index (*SP500return*), the CBOE S&P 500 implied volatility index (*VIX*), the 2-year constant-maturity Treasury yield (*r2*), the difference between the 10-year and 2-year constant-maturity Treasury yields (*TSSlope*), and the difference between the BofA Merrill Lynch US High Yield BBB (BB) and AAA (BBB) Effective Yields (*BBB_AAA* and *BB_BBB*). The data sample includes 491 U.S. CDS firms with 53,356 monthly observations from January 2001 until October 2014.

Variables	CDS5y	Ambiguity	Risk	r2	Leverage	Rating	Liquidity	Size	SP500Ambiguity	SP500Risk	SP500Return	VIX	TSSlope	BBB_AAA	BB_BBB
CDS5y	1.00														
Ambiguity	-0.27	1.00													
Risk	0.44	-0.20	1.00												
r2	-0.14	0.05	-0.05	1.00											
Leverage	0.24	-0.04	0.07	-0.03	1.00										
Rating	0.50	-0.31	0.16	-0.06	0.32	1.00									
Liquidity	-0.12	0.10	-0.03	0.41	-0.01	-0.13	1.00								
Size	-0.17	0.21	-0.07	-0.02	-0.16	-0.54	0.07	1.00							
SP500Ambiguity	-0.02	0.22	0.15	0.02	-0.01	0.03	0.08	0.03	1.00						
SP500Risk	0.13	-0.27	0.38	-0.10	0.03	-0.00	-0.06	-0.03	0.53	1.00					
SP500Return	-0.02	0.17	-0.13	-0.08	-0.01	0.02	-0.03	0.01	-0.15	-0.42	1.00				
VIX	0.22	-0.46	0.34	-0.29	0.05	-0.00	-0.19	-0.05	-0.00	0.75	-0.35	1.00			
TSSlope	0.12	-0.14	0.07	-0.83	0.05	0.01	-0.43	-0.01	-0.09	0.16	0.03	0.35	1.00		
BBB_AAA	0.25	-0.37	0.23	-0.55	0.05	0.03	-0.32	-0.04	-0.16	0.42	-0.08	0.80	0.51	1.00	
BB_BBB	0.23	-0.43	0.29	-0.30	0.05	0.01	-0.19	-0.06	-0.09	0.60	-0.23	0.92	0.34	0.83	1.00

Table 4: Determinants of CDS Spread Levels

This table presents the results from the projection of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities, i.e., Ambiguity, (*Ambiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*Risk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). All variables are defined at the monthly frequency. The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) CDS5y	(2) CDS5y	(3) CDS5y	(4) CDS5y	(5) CDS5y	(6) CDS5y	(7) CDS5y
Ambiguity	-4.1275***		-3.7312***	-1.9976***	-1.1364***	-1.7079***	-0.5551***
	(0.2812)		(0.2619)	(0.1960)	(0.1455)	(0.2049)	(0.0986)
Risk		7.3805***	5.3405***	3.4772***	2.5315***	2.6963***	1.5936***
		(1.1811)	(0.8422)	(0.4779)	(0.3850)	(0.3869)	(0.2445)
Leverage				1.2579***	0.9137***	2.7149***	1.7738***
				(0.2151)	(0.2209)	(0.2945)	(0.2707)
Rating				0.2151***	0.2346***	0.1944***	0.1804***
				(0.0073)	(0.0081)	(0.0104)	(0.0093)
Liquidity				-0.0352***	0.0037	-0.0467***	0.0235***
				(0.0043)	(0.0040)	(0.0051)	(0.0040)
Size				0.0007*	0.0006	-0.0052***	-0.0042***
				(0.0004)	(0.0004)	(0.0011)	(0.0009)
Constant	-4.2005***	-4.8338***	-4.3149***	-6.4191***	-6.6011***	-6.3520***	-6.3162***
	(0.0615)	(0.0525)	(0.0597)	(0.0999)	(0.0851)	(0.1029)	(0.0957)
Observations	53,356	53,356	53,356	53,356	53,356	53,356	53,356
TIME FE	No	No	No	No	Yes	No	Yes
FIRM FE	No	No	No	No	No	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.198	0.086	0.241	0.652	0.754	0.402	0.653

Table 5: Predictive Regressions of CDS Spread Levels

This table presents the results from the projection of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly lagged variance of the outcome probabilities, i.e., Ambiguity, (*Ambiguity*), the monthly lagged variance of daily equity returns, i.e., equity volatility (*Risk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	CDS5y	CDS5y	CDS5y	CDS5y
Ambiguity_{t-1}	-0.5722***			-0.3235***
	(0.0932)			(0.0543)
Risk_{t-1}	1.4829***			1.0968***
	(0.2234)			(0.1727)
Ambiguity_{t-2}		-0.5647***		-0.2623***
		(0.0932)		(0.0445)
Risk_{t-2}		1.3105***		0.8691***
		(0.1972)		(0.1037)
Ambiguity_{t-3}			-0.5402***	-0.2986***
			(0.0904)	(0.0483)
Risk_{t-3}			1.1936***	0.7374***
			(0.1954)	(0.1537)
Constant	-6.3301***	-6.3837***	-6.4919***	-6.4473***
	(0.0961)	(0.0993)	(0.0983)	(0.0992)
Observations	52,617	51,896	51,311	51,311
CONTROLS	All	All	All	All
TIME FE	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes
CLUSTER TIME	No	No	No	No
Adj. R^2	0.658	0.658	0.659	0.667

Table 6: Determinants of CDS Spread Levels - Aggregate Controls

This table presents the results from the projection of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities, i.e., Ambiguity, (*Ambiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*Risk*), aggregate market ambiguity (*SP500Ambiguity*), aggregate market risk (*SP500Risk*), as well as all firm-specific control variables as defined in the caption of Table 5, and several aggregate control variables, including the constant maturity 2-year Treasury rate (*r2*), the monthly return on the S&P500 index (*SP500return*), the CBOE S&P 500 implied volatility index (*VIX*), the 2-year constant-maturity Treasury yield (*r2*), the difference between the 10-year and 2-year constant-maturity Treasury yields (*TSSlope*), and the difference between the BofA Merrill Lynch US High Yield BBB (BB) and AAA (BBB) Effective Yields (*BBB_AAA* and *BB_BBB*). The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) CDS5y	(2) CDS5y	(3) CDS5y	(4) CDS5y	(5) CDS5y	(6) CDS5y
Ambiguity	-2.4807***				-1.4111***	-0.7252***
	(0.1575)				(0.1747)	(0.0915)
Risk		4.2269***			2.6864***	1.5809***
		(0.5147)			(0.3295)	(0.2316)
SP500Ambiguity			-0.3786***		-0.7972***	-0.1124***
			(0.0246)		(0.0660)	(0.0292)
SP500Risk				627.1943***	594.6115***	18.3467
				(17.9855)	(46.0629)	(20.3889)
Leverage						2.1891***
						(0.2708)
Rating						0.1654***
						(0.0083)
Liquidity						0.0004
						(0.0025)
Size						-0.0039***
						(0.0008)
r2						-0.1312***
						(0.0098)
SP500Return						-0.4987***
						(0.0438)
TSSlope						-0.0272**
						(0.0134)
VIX						-0.0910
						(0.1092)
BBB_AAA						0.2864***
						(0.0135)
BB_BBB						0.0313***
						(0.0103)
Constant	-4.4191***	-4.7973***	-4.6743***	-4.8302***	-4.5134***	-6.5849***
	(0.0209)	(0.0060)	(0.0048)	(0.0023)	(0.0181)	(0.1036)
Observations	53,356	53,356	53,356	53,356	53,356	53,356
FIRM CONTROLS	No	No	No	No	No	All
TIME FE	No	No	No	No	No	No
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	No	No	No	No	No	No
Adj. R^2	0.128	0.066	0.010	0.071	0.203	0.612

Table 7: Determinants of CDS Slope Levels

This table presents the results from the projection of the natural logarithm of the monthly slope, i.e., the difference between the 10-year and the 1-year senior unsecured CDS spread levels (*slope*) on the monthly variance of the outcome probabilities, i.e., Ambiguity, (*Ambiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*Risk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) slope	(2) slope	(3) slope	(4) slope	(5) slope
Ambiguity	-1.1258***		-1.0116***	-0.6828***	-0.2323***
	(0.2352)		(0.2286)	(0.0970)	(0.0790)
Risk		3.4093***	2.1846**	0.4941*	-0.3165
		(1.1913)	(0.8721)	(0.2842)	(0.3148)
Leverage				0.6184***	0.8064***
				(0.1346)	(0.2353)
Rating				0.1634***	0.1142***
				(0.0067)	(0.0101)
Liquidity				0.0135***	0.0179***
				(0.0031)	(0.0039)
Size				0.0001	-0.0038***
				(0.0003)	(0.0005)
Constant	-4.9426***	-5.1298***	-4.9780***	-6.8211***	-6.3768***
	(0.0675)	(0.0496)	(0.0675)	(0.0544)	(0.0931)
Observations	47,945	47,945	47,945	47,945	47,945
TIME FE	No	No	No	Yes	Yes
FIRM FE	No	No	No	No	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.020	0.008	0.024	0.674	0.532

Table 8: Crisis Effects

This table presents the results from the projection of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities, i.e., Ambiguity, (*Ambiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*Risk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The regression tests include a crisis indicator, which takes the value one in years 2007-2009, and zero otherwise (*crisis*). The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) CDS5y	(2) CDS5y	(3) CDS5y	(4) CDS5y	(5) CDS5y	(6) CDS5y	(7) CDS5y
Ambiguity	-3.6866***		-3.3757***	-1.5774***	-1.0289***	-1.1709***	-0.4737***
	(0.2570)		(0.2618)	(0.1648)	(0.1336)	(0.1567)	(0.0951)
Risk		10.9416**	7.4247**	3.8286***	2.9089***	2.9695***	1.9449***
		(4.3541)	(2.9861)	(1.3569)	(1.0201)	(1.0029)	(0.5983)
crisis	0.2245**	0.1568	0.1561	0.2415***	0.0261	0.3229***	-0.0177
	(0.1053)	(0.1050)	(0.1072)	(0.0892)	(0.0685)	(0.0783)	(0.0591)
Ambiguity_x_crisis	-2.6960***		-2.2676***	-2.4345***	-0.7557**	-2.5250***	-0.6198**
	(0.7418)		(0.6810)	(0.4801)	(0.3743)	(0.4159)	(0.2473)
Risk_x_crisis		-4.8965	-2.9081	-0.8535	-0.5288	-0.8834	-0.4811
		(4.4657)	(3.0708)	(1.4362)	(1.0833)	(1.0651)	(0.6510)
Leverage				1.2632***	0.9209***	2.6949***	1.7796***
				(0.2153)	(0.2207)	(0.2941)	(0.2702)
Rating				0.2155***	0.2341***	0.1937***	0.1804***
				(0.0074)	(0.0082)	(0.0104)	(0.0092)
Liquidity				-0.0347***	0.0037	-0.0487***	0.0235***
				(0.0041)	(0.0040)	(0.0046)	(0.0040)
Size				0.0007*	0.0005	-0.0052***	-0.0042***
				(0.0004)	(0.0004)	(0.0011)	(0.0009)
Constant	-4.2568***	-4.8851***	-4.3591***	-6.4885***	-6.6088***	-6.4245***	-6.3254***
	(0.0624)	(0.0607)	(0.0700)	(0.0981)	(0.0728)	(0.1014)	(0.0949)
Observations	53,356	53,356	53,356	53,356	53,356	53,356	53,356
TIME FE	No	No	No	No	Yes	No	Yes
FIRM FE	No	No	No	No	No	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.210	0.094	0.252	0.661	0.755	0.427	0.654

Table 9: Robustness Tests

This table presents the results from the projection of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities, i.e., Ambiguity, (*Ambiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*Risk*), and all firm-specific controls as described in the benchmark regressions. In addition, the table controls for default probability implied by the naive Merton distance-to-default measure of Bharath and Shumway (2008) (π_{MERTON}), high frequency equity volatility and jump risk measures of Zhang et al. (2009) (*VRP, ZZZ_HM, ZZZ_HV, ZZZ_HS, ZZZ_HK, JI, JV, JN, JP*), accounting variables include the market-to-book ratio (*MB*), return on assets (*ROA*), return on equity (*ROE*), the dividend payout ratio (*DivPayRatio*), and the company's monthly stock return (*Ret*). Column (5) includes industry fixed effects. Column (6) is restricted to the year 2009, while column (7) is restricted to financial firms in year 2009. The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) CDS5y	(2) CDS5y	(3) CDS5y	(4) CDS5y	(5) CDS5y	(6) CDS5y	(7) CDS5y
Ambiguity	-0.5691***	-0.5141***	-0.4391***	-0.5538***	-0.5608***	0.8319***	0.4865
	(0.0906)	(0.0942)	(0.0865)	(0.0916)	(0.0915)	(0.2049)	(0.7766)
Risk	1.1403***	1.1648***	1.5405***	1.5872***	1.5898***	0.4758***	0.5474*
	(0.2158)	(0.2334)	(0.2599)	(0.2358)	(0.2354)	(0.1201)	(0.2784)
π_{MERTON}	0.6586***						
	(0.0504)						
VRP		0.0390***					
		(0.0112)					
ZZZ_HM		-84.8939***					
		(7.2758)					
ZZZ_HV		87.8303***					
		(18.6656)					
ZZZ_HS		-0.0086					
		(0.0061)					
ZZZ_HK		0.0046***					
		(0.0009)					
JI		0.0018**					
		(0.0008)					
JV		0.0470*					
		(0.0279)					
JP		-0.1017					
		(0.0972)					
JN		0.0467					
		(0.1099)					
MB			-0.2164***				
			(0.0270)				
ROE			0.0014				
			(0.0018)				
ROA			-1.1408***				
			(0.2831)				
DividendRatio			0.4528				
			(0.3696)				
Ret				0.0414			
				(0.0273)			
Observations	53,346	44,834	41,983	53,346	53,356	4,265	553
TIME FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY FE	No	No	No	No	Yes	No	No
FIRM CONTROLS	All	All	All	All	All	All	All
CONSTANT	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	No	No	No	No	No	No	No
Adj. R^2	0.675	0.688	0.671	0.657	0.660	0.612	0.581

Figure 1: Ambiguity, Risk, and Credit Spreads

This figure illustrates the relationship between risk (upper two panels) and credit spreads, as well as ambiguity (lower two panels) and credit spreads using the stylized model developed in Section II. The left-side column examines heterogeneity in the degree of risk aversion $((\gamma_B, \gamma_S) = (0.5, 2), (2, 2), (4, 2))$, keeping ambiguity aversion for the buyer and seller equal to $\eta_B = \eta_S = 2$. The right-side column examines heterogeneity in the degree of ambiguity aversion $((\gamma_B, \gamma_S) = (0.5, 1), (1, 1), (2, 1))$, keeping risk aversion for the buyer and seller equal to $\gamma_B = \gamma_S = 2$. All graphs assume equal wealth $w = 2$, and face value $N = 1$. When we examine the impact of ambiguity on spreads, we keep risk constant at $1 - R = 0.5$. When we examine the impact of risk on spreads, we keep ambiguity constant at $\mho^2 = 0.01$.

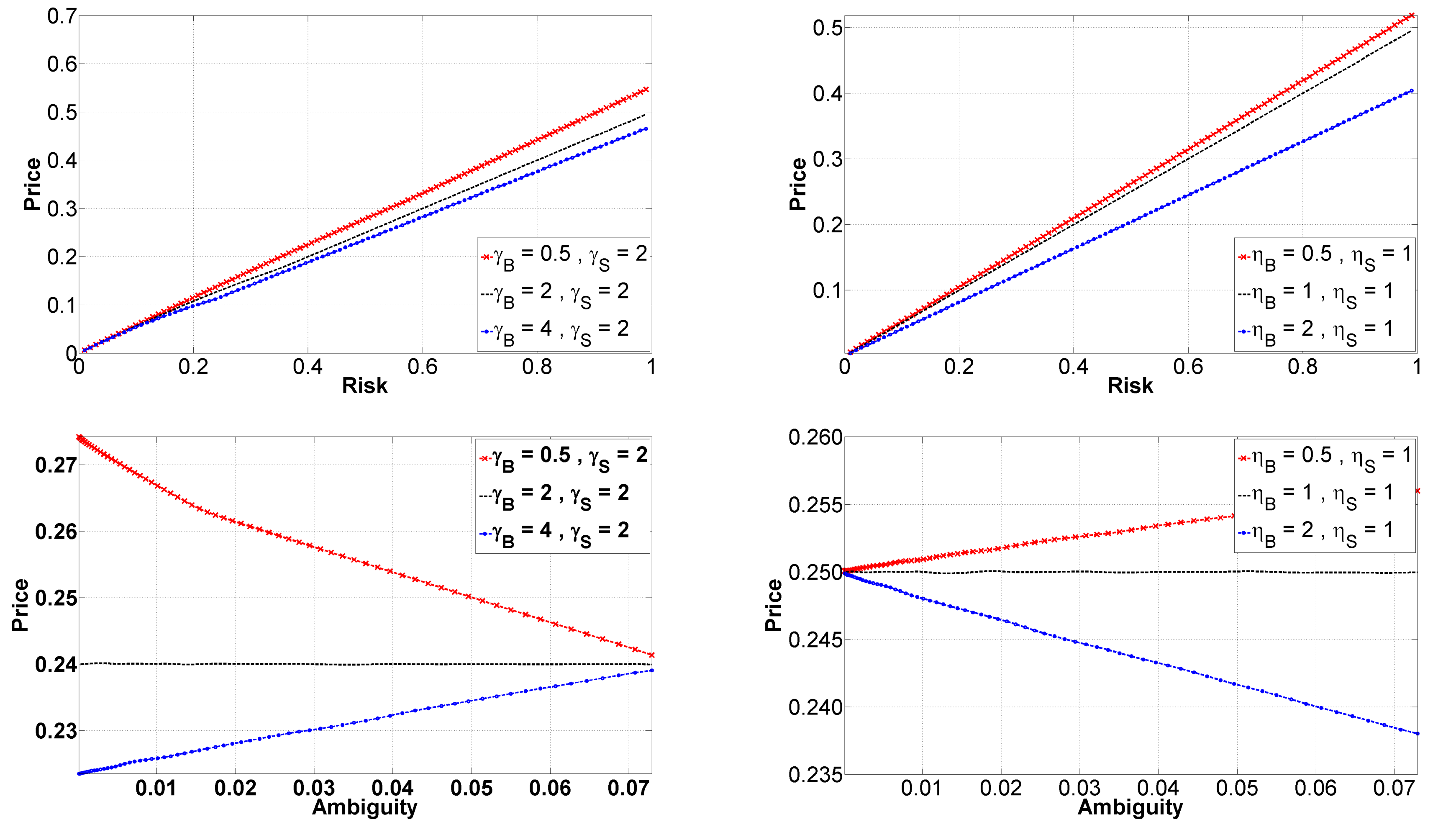
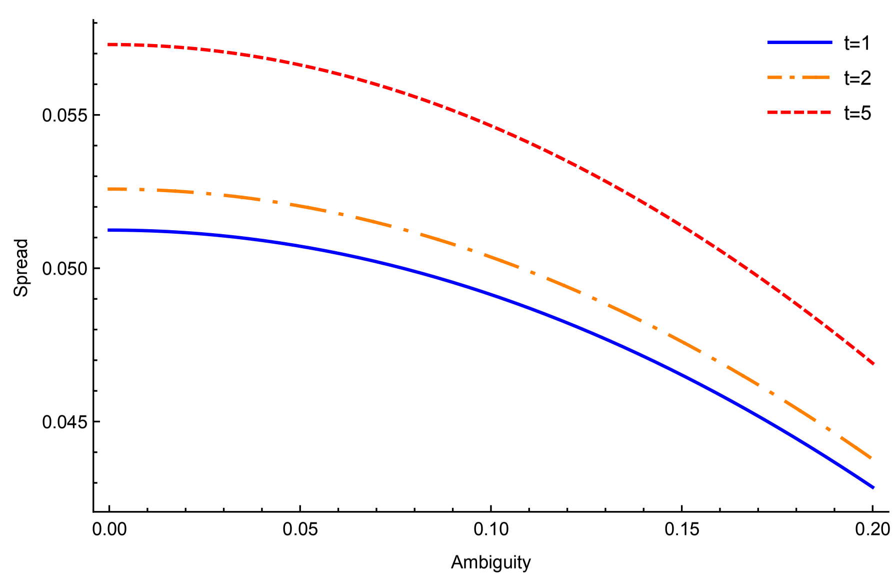


Figure 2: Sensitivity Analysis of Credit Spreads to Ambiguity and Risk

These graphs depict the sensitivity of credit spreads to ambiguity and risk, respectively. Credit spreads are computed using the Merton model such that risky debt equals a portfolio of riskless debt with face value $K = 100$ and a short position in a put option on the assets of the firm with strike price K. It plots the credit spread as a function of ambiguity and risk for three different maturities equal to one, two, and five time periods. The value of the put option is computed using a symmetric one-period binomial model and Equation (13) as explained in section II.4, assuming a risk-free rate r of 0 percent, initial debt value of 100, a coefficient of ambiguity aversion η equal to 2, and a risk neutral investor. To examine the sensitivity to ambiguity (left graph), we keep risk constant at a level of 20 percent, implying equal up and down movements of 20 percent. To examine the sensitivity to risk (right graph), we keep risk ambiguity at a level of 10 percent, implying a deviation up and down from expected probabilities equal to 10 percent.



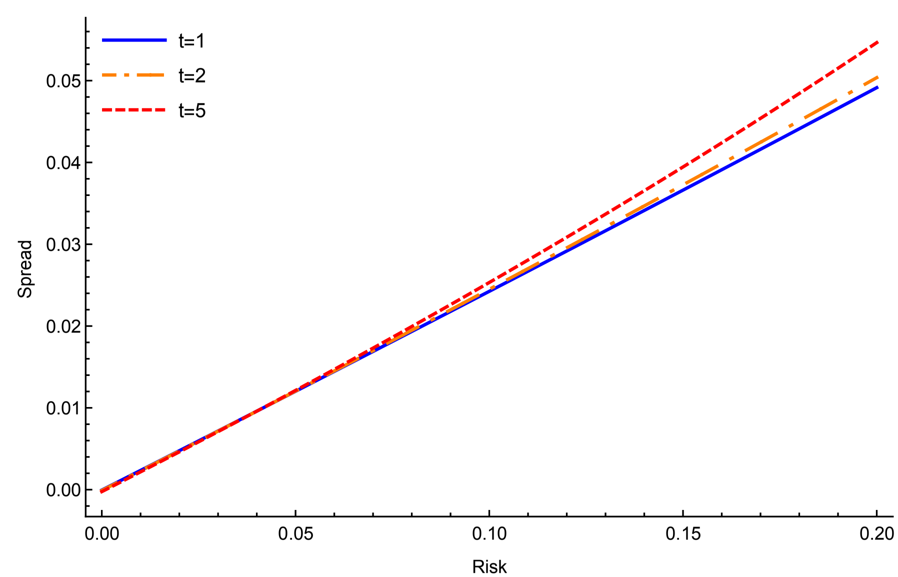
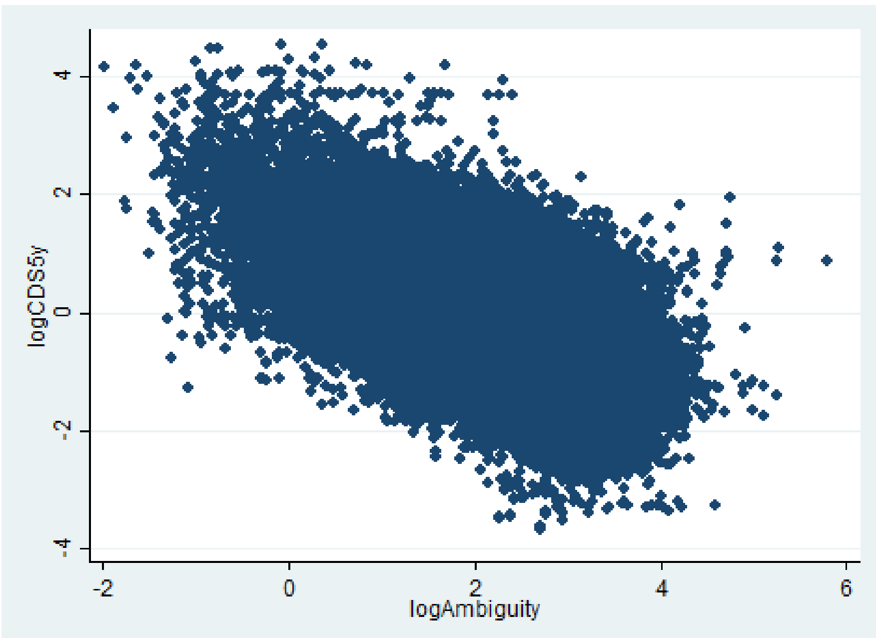


Figure 3: Scatter Plots for Risk and Ambiguity

The left graph illustrates a scatter plot for all pairs of observations for the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*logCDS5y*) against the natural logarithm of the monthly measure of ambiguity (*logAmbiguity*). The right graph illustrates a scatter plot for all pairs of observations for the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*logCDS5y*) against the natural logarithm of the monthly measure of risk (*logRisk*).



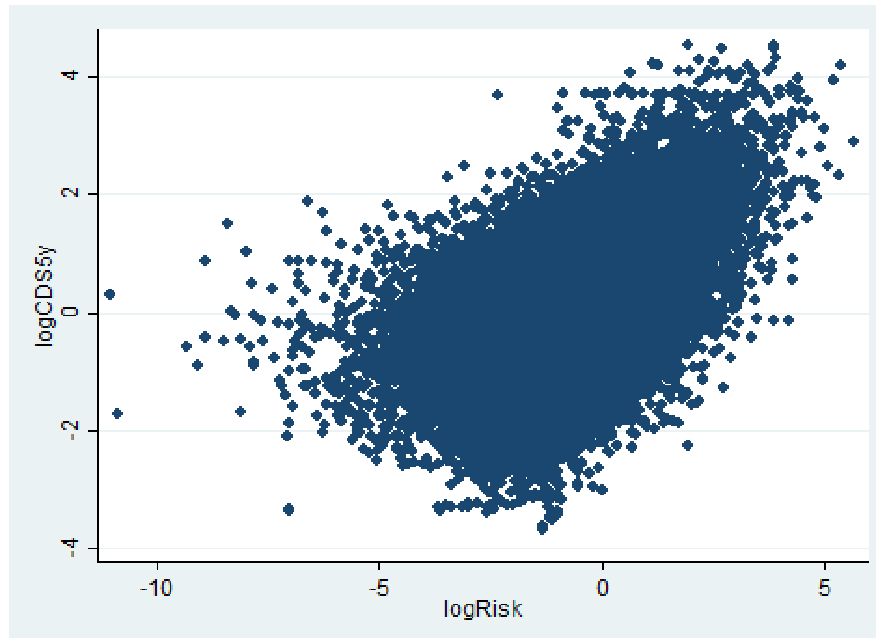


Table A-1: Data Appendix

This table reports the definitions and data sources of all variables used in the analysis. The sources are Markit CDS (Markit), the Chicago Center for Research in Security Prices (CRSP), Trade and Quote data (TAQ), Compustat, and the St.Louis Federal Reserve Economic database (FRED).

Variable	Description	Data Construction/Aggregation Method	Frequency	Source
CDS5y	5-year senior unsecured CDS spread with modified restructuring credit event clause; Annual spread in %	Monthly Average, end-of-month spread used for robustness	Monthly	Markit
Ambiguity	Variance of the outcome (return) probabilities; Monthly Value in % squared	Monthly variance of daily return probabilities computed using 162 return bins ranging from below -40% to above 40% and using intra-day return data sampled at 5-minute intervals	Monthly	TAQ
Risk	Variance of returns; Monthly Value in % squared	Monthly variance of daily returns	Monthly	CRSP
Leverage	Total amount of outstanding debt divided by the sum of total debt and equity, expressed in %	Total debt is computed by summing up COMPUSTAT data items 45 and 51. Equity is computed by multiplying the number of shares outstanding with the end-of-month share price.	Quarterly	COMPUSTAT
Rating	Standard & Poor's long-term issuer credit rating	Ratings are mapped into a numerical scale from 1 for AAA to 21 for C	Monthly	COMPUSTAT
Liquidity	CDS liquidity or depth, defined as the number of dealer quotes used in the computation of the mid-market spread	Monthly Average	Monthly	Markit
Size	Market Capitalization, measured in million USD	Number of shares outstanding times the end-of-month stock price	Monthly	CRSP
SP500Ambiguity	Aggregate Ambiguity, measured as the variance of the outcome (return) probabilities of the S&P500 ; Monthly Value in % squared	Monthly variance of daily return probabilities computed using 162 return bins ranging from below -40% to above 40% and using intra-day return data sampled at 5-minute intervals	Monthly	TAQ
SP500Risk	Aggregate Risk, measured as the variance of returns of the S&P500; Monthly Value in % squared	Monthly variance of daily returns	Monthly	CRSP
SP500return	Aggregate market return, measured as monthly return on the S&P500 stock market index; Monthly Value in %	Difference of the natural logarithm of two adjacent end-of-month S&P500 index prices	Monthly	CRSP
r2	Monthly 2-year constant-maturity Treasury yield	Monthly Average, Annualized (%)	Monthly	FRED
TSSlope	Difference between 10-year and 2-year constant-maturity Treasury yields	Monthly Average, Annualized (%)	Monthly	FRED
VIX	CBOE S&P 500 Volatility Index	Monthly Average, Annualized (%)	Monthly	FRED
BBB_AAA	Difference between the BofA Merrill Lynch US BBB and AAA Effective Yields	Monthly Average, Annualized (%)	Monthly	FRED
BB_BBB	Difference between the BofA Merrill Lynch US BB and BBB Effective Yields	Monthly Average, Annualized (%)	Monthly	FRED

Table A-2: Determinants of CDS Spread Changes

This table presents the results from the projection of the percentage changes of monthly 5-year senior unsecured CDS spread levels (*lnCDS5y*) on the percentage changes of the monthly variance of the outcome probabilities, i.e., Ambiguity, (*lnAmbiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*lnRisk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*lnLeverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*lnLiquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*lnSize*). The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%.

VARIABLES	(1) lnCDS5y	(2) lnCDS5y	(3) lnCDS5y	(4) lnCDS5y	(5) lnCDS5y	(6) lnCDS5y	(7) lnCDS5y
lnAmbiguity	-0.0692***		-0.0639***	-0.0632***	-0.0230***	-0.0629***	-0.0222***
	(0.0131)		(0.0121)	(0.0120)	(0.0049)	(0.0119)	(0.0047)
lnRisk		0.0156***	0.0094***	0.0092***	0.0051***	0.0092***	0.0049***
		(0.0037)	(0.0023)	(0.0023)	(0.0011)	(0.0022)	(0.0010)
lnLeverage				0.7334***	0.4411***	0.6965***	0.3807***
				(0.2346)	(0.1358)	(0.2271)	(0.1329)
Rating				-0.0027***	-0.0032***	-0.0106***	-0.0136***
				(0.0008)	(0.0006)	(0.0024)	(0.0015)
lnLiquidity				0.0577***	0.0606***	0.0564***	0.0601***
				(0.0207)	(0.0113)	(0.0202)	(0.0110)
lnSize				-0.0052**	-0.0058***	-0.0201*	-0.0350***
				(0.0023)	(0.0016)	(0.0105)	(0.0051)
Constant	0.0000	-0.0002	0.0000	0.0348***	0.0335***	0.1368***	0.1656***
	(0.0067)	(0.0071)	(0.0066)	(0.0135)	(0.0074)	(0.0125)	(0.0182)
Observations	52,865	52,865	52,865	52,865	52,865	52,865	52,865
TIME FE	No	No	No	No	Yes	No	Yes
FIRM FE	No	No	No	No	No	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.047	0.014	0.052	0.058	0.319	0.052	0.319

Table A-3: Determinants of CDS Spread Changes - Aggregate Controls

This table presents the results from the projection of the percentage changes of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*lnCDS5y*) on the percentage changes of the monthly variance of the outcome probabilities, i.e., Ambiguity, (*lnAmbiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*lnRisk*), aggregate ambiguity (*lnSP500Ambiguity*), aggregate risk (*lnSP500Risk*), as well as all firm-specific control variables as defined in the caption of Table 5, and several aggregate control variables, including the constant maturity 2-year Treasury rate (*r2*), the monthly return on the S&P500 index (*SP500return*), the CBOE S&P 500 implied volatility index (*lnVIX*), the 2-year constant-maturity Treasury yield (*lnr2*), the difference between the 10-year and 2-year constant-maturity Treasury yields (*lnTSSlope*), and the difference between the BofA Merrill Lynch US High Yield BBB (BB) and AAA (BBB) Effective Yields (*lnBBB_AAA* and *lnsBB_BBB*). The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	lnCDS5y	lnCDS5y	lnCDS5y	lnCDS5y	lnCDS5y	lnCDS5y
Ambiguity	-0.0428***				-0.0123***	-0.0081***
	(0.0031)				(0.0015)	(0.0010)
Risk		0.0727***			0.0251***	0.0166***
		(0.0122)			(0.0041)	(0.0026)
logSP500Ambiguity			-0.2459***		-0.0418**	-0.0359***
			(0.0690)		(0.0179)	(0.0065)
logSP500Risk				0.2258***	-0.0064	0.0046*
				(0.0390)	(0.0146)	(0.0025)
Leverage					0.0116***	0.0221***
					(0.0022)	(0.0028)
Rating					0.2306***	0.1675***
					(0.0081)	(0.0084)
Liquidity					-0.0023	0.0008
					(0.0036)	(0.0023)
Size					0.0007*	-0.0038***
					(0.0004)	(0.0010)
r2					-0.1117***	-0.1329***
					(0.0196)	(0.0096)
SP500Return					-0.0050	-0.0050***
					(0.0032)	(0.0005)
TSSlope					-0.0117	-0.0357***
					(0.0257)	(0.0130)
VIX					-0.0154	-0.0113***
					(0.0131)	(0.0033)
BBB_AAA					0.2775***	0.2884***
					(0.0523)	(0.0145)
BB_BBB					0.0458	0.0414***
					(0.0442)	(0.0099)
Constant	0.4193***	-0.2104***	0.5313***	1.0039***	-2.2997***	-1.8578***
	(0.0631)	(0.0550)	(0.1750)	(0.1916)	(0.1728)	(0.1070)
Observations	48,372	48,372	48,372	48,372	48,372	48,372
FIRM CONTROLS	No	No	No	No	All	All
TIME FE	No	No	No	No	No	No
FIRM FE	No	No	No	No	No	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.047	0.014	0.011	0.018	0.057	0.235

Table A-4: Determinants of CDS Slope Changes

This table presents the results from the projection of the percentage changes of the monthly slope, i.e., the difference between the 10-year and the 1-year senior unsecured CDS spread levels (*slope*) on the percentage changes of the monthly variance of the outcome probabilities, i.e., Ambiguity, (*lnAmbiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*lnRisk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*lnLeverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*lnLiquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*lnSize*). The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%.

VARIABLES	(1) lnslope	(2) lnslope	(3) lnslope	(4) lnslope	(5) lnslope	(6) lnslope	(7) lnslope
lnAmbiguity	-0.0241***		-0.0220***	-0.0216***	-0.0089**	-0.0217***	-0.0089**
	(0.0069)		(0.0067)	(0.0067)	(0.0040)	(0.0067)	(0.0039)
lnRisk		0.0058***	0.0036**	0.0036**	0.0000	0.0036**	0.0001
		(0.0020)	(0.0018)	(0.0017)	(0.0013)	(0.0017)	(0.0013)
lnLeverage				-0.1050	0.1224	-0.1128	0.1094
				(0.2036)	(0.1663)	(0.2010)	(0.1638)
Rating				0.0021**	0.0009	0.0058**	0.0020
				(0.0009)	(0.0009)	(0.0026)	(0.0021)
lnLiquidity				0.0544***	0.0426***	0.0548***	0.0427***
				(0.0187)	(0.0145)	(0.0183)	(0.0144)
lnSize				0.0011	-0.0002	0.0031	-0.0016
				(0.0019)	(0.0014)	(0.0121)	(0.0062)
Constant	0.0110**	0.0110**	0.0110**	-0.0100	0.0212***	-0.0457**	0.0126
	(0.0053)	(0.0054)	(0.0053)	(0.0108)	(0.0070)	(0.0202)	(0.0513)
Observations	46,682	46,682	46,682	46,682	46,682	46,681	46,681
TIME FE	No	No	No	No	Yes	No	Yes
FIRM FE	No	No	No	No	No	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.002	0.001	0.002	0.003	0.058	0.003	0.048

Table A-5: Determinants of CDS Spreads - End-of-month Spreads

This table presents the results from the projection of monthly 5-year senior unsecured CDS spreads, both log-levels and percentage changes, measured using the last observable observation in the month (*CDS5y* and *lnCDS5y*) on the monthly variance of the outcome probabilities, i.e., Ambiguity, (*Ambiguity*), the monthly variance of daily equity returns, i.e., equity volatility (*Risk*), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity (*Leverage*), the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C (*Rating*), CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread (*Liquidity*), and firm size in million USD, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). All variables are defined at the monthly frequency. The data sample includes 491 U.S. CDS firms for the period of January 2001 until October 2014. Standard errors are clustered by firm (*CLUSTER FIRM*), by time (*CLUSTER TIME*), or double clustered. ***, **, and * denotes statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Levels			Changes	
VARIABLES	CDS5y	CDS5y	CDS5y	lnCDS5y	lnCDS5y	lnCDS5y
Ambiguity	-0.5584***		-0.7279***	-0.0246***		-0.0208***
	(0.0907)		(0.0909)	(0.0037)		(0.0026)
Risk	1.6218***		1.6001***	0.0035***		0.0043***
	(0.2386)		(0.2346)	(0.0008)		(0.0008)
Ambiguity_{t-1}		-0.5663***			-0.0001	
		(0.0926)			(0.0023)	
Risk_{t-1}		1.4886***			0.0033***	
		(0.2221)			(0.0007)	
Constant	-6.3180***	-6.3265***	-6.5812***	0.1815***	0.1100***	0.1125***
	(0.0951)	(0.0967)	(0.1030)	(0.0229)	(0.0183)	(0.0110)
Observations	53,282	52,550	53,282	52,722	52,012	52,722
FIRM CONTROLS	All	All	All	All	All	All
AGG. CONTROLS	No	No	All	No	No	All
TIME FE	Yes	Yes	No	Yes	Yes	No
FIRM FE	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER FIRM	Yes	Yes	Yes	Yes	Yes	Yes
CLUSTER TIME	No	No	No	No	No	No
Adj. R^2	0.649	0.650	0.605	0.228	0.236	0.166