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Ambiguity, Volatility, and Credit Risk[‡]

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Abstract

We explore the implications of ambiguity for the pricing of credit default swaps (CDSs). A model of heterogeneous investors with independent preferences for ambiguity and risk shows that, because CDS contracts are assets in zero net supply, the net credit risk exposure of the marginal investor determines the sign of the impact of ambiguity on CDS spreads. We find that ambiguity economically, significantly negatively affects CDS spreads, on average, suggesting that the marginal investor is a net buyer of credit protection. A 1-standard-deviation increase in ambiguity is estimated to decrease CDS spreads by approximately 6%.

Keywords: CDS, Derivatives, Heterogeneous Agents, Insurance, Knightian uncertainty, Risk aversion
JEL Classification: C65, D81, D83, G13, G22

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1 Introduction

Many asset pricing models explicitly or implicitly presume that there is perfect information about the probabilities of all future asset outcomes. However, when these probabilities are not perfectly known, the willingness to pay for an asset may depend both on preferences for uncertainty about outcomes and on preferences for uncertainty about the likelihoods of these outcomes. 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. While the effect of risk on asset prices has been well studied, the impact of ambiguity has been little explored from an empirical perspective. The key objective of this paper is to assess the role of ambiguity in pricing credit default swaps (CDSs). 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 CDSs are insurance contracts that provide credit protection, their payoffs are directly linked to the (uncertain) likelihood of a firm-specific credit event (i.e., default).

To extract testable 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 between risk and ambiguity. Endowed with equal wealth, risk- and ambiguity-averse investors decide whether to optimally buy or sell credit protection on the underlying referenced debt. Each investor's decision depends on their relative sensitivity to risk and ambiguity. One key driver of the model is that, in the presence of ambiguity, investors overweight (underweight) the probabilities of the unfavorable (favorable) outcomes. For assets in positive net supply, a default is an unfavorable outcome. In contrast, for assets in zero net supply, such as CDSs, default is a favorable event if the investor is buying the credit protection, and an unfavorable one if the investor is selling it. Thus, whether a greater probability is assigned to the default or solvency outcome depends on the net exposure to default risk. The market-clearing condition imposes that, in equilibrium, the net exposure of the marginal investor will determine the impact of ambiguity on CDS spreads.

We derive two testable hypotheses from the model. The first hypothesis suggests that risk unambiguously has a positive effect on CDS spreads, regardless of the investor's preferences or credit exposures. The second hypothesis suggests that the impact of ambiguity on spreads depends on the net credit risk exposure of the marginal investor in the CDS market. Everything else equal,

the marginal investor is either the investor with lower risk aversion (greater risk-bearing capacity) or the investor with greater sensitivity to ambiguity. If the buyer is less risk averse or more ambiguity averse than the seller, CDS spreads are decreasing in the amount of ambiguity.

To test these hypotheses, we independently estimate ambiguity and risk using high-frequency stock price data. The empirical measure of ambiguity is rooted in the decision theory framework of expected utility with uncertain probabilities (EUUP, Izhakian 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 outcomes. The separation of risk and ambiguity is an important prerequisite for our empirical assessment of the impact of ambiguity on CDS spreads.

We examine a sample of 491 U.S. firms with 53,356 monthly CDS spread observations from January 2001 to October 2014. Our key findings show that ambiguity and risk have distinct and opposite effects on CDS spreads. Ambiguity has a negative effect on CDS spreads, as opposed to the positive effect of risk. In a univariate regression, ambiguity explains about 20% of the variation in the level of CDS spreads. Risk, on the other hand, explains about 17%, and with a larger economic significance than that of ambiguity. Multivariate regression results show that a 1-standard-deviation change in ambiguity and risk decreases and increases the level of CDS spreads by 6% and 12%, respectively, corresponding to a magnitude of 10 and 20 basis points (bps) for the average firm. Subject to the specification of the empirical model, the explanatory power of regressions for spread *levels* is up to 67%, in terms of adjusted R^2, and for spread *changes* is up to 33%. We find qualitatively similar results for regression specifications with CDS percentage changes or natural logarithms of CDS spread levels.

To mitigate concerns that firms with higher levels of CDS spreads endogenously have lower degrees of ambiguity, we examine the predictability of ambiguity and risk on the level of CDS spreads and their changes. We find that both lagged measures of ambiguity and risk help predict the level of CDS spreads. We test the two additional conjectures 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. The findings indeed confirm that ambiguity and risk have a more pronounced negative and positive impact, respectively, on longer horizon contracts.

By our model, the findings of a negative relation between CDS spreads and ambiguity sug-

gest that the marginal investor in the CDS market is on average net short credit risk, that is, a CDS buyer. In light of that conclusion, we examine published information on the aggregate gross amounts of CDS bought and sold by different types of counterparties, because information on the CDS holdings for the 491 U.S. firms in our data is not publicly available. The Bank for International Settlements (BIS) biannually reports survey-based statistics on gross notional amounts of CDS bought and sold on a worldwide consolidated basis. Additional information is available from the Depository Trust and Clearing Corporation (DTCC), which weekly reports the gross and net notional amounts of CDS outstanding since November 2008. These data sources suggest that many major counterparties, including derivatives dealers, are, on average, net buyers of CDS protection. These data are also consistent with earlier anecdotal evidence that banks and broker-dealers, who dominate the heavily concentrated market, are net buyers of CDSs (Allen and Gale 2005; Minton et al. 2009; Bongaerts et al. 2011; Peltonen et al. 2014; Duffie et al. 2015). Interestingly, there is time variation in the reported net CDS exposures. While many counterparties are net buyers of CDSs most of the time, several counterparties switch from being net buyers of CDSs to becoming net sellers toward the end of the global financial crisis (GFC). The statistics on CDS positions are consistent with the evidence that intermediaries are, on average, net sellers of CDS contracts in 2010–2012 (Siriwardane 2019; Eisfeldt et al. 2018), and evolve from being net sellers to net buyers of CDS protection over 2013–2015 (Cetina et al. 2018). In addition, we find differences in time variation of net CDS exposures across industries.

To further explore the time variation in net exposures, we test the sensitivity of CDS spreads to ambiguity using rolling regression windows of 36 months. We find that the negative effect of ambiguity on spreads intensified at the beginning of the GFC. Then, in late 2008, after Lehman Brothers filed for bankruptcy, the sign switched and remained positive during 2009–2011 and then turned negative again until the end of the sample period in October 2014. This time-varying pattern in the sensitivity of CDS spreads to ambiguity is similar to the pattern in net CDS exposures reported for dealers by the BIS and the DTCC. Thus, assuming that dealers set prices in CDS markets, our model suggests that the relation between ambiguity and CDS spreads is negative because dealers are net short credit risk, on average, and that the relation becomes positive when dealers become net sellers of CDS contracts.

All findings remain robust when we control for other firm-specific variables including leverage,

Standard and Poor's (S&P's) long-term credit ratings, CDS illiquidity, and firm size. The findings are also robust when we control for observable and unobservable macroeconomic risk factors, and (unobservable) time invariant firm heterogeneity. In addition, the results remain robust when we control for other aggregate market risk factors including the CBOE option-implied volatility index (VIX), high-yield and investment-grade credit spreads, and the return on the S&P 500 Index. Overall, our results strongly support the view that ambiguity captures a dimension of uncertainty that is different from risk.

To verify that our findings are consistent with the literature and to show that alternative channels do not explain our findings, we conduct a battery of robustness tests. Our conclusions remain unchanged when we control for the probability of default implied by the Merton distance-to-default, equity volatility, jump risk measures constructed using high-frequency stock returns, historical and risk-neutral skewness and kurtosis, and various accounting and balance sheet information. Further, the magnitude of the negative regression coefficient attributed to ambiguity does not change when we control for the contemporaneous stock return, equity illiquidity, or time-varying industry effects. In additional robustness tests, we confirm that variations to the measurement of ambiguity do not alter our conclusions. Moreover, alternative proxies for ambiguity such as the volatility of the mean return, the volatility of volatility, or analyst earnings forecast dispersion, do not change the significance or the magnitude of the ambiguity coefficient.

In this paper, we combine two streams of the literature: one on the determinants of credit spreads and their changes, and the other on the implications of ambiguity for asset prices. With respect to the former, structural credit risk models imply that asset volatility and leverage are key determinants of credit spreads (Black and Scholes 1973; Merton 1974). Collin-Dufresne et al. (2001) conclude that structural factors have limited explanatory power for yield spread changes. In contrast, Ericsson et al. (2009) find that structural variables provide the explanatory power for the level and changes of CDS spreads. Others highlight the significant explanatory power of total and idiosyncratic firm-specific volatility (Campbell and Taksler 2003), and the information captured by option-implied and historical volatility for CDS and bond spreads (Cremers et al. 2008; Cao et al. 2010). Zhang et al. (2009) deduce the level of CDS spreads using high-frequency return-based volatility and jump risk measures. 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). Bongaerts et al. (2011) show that in the presence of heterogeneous investors, illiquid CDS contracts may trade at higher prices when short-sellers have lower risk aversion, more wealth, or shorter trading horizons. Finally, Siriwardane (2019) documents that negative capital shocks to CDS sellers increase CDS prices. Table 1 provides a summary of the main determinants of CDS spreads used in the literature.[1]

Knight (1921) introduced the concept of uncertainty (ambiguity) by the conditions under which the odds of future events are either not unique or unknown. The theoretical success of preferences for ambiguity to match asset prices (Chen and Epstein 2002; Cao et al. 2005; Liu et al. 2005; Epstein and Schneider 2008; Illeditsch 2011; Boyarchenko 2012; Drechsler 2013; Faria and Correia-da Silva 2014) has motivated direct empirical tests of the role of ambiguity in equity returns (Anderson et al. 2009; Ulrich 2013; Williams 2015; Antoniou et al. 2015; Brenner and Izhakian 2018). A few studies examine the implications of ambiguity for options, but they focus on the theoretical aspects (Liu et al., 2005; Drechsler, 2013; Faria and Correia-da Silva, 2014). Izhakian and Yermack (2017) empirically show that expected ambiguity significantly positively affects employees' decisions to exercise their vested stock options early, as it lowers expected future option values. Izhakian et al. (2018) show that ambiguity is a positive predictor of firm leverage. One key distinction of our paper from prior studies is that we examine the equilibrium implications of ambiguity for the pricing of assets when net supply is zero. In many ambiguity models, agents overweight the probability of unfavorable outcomes and underweight the probabilities of favorable outcomes. For assets in zero net supply, the unfavorable outcome depends on the net risk exposure, while for assets in positive net supply, the favorable outcome is implicitly predetermined.

2 Model and Hypotheses

We develop a static general equilibrium model to examine the relation of risk and ambiguity to credit spreads. Our model rests on three key assumptions: preferences for ambiguity that are independent

[1]See also Blanco et al. (2005) and Das et al. (2009) for the role of accounting information in CDS spreads. Augustin et al. (2014) provide a review of the determinants of CDS spreads. Other market frictions that have been shown to affect credit spreads are liquidity and liquidity risk in CDSs (Longstaff et al. 2005; Tang and Yan 2007; Bongaerts et al. 2011; Qiu and Yu 2012; Junge and Trolle 2015) 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), restructuring risk (Berndt et al. 2007), and regulatory capital constraints (Lando and Klingler 2018). Semenov (2017) examines a negative risk-return trade-off in the context of bond spreads.

of those for risk; investors with heterogeneous preferences for risk and ambiguity; and the existence of an asset in zero net supply. In general equilibrium, heterogeneous investors (either their attitude toward risk and ambiguity or to attitude toward their beliefs) are necessary to generate trade in an asset in zero net supply, and thereby to identify the impact of ambiguity on CDS spreads, which depends on the net CDS demand of the marginal investor. The assumption that preferences for ambiguity are outcome independent is necessary to differentiate the effect of ambiguity from that of risk. The Online Appendix OA.1 presents a simplified asset pricing framework to illustrate how ambiguity and risk affect CDS spreads.

To develop some intuition for the effect of ambiguity and risk on the pricing of CDSs, consider a simplified structural credit risk framework in which a firm defaults if the value of its assets falls below the face value of debt N. If the firm's *risk* increases, as illustrated in panel A of Figure 1, the left-tail probability mass increases, making the default insurance more valuable. A classic feature of many ambiguity models is that ambiguity-averse investors act as if they overweight (underweight) the probabilities of unfavorable (favorable) outcomes.[2] Default is an unfavorable outcome from the perspective of an ambiguity-averse investor who is positively exposed to default risk. Therefore, this investor overweights the probability of default, as shown in panel B of Figure 1. In contrast, from the perspective of an ambiguity-averse investor who is negatively exposed to (i.e., short) credit risk, default is a favorable outcome. Therefore, this investor underweights the left-tail probability of default, as shown in panel C of Figure 1. This illustration suggests that the effect of ambiguity on the value of the CDS insurance depends on whether or not an investor is positively or negatively exposed to default risk.

2.1 Preferences for ambiguity

We follow the theoretical framework of expected utility with uncertain probabilities (EUUP, Izhakian, 2017) for the development of our static general equilibrium model, as it contains features that are helpful for the empirical validation of our predictions. Most importantly, a by-product of EUUP is a model-derived risk-independent measure of ambiguity that is rooted in axiomatic decision theory. This feature is due to outcome-independent preferences for ambiguity, which allows for the

[2]This may be explicitly defined (e.g., cumulative prospect theory, Tversky and Kahneman 1992) or implied by the decision rule (e.g., max-min expected utility with multiple priors, Gilboa and Schmeidler 1989).

separation of ambiguity from risk, as well as attitudes from beliefs.[3] Figures OA.1 and OA.2 in the Online Appendix provide simulated evidence using discrete and continuous probability distributions to support the independence between ambiguity and risk.

The main concept behind EUUP formulation is that the preferences for ambiguity are applied exclusively to uncertain probabilities of future events. Thus, aversion to ambiguity is defined as an aversion to mean-preserving spreads in probabilities, which are outcome independent. As such, we employ the Rothschild and Stiglitz (1970) approach and measure ambiguity independently of risk as the volatility of the probabilities of future outcomes.

Formally, in the EUUP framework employed in our model, an investor, who values a risky and ambiguous payoff X, possesses a set $\mathcal{P}$ of priors P (cumulative probabilities) over events, equipped with a prior probability ξ (a probability of a probability distribution). Each cumulative probability $\mathrm{P} \in \mathcal{P}$ is associated with a marginal probability function $\varphi(\cdot)$. In the absence of ambiguity, $\mathcal{P}$ is singleton, meaning that there is only one objective probability distribution. Using these beliefs, an investor assesses the expected utility of a risky and ambiguous payoff $\mathrm{V}(X)$ by:

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

where the (unique) expected marginal and cumulative probability of x are computed using ξ, such that $\mathrm{E}[\varphi(x)] \equiv \int_{\mathcal{P}} \varphi(x)\, d\xi$ and $\mathrm{E}[\mathrm{P}(x)] \equiv \int_{\mathcal{P}} \mathrm{P}(x)\, d\xi$, with $\mathrm{Var}[\varphi(x)] \equiv \int_{\mathcal{P}} \big(\varphi(x) - \mathrm{E}[\varphi(x)]\big)^2 d\xi$ defining the variance of the marginal probability. See Izhakian (2016), Theorem 2.

As the investor is ambiguity-averse, the investor may compound the set of priors $\mathcal{P}$ and the prior ξ over $\mathcal{P}$ in a nonlinear way. This aversion, captured by a strictly increasing, concave, and twice-differentiable continuous function $\Upsilon : [0,1] \to \mathbb{R}$, is applied to the valuation of probabilities.[4] Distinguishably, risk aversion is captured by a strictly increasing, concave, and twice-differentiable continuous utility function $\mathrm{U} : \mathbb{R} \to \mathbb{R}$, applied to the valuation of outcomes.

[3] The independent measurement of risk and ambiguity poses a challenge for other frameworks that do not separate ambiguity from attitude toward ambiguity (Gilboa and Schmeidler, 1989; Schmeidler, 1989) or outcome-dependent preferences for ambiguity (Klibanoff et al., 2005; Chew and Sagi, 2008).

[4] Ambiguity aversion is reflected in the preference of an investor for the expectation of an uncertain payoff probability over the uncertain probability itself. Recall that risk aversion arises when the expectation of the uncertain outcome is preferred over the uncertain outcome itself. When the investor is ambiguity neutral, $\Upsilon(\cdot)$ is linear and Equation (1) collapses to the standard expected utility framework.

Ambiguity, as modeled by Equation (1), affects expected utility through the investor's perceived probabilities, which may be viewed as the objective probabilities adjusted for ambiguity. These (unique) perceived probabilities are a function of the extent of ambiguity, measured by $\mathrm{Var}\left[\varphi\left(x\right)\right]$, and the investor's aversion to ambiguity, captured by $-\frac{\Upsilon''(\cdot)}{\Upsilon'(\cdot)} > 0$. Both a higher aversion to ambiguity or a higher extent of ambiguity result in lower (underweighted) perceived probabilities of the "good" states, and higher (overweighted) perceived probabilities of the "bad" states. The indeterminate sign $+/-$ in Equation (1) reflects that the investor either overweights or underweights the probability, depending on the exposure toward outcome x.

The parameter k defines the reference point relative to which outcomes may be classified as unfavorable (a loss) or favorable (a gain). Without loss of generality, we normalize the utility function at the reference point k to $\mathrm{U}\left(k\right) = 0$. The existence of a reference point is inherited from the cumulative prospect theory (CPT) of Tversky and Kahneman (1992), allowing for reference-dependent attitudes toward risk and ambiguity, and thereby reference-dependent utility.[5]

2.2 Valuation and development of hypotheses

Inspired by structural models of default risk, in our static general equilibrium model, we assume a one-period closed economy with one levered firm with a face value of debt N. After one period, the value of the firm's assets increases to V_H or decreases to V_L, with $V_L < N < V_H$. The firm defaults (default state DF) if the value of assets drops below the face value of debt; otherwise, it remains solvent (solvency state SL). The payoff of a CDS contract (credit protection) written on the debt issued by the firm is zero if the firm remains solvent. If the firm defaults, the CDS contract covers the loss, which is determined by the difference between the face value of debt and the residual firm value in default (V_L), which is lower than the face value of the debt. Thereby, in our model, the spread in outcomes $\Delta = V_H - V_L$ is a reduced-form mechanism for modeling risk (i.e., the uncertainty in outcomes), which, together with ambiguity, is one of the two main state variables in our model. A mean-preserving widening of the gap between the asset values in the default and solvency states thus implies greater risk.

[5] CPT extends the Choquet expected utility (CEU), proposed by Schmeidler (1989), by adding reference-dependent utility. In our EUUP model in Equation (1), we refine the CEU and CPT models by suggesting an endogenous construction of the capacities (subadditive probabilities), which are exogenously imposed in these models. Unlike in CPT, we do not assume asymmetric utility from losses over gains (loss aversion). Eliminating the reference-dependent utility (conceptually, setting $k = -\infty$) would still have a similar effect to that of reference-dependent utility, because the probabilities of unfavorable outcomes are underweighted by less than the probabilities of the favorable outcomes.

We assume the existence of two investors who can purchase or sell h units of the CDS.[6] Both investors are endowed with the same wealth, w, and thus face the same budget constraint. They also encounter the same degree of ambiguity and risk, but may differ in their aversion to ambiguity and risk.[7] Furthermore, both investors exhibit a neutral time preference, implying a zero risk-free rate. The motivation for selling or buying CDS contracts is driven by differences in the investors' perceived probabilities of default and solvency, which are determined by their aversion to ambiguity. In contrast, in an economy with assets in zero net supply (CDS) and homogeneous investors (same preferences and beliefs), trade would break down, as both investors would want to simultaneously buy or sell the CDS contract.

As the CDS contract is in zero net supply, an investor with a short exposure to default risk (long CDS) perceives the positive payoff from the CDS contract in the default state as favorable. In contrast, an investor with a long exposure to default risk, who sells the CDS, perceives the solvency state as favorable. Accordingly, investors aggregate the objective probabilities and form the unique perceived probability, which, in the default or solvency state, is given by

$$\mathrm{Q}(x) \quad = \quad \mathrm{E}\left[\varphi\left(x\right)\right]\left(1 \pm \frac{\Upsilon''\left(\mathrm{E}\left[\mathrm{P}\left(x\right)\right]\right)}{\Upsilon'\left(\mathrm{E}\left[\mathrm{P}\left(x\right)\right]\right)}\mathrm{Var}\left[\varphi\left(x\right)\right]\right), \tag{2}$$

and determined by the net credit risk exposure of the investor. In the absence of ambiguity ($\mathrm{Var}\left[\varphi\left(x\right)\right] = 0$) or ambiguity aversion ($\frac{\Upsilon''(\mathrm{E}[\mathrm{P}(x)])}{\Upsilon'(\mathrm{E}[\mathrm{P}(x)])} = 0$), perceived probabilities collapse to the uniquely defined objective expected probabilities.[8] Thus, faced with an asset in zero net supply, an investor solves the following two optimization problems in order to determine the optimal holdings of credit protection:

$$\begin{aligned} \max_{h} \quad & \mathrm{Q}(DF)\mathrm{U}\left(w - hp + h\left(N - V_L\right)\right) + \left[1 - \mathrm{Q}(DF)\right]\mathrm{U}\left(w - hp\right) \\ \text{s.t.} \quad & 0 \leq h \leq \frac{w}{p} \qquad \text{and} \qquad 0 < p < N - V_L \end{aligned} \tag{3}$$

and

$$\begin{aligned} \max_{h} \quad & \left[1 - \mathrm{Q}(SL)\right]\mathrm{U}\left(w + hp - h\left(N - V_L\right)\right) + \mathrm{Q}(SL)\mathrm{U}\left(w + hp\right) \\ \text{s.t.} \quad & 0 \leq h \leq \frac{w}{N - V_L - p} \qquad \text{and} \qquad 0 < p < N - V_L, \end{aligned} \tag{4}$$

[6]The amount h can be interpreted as the fraction of the face value of debt that the buyer of insurance would like to maintain. Thus, $h = 1$ means full coverage; $h > 1$ means over-insurance; and $h < 1$ means partial insurance.

[7]Equilibrium prices are determined by investors' differences in marginal utility, which is a function of risk-bearing capacity. In turn, risk-bearing capacity is subject to investor wealth and innate risk aversion. For simplicity, we assume homogeneous wealth and focus on investor heterogeneity in risk or ambiguity aversion.

[8]Perceived probabilities, which are a nonlinear aggregation of a set of probability distributions, are different from risk-neutral probabilities, which reflect a linear transformation of an objective and unique probability distribution.

where p is the price of the CDS contract that is fully settled upfront.[9] When the utility of the maximization problem in Equation (3) is higher (lower) than that in Equation (4), the investor optimally purchases (sells) an amount h_B (h_S) of the CDS contract.

To guarantee the existence of an equilibrium with trade, we specify the market-clearing condition,

$$h_B \quad = \quad h_S, \tag{5}$$

requiring that the units of CDS contracts purchased by the buyer h_B are equal to the units sold by the seller h_S. However, an equilibrium does not necessarily exist, for example, when both investors optimally hold short or long positions in the CDS contract, or when the lowest optimal price for the seller is too high for the buyer. We focus exclusively on interior solutions to the maximization problems in Equations (3) and (4) for which the market-clearing condition in Equation (5) holds.

The equilibrium price p of the CDS contract is determined by the intensities of risk and ambiguity aversion, and the initial wealth of both investors. To derive testable predictions, we consider a buyer (B) and a seller (S) who exhibit constant absolute risk aversion (CARA) and 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 the buyer and seller may have different aversions to risk $\{\gamma_B, \gamma_S\}$ and ambiguity $\{\eta_B, \eta_S\}$. The assumption behind CARA and CAAA is for tractability only, as it allows for analytical solutions to the optimization problem. Using numerical solutions, as discussed below, we show in Figure 2 that the same implications for the impact of ambiguity and risk on the pricing of CDS contracts hold for investors with constant relative-risk aversion (CRRA) and constant relative ambiguity aversion (CRAA). With the aforementioned assumptions, we obtain the following proposition.

Proposition 1 *If the buyer and the seller are characterized by CARA and CAAA, and the boundary conditions in Equations* (3) *and* (4) *are slack, then higher firm-specific risk results in higher CDS spreads; that is,* $\frac{\partial p}{\partial \Delta} > 0$.[10]

In Proposition 1, we suggest that the positive effect of risk on the CDS spread does not depend

[9] By convention, CDS contracts are quoted in running spreads. Since the implementation of the Big Bang Protocol in 2009 by the International Swaps and Derivatives Association (ISDA), CDS contracts are traded with fixed coupons and upfront payments. Thus, the price p, which reflects the net present value of all the expected future insurance payments implied by the credit protection, can be interpreted as a contract that is entirely settled upfront with a 0 bps coupon.

[10] Like Rothschild and Stiglitz (1970), we say an underlying security becomes riskier if its new payoffs can be written as a mean-preserving spread of the old payoffs. In this proposition, we do not assume that risk is measured by the variance of payoffs or that returns are normally distributed.

on the net credit risk exposure of the marginal investor (net short or net long credit risk), or on the intensity of risk aversion. In response to an increase in risk, the buyer's demand for the CDS increases as additional value is added to each unit of insurance, which increases the value of the CDS. The seller, on the other hand, increases the supply of the CDS, given the increased profit opportunities from the increasing demand for risk sharing, which reduces the value of the CDS. Proposition 1 highlights that, with respect to risk, the demand effect always supersedes the supply effect, thus risk always positively affects CDSs in equilibrium. The appendix provides the proof. In our model, we also obtain the following proposition.

Proposition 2 *If the buyer and the seller are characterized by CARA and CAAA with identical risk aversion, and the boundary conditions in Equations* (3) *and* (4) *are slack, then higher firm-specific ambiguity leads to a lower CDS spread (i.e.,* $\frac{\partial p}{\partial \upsilon^2} < 0$*) if*

$$\eta_B \frac{\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]}{\mathrm{Q}(DF)\left[1-\mathrm{Q}(DF)\right]} \quad > \quad \eta_S \frac{\mathrm{E}\left[\mathrm{P}\left(SL\right)\right]}{\mathrm{Q}(SL)\left[1-\mathrm{Q}(SL)\right]} \tag{6}$$

and to a higher CDS spread (i.e., $\frac{\partial p}{\partial \upsilon^2} > 0$*) if*

$$\eta_B \frac{\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]}{\mathrm{Q}(DF)\left[1-\mathrm{Q}(DF)\right]} \quad < \quad \eta_S \frac{\mathrm{E}\left[\mathrm{P}\left(SL\right)\right]}{\mathrm{Q}(SL)\left[1-\mathrm{Q}(SL)\right]}. \tag{7}$$

In Proposition 2, we suggest that the sign of the impact of ambiguity on the CDS spread depends on the intensity of the ambiguity aversion of the marginal price setter in the CDS market. A CDS buyer is willing to pay a higher price when the perceived probability of default is high. However, as the buyer underweights (overweights) the probability of default (solvency), higher ambiguity reduces the buyer's perceived probability of default, such that the value of the credit protection offered by the CDS contract is reduced. Therefore, the buyer's demand for the CDS decreases. At the same time, as the seller underweights (overweights) the probability of solvency (default), higher ambiguity reduces the seller's perceived probability of solvency, such that the seller reduces the supply of CDS contracts. When the buyer (seller) is more ambiguity averse than the seller (buyer), such that inequality (6) (inequality (7)) holds, an increase in ambiguity results in a lower (higher) value of the CDS contract. For the proof, see the appendix.

Figure 2 numerically shows that similar predictions arise for investors with CRRA and CRAA risk and ambiguity preferences. Panels A and B show the relation between risk and CDS spreads, illustrating the cases of two investors with equal ambiguity aversion and heterogeneous risk aversion (panel A), as well as equal risk aversion and heterogeneous ambiguity aversion (panel B). Similarly,

panels C and D show the relation between ambiguity and CDS spreads. When the two investors have CRRA risk preferences, and the buyer has greater (lower) risk-bearing capacity than the seller (i.e., a lower (higher) risk aversion), the relation between ambiguity and CDS spreads is predicted to be negative (positive). Moreover, the impact of ambiguity on CDS spreads is negative (positive) when the buyer has a greater (lower) aversion to ambiguity than the seller. Supported by the predictions implied by Propositions 1 and 2, the following are our two hypotheses.

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

Hypothesis 2 *Credit spreads are lower for a higher degree of firm-specific ambiguity, when the marginal investor is a net CDS buyer. Credit spreads are higher for a higher degree of firm-specific ambiguity, when the marginal investor is a net CDS seller.*

2.3 Model extensions

To better understand the importance of our assumptions, it is worth discussing extensions of our model before we turn to test our hypotheses. Online Appendix (Section OA.2) provides the formal proofs of these extensions.

As discussed above, in the presence of an asset in zero-net supply (e.g., a CDS), trade breaks down when investors have homogeneous preferences and beliefs. In this case, there may not be an equilibrium price formation, as both investors may want to simultaneously buy or sell the CDS contract. An equilibrium is restored if, instead, the asset is in positive supply, in which case the sign of the impact of ambiguity and risk on prices is the same. A similar result obtains in the presence of an asset in positive net supply when investors are heterogeneous with respect to preferences and beliefs.

Finally, when the investor holds the underlying bond (in positive supply) and the CDS contract, the investors' maximization problem can be redefined in terms of the net CDS demand, that is, the CDS exposure in excess of the exposure from the asset in positive supply. That is, the maximization problem collapses to the investor's net credit risk exposure. Therefore, it is straightforward to generalize the uncovered ("naked") CDS positions we consider above to the case of (partially) covered CDS positions.

3 Data

The primary data sources we use are Markit, one of the major data providers for CDS spreads, and intraday trade and quote (TAQ) data for the estimation of the firm-specific degrees of ambiguity and risk. We source stock price information from the Center for Research in Security Prices (CRSP), company-specific balance sheet information from Compustat, and macroeconomic control variables from the St. Louis Federal Reserve Economic Data (FRED) 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 firms for which we have 53,356 monthly CDS spread observations, from January 2001 to October 2014, for which we can extract joint information on CDS, ambiguity, and risk.

3.1 Credit default swaps

We approximate the credit risk of a company's debt using CDS spreads. In frictionless markets, CDSs ought to be equivalent to the yield spread on a defaultable par bond over a benchmark risk-free rate (Duffie, 1999). The indicative midmarket dealer quotes reflect constant-maturity spreads based on standardized contracts. This facilitates a direct price comparison across companies, as CDS spreads are less affected than bonds by covenants and contractual differences. Markit makes information available for over 3,000 international firms. We start with the 1,259 unique U.S. parent company identifiers for which we can match a corresponding identifier in CRSP, excluding all CDS contracts written on subsidiaries and private firms. For CDSs, 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. We obtain similar results if we use CDS contracts with the no restructuring credit event clause. Our reported results are based on monthly averages of daily CDS spreads. All results are, however, robust to the use of end-of-month CDS spreads, as shown in the Online Appendix.

3.2 Estimating ambiguity and risk

The main motivation for our use of the EUUP framework is that Equation (1) naturally implies a risk-independent measure of (objective) ambiguity, denoted by $\mho^2$. Using the EUUP framework,

the degree of ambiguity can be measured by the volatility of uncertain *probabilities*, as the degree of risk can be measured by the volatility of uncertain *outcomes*. Formally, the measure of ambiguity is defined as

$$\mho^2 [X] \equiv \int \mathrm{E} [\varphi (x)] \mathrm{Var} [\varphi (x)] dx, \tag{8}$$

which represents a weighted average of the variances of probabilities. We follow Izhakian and Yermack (2017) and estimate the monthly degree of ambiguity for each firm using intraday stock return data from the TAQ database.[11]

As investors share the same information set, all have an identical set of priors over the intraday return distribution. Each prior in the set is represented by the observed daily intraday returns on the underlying asset, and the number of priors in the set depends on the number of trading days in the month. The set of priors thus consists of 18–22 realized distributions over a month. For practical implementations, we discretize return distributions into n bins $B_i = (r_i, r_{i-1}]$ of equal size, such that each distribution is represented as a histogram, as demonstrated in Figure 3. The height of the bar of a particular bin is computed as the fraction of daily intraday returns observed in that bucket, and thus represents the probability of the outcomes in that bin. Equipped with these 18–22 daily return histograms, we can compute the expected probability of being in a particular bin across the daily return distributions, $\mathrm{E} [\mathrm{P} (B_i)]$, as well as the variance of these probabilities, $\mathrm{Var} [\mathrm{P} (B_i)]$. Using these values, the monthly degree of ambiguity of firm j is then computed as follows:

$$\mho^2 [r_j] \equiv \frac{1}{\sqrt{w (1-w)}} \sum_{i=1}^{n} \mathrm{E} [\mathrm{P}_j (B_i)] \mathrm{Var} [\mathrm{P}_j (B_i)] . \tag{9}$$

To minimize the impact of the bin size selection on the value of ambiguity, we apply a sort of Sheppard's correction and scale the weighted-average volatilities of probabilities to the size of the bins by $\frac{1}{\sqrt{w(1-w)}}$, where $w = r_{j,i} - r_{j,i-1}$.

In our implementation, we sample 5-minute stock returns from 9:30 to 16:00, as this eliminates microstructure effects (Andersen et al., 2001; Ait-Sahalia et al., 2005). Thus, we obtain daily histograms of up to 78 intraday returns. If we observe no trade in a specific time interval, we compute returns based on the volume-weighted average of the nearest trading prices. We ignore

[11] The measure of objective ambiguity, defined in Equation (8) and a matter of beliefs (or information), is distinct from aversion to ambiguity, a matter of tastes. The former is estimated from historical data, whereas the latter is endogenously determined by estimation.

returns between closing and next-day opening prices to eliminate the impact of overnight price changes and dividend distributions. We drop all days with less than 15 different 5-minute returns; we also drop months with less than 15 intraday return distributions. In addition, we drop extreme returns (plus or minus 5% log returns over 5 minutes), as many of them are due to improper orders that were canceled by the stock exchange. Our results are robust to a lower cutoff level for extreme returns (1%), as well as to the inclusion of extreme price changes.

For the bin formation, we divide the range of daily returns into 162 intervals. To support all daily intraday return distributions, whose support may not overlap, we start out with more bins than daily intraday returns. We form a grid of 160 bins, from -40% to 40%, each of width 0.5%, in addition to the left and right tails, defined as $(\infty, -40\%]$ and $(+40\%, +\infty)$, respectively. We compute the mean and the variance of probabilities for each interval, assigning equal likelihood to each distribution (all histograms are equally likely).[12] That some bins may not be populated with return realizations makes computing their probability difficult to do. Therefore, we assume a normal return distribution and use its moments to extrapolate the missing return probabilities. That is, $\mathrm{P}_j[B_i] = \left[\Phi(r_i; \mu_j, \sigma_j) - \Phi(r_{i-1}; \mu_j, \sigma_j)\right]$, where $\Phi(\cdot)$ denotes the cumulative normal probability distribution, characterized by its mean μ_j and the variance σ_j^2 of the returns. Like French et al. (1987), we compute the variance of the returns by applying the adjustment for nonsynchronous trading, as proposed by Scholes and Williams (1977). Doing so also mitigates microstructure effects.[13] In our robustness tests, which we discuss in Section 5, we compute ambiguity assuming a nonnormal probability distribution, and a nonparametric statistical distribution, by using intraday returns at different frequencies, and by varying the number of return bins.

An important characteristic of the measure of ambiguity implied by EUUP is that it is risk independent (up to a state space partition), which allows for an independent examination of the impacts of risk and ambiguity on asset prices. Other proxies for ambiguity that have been used in the literature for empirical applications include the disagreement of analyst forecasts (Drechsler, 2013),

[12] The assignment of equal likelihoods is equivalent to assuming that the daily ratios $\frac{\mu_j}{\sigma_j}$ are Student's t-distributed, implying that cumulative probabilities are uniformly distributed (e.g., Proposition 1.27, p. 21 in Kendall and Stuart 2010). This is consistent with investors not having superior information to infer a greater likelihood of a particular probability distribution and thus assigning equal weights to each possible distribution.

[13] Scholes and Williams (1977) suggest adjusting the volatility of returns for nonsynchronous trading as $\sigma_t^2 = \frac{1}{N_t}\sum_{i=1}^{N_t}(r_{t,i} - \mathrm{E}[r_{t,i}])^2 + 2\frac{1}{N_t - 1}\sum_{i=2}^{N_t}(r_{t,i} - \mathrm{E}[r_{t,i}])(r_{t,i-1} - \mathrm{E}[r_{t,i-1}])$. Our results are similar without the Scholes-Williams correction for nonsynchronous trading.

the volatility of return volatility (Faria and Correia-da Silva, 2014), and the volatility of the mean return (Franzoni, 2017). As these measures are sensitive to changes in the set of outcomes, they are risk-dependent and therefore less useful for the purpose of our study.[14] For similar considerations, skewness (as well as kurtosis and other moments of the return distribution) and $\mho^2$ are different, as the former is outcome dependent and the latter is outcome independent. This is true regardless of whether higher order moments are measured under the historical or the risk-neutral probability distribution. We show empirically in Section 5 that skewness and kurtosis are only weakly related to our measure of ambiguity. To support the independence of ambiguity to risk, skewness, and kurtosis, we report in the Online Appendix simulated evidence using distributions with both discrete and continuous state spaces. Figure OA.1 demonstrates that ambiguity is strictly independent of risk (as well as of skewness and kurtosis) when the set of possible events (the induced partition of the state space into events) does not change when risk, skewness, and kurtosis increase. Figure OA.2 demonstrates that ambiguity is weakly independent (insignificant change) of these three outcome-dependent measures if the set of events changes in response to their increase.

Figure 3 may also intuitively illustrate how ambiguity is independent of risk. Consider, for example, an extreme return (i.e., a stock price jump). If the set of events (partition of the state space) remains unchanged, one of the bins will simply contain a higher return, but the probability of being in that particular bin, or any other bin, remains unchanged. Therefore, ambiguity remains unchanged.[15] If, on the other hand, the set of events changes, then one additional bin will be added to the histogram, thereby characterizing a new event. This may also affect the population of other bins, and could, therefore, affect the ambiguity measure. However, both the expected probability of experiencing a return in this new bin and the probability variance associated with it are small. Thus, such an extreme return would have a negligible impact on ambiguity, as the effect on ambiguity is by the product of the expected probability and the variance of probability, which is even smaller.

Brenner and Izhakian (2018) study the implications of ambiguity in the aggregate market and suggest that, in their sample, $\mho^2$ does not capture other well-known "uncertainty" factors including

[14] Consider, for example, the risk-dependent variance of the mean. If each outcome associated with an event is multiplied by a constant $\alpha \neq 0$, both the variance of the mean and risk are α^2 times greater, whereas the event probabilities associated with each outcome and, thus, ambiguity remain unchanged.

[15] Consider, for example, a return on an investment that is determined by a coin toss with unknown probabilities, where tails yields a 1% return and heads a 2% return. If after ten coin tosses the return for head changes to 10% (i.e., a jump), ambiguity remains unchanged, because no new information about the probability is obtained.

skewness, kurtosis, variance of variance, variance of mean, downside risk, mixed data sampling measure of forecasted volatility (MIDAS), or investors' sentiment, among several others. In our robustness tests in Section 5, we examine many of these uncertainty factors at the firm level.

Along with objective ambiguity, objective risk serves as an important explanatory variable in our analysis. We compute risk using the same 5-minute returns that we use to measure ambiguity. For each individual stock j on each day, we compute the variance of intraday returns, applying the Scholes and Williams (1977) correction for nonsynchronous trading and a correction for heteroscedasticity (e.g., French et al., 1987). In a given month t, we then compute the monthly variance of stock returns $\mathbb{V}\text{ar}_{j,t}$ using the average of daily variances, scaled to a monthly frequency.

3.3 Other explanatory variables

In the Merton (1974) model, 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 2-year constant-maturity Treasury yield (*r2*). Other firm-specific controls include firm size in $billion, 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 midmarket spread (*Liquidity*), and S&P's long-term issuer credit rating, mapped into a numerical scale ranging from 1 for AAA to 21 for C (*Rating*). Thus, we introduce these and other variables based on the prior studies listed in Table 1.

We gather balance sheet information from Compustat, and common macroeconomic variables from the St. Louis Federal Reserve Economic database. These include aggregate risk, return, and ambiguity based on the S&P 500 Index (*SP500Risk*, *SP500Ret*, and *SP500Ambiguity*), the CBOE S&P 500 implied volatility index (*VIX*), the difference between the 10-year and the 2-year constant-maturity Treasury yields (*TSSlope*), and the difference between the BofA Merrill Lynch U.S. High-Yield BBB (BB) and AAA (BBB) effective yields (*BBB_AAA* and *BB_BBB*). Table OA.1 in the Online Appendix offers a detailed description of the data sources and construction.

3.4 Summary statistics

Table 2 reports summary statistics. For the 491 firms with 53,356 monthly CDS spread observations between January 2001 and October 2014, the average CDS spread is 162 bps, whereas the median is 79 bps. More granular unreported summary statistics by rating categories suggest that the average credit spread increases from 48 bps for firms rated AA or higher to 592 bps for companies rated B or lower. The average (median) monthly degree of firm ambiguity, as measured by the standard deviation of the return probabilities, is 20.11% (19.25%), while the average monthly (median) volatility of stock returns is 8.21% (6.73%), implying positive skewness for both measures.[16]

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 BBB credit rating. The average risk-free borrowing rate is 2.05% during our sample period. On average, the CDS of a firm is quoted by six to seven dealers.

Table 3 reports the average pairwise correlation coefficients between all of our explanatory variables. Focusing on the correlation between ambiguity and risk, our key variables of interest, we find that they are negatively correlated with a magnitude of 27%. This underscores the fact that both our ambiguity and risk measures capture different aspects of uncertainty. Figure 4 plots the natural logarithm of the 5-year CDS spread (in basis points) against the natural logarithm of ambiguity and risk. These scatterplots show that risk is positively associated with the credit spread level, a well-known result, whereas ambiguity bears a negative relation, a finding that, to our knowledge, is new to the literature.

4 Empirical Methodology and Analysis

In this section, we test our hypotheses. We provide evidence on the relation between CDS spreads and ambiguity, and on CDS exposures. In addition, we examine time variation in the relation between CDS spreads and ambiguity. We conclude this section by discussing our findings through the lens of our model.

[16] CDS contracts tend to be written on large firms with comparatively low volatility and high leverage. Our sample only consists of firms with available CDS data, so the return volatility in our sample is low relative to that of the universe of CRSP firms.

4.1 Main test of the hypotheses

To test Hypotheses 1 and 2, we first regress the natural logarithm of the level of 5-year CDS spreads on ambiguity, risk, and additional control variables:

$$\ln\left(CDS_{j,t}\right) = \alpha + \beta_A \cdot Ambiguity_{j,t} + \beta_R \cdot Risk_{j,t} + \delta^\top \cdot X_{j,t} + \zeta_j + \theta_t + \varepsilon_{j,t}, \tag{10}$$

where $X_{j,t}$ is a vector of firm-specific control variables for firm j, and $\varepsilon_{j,t}$ represents i.i.d. standard normal errors. The control variables are firm leverage, the firm's S&P long-term credit rating, CDS liquidity, and firm size. We include time fixed effects θ_t to account for unobservable macroeconomic factors that may affect credit spreads over time, and firm fixed effects ζ_j to 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. 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). Table OA.2 of the Online Appendix confirms that all findings are qualitatively similar if we use percentage changes in CDS spreads. The main coefficients of interest are the sensitivity of CDS spreads to ambiguity (β_A) and risk (β_R).

Table 4 reports the main findings. The results in Column 1 suggest a significant negative relation between CDS spreads and ambiguity. In this univariate regression, ambiguity attains an explanatory power of 20%. The magnitude of the coefficient indicates that a 1-standard-deviation increase in ambiguity results in a 38% decrease in the CDS spread. Given that the average CDS spread is 162 bps, this implies that, on average, a 1-standard-deviation increase in ambiguity results in a spread that is 62 bps lower. The univariate regression results in Column 2 confirm the significant and positive relation between CDS spreads and risk. The explanatory power amounts to 17%, lower than that for ambiguity. A 1-standard-deviation increase in risk results in an increase of about 89 bps in CDS spreads, on average, an increase of 55%. When we include both ambiguity and risk in the regression, the magnitudes of the coefficients decrease slightly. Both remain significant at the 1% level, with a joint explanatory power of 28%. This underscores that ambiguity and risk capture different dimensions of uncertainty, and that both are significant determinants of CDS spreads.

Next, we add the firm-specific control variables to the regression. Their coefficients in Columns 4 and 5 all have the expected sign and are statistically significant. Namely, credit spreads are positively associated with leverage and deteriorating credit ratings, while companies covered by

more dealers tend to have lower CDS spreads, on average. Next, we add time and firm fixed effects to the regressions. While the battery of fixed effects does absorb a significant amount of variation in CDS spreads, ambiguity and risk still have incremental explanatory power, as shown in Columns 6 to 8. On average, a 1-standard-deviation increase in ambiguity is associated with a 10-bps (6%) decrease in CDS spreads, whereas a 1-standard-deviation increase in risk is associated with a 20-bps (12%) increase in spreads. The explanatory power of these regression tests ranges between 51% and 67%, which compares well with that in Bharath and Shumway (2008), Zhang et al. (2009), and Bai and Wu (2016). The robustness regression tests with percentage changes in CDS spreads, reported in Table OA.2 of the Online Appendix, yield adjusted R^2s of up to 33%.

4.2 Predictive regression tests

Next, we examine whether lagged ambiguity and risk exhibit predictive power for CDS spreads. Specifically, we run the following regression:

$$\begin{aligned}\ln\left(CDS_{j,t}\right) = \alpha + \sum_{i=1}^{3} \beta_{A,i} \cdot Ambiguity_{j,t-i} + \sum_{i=1}^{3} \beta_{R,i} \cdot Risk_{j,t-i} \\ + \delta^{\top} \cdot X_{j,t} + \zeta_j + \theta_t + \varepsilon_{j,t},\end{aligned} \tag{11}$$

where we include up to 3-month lagged ambiguity and risk, firm-specific controls, and firm and time fixed effects in each regression.

The findings reported in Table 5 suggest that the economic significance of lagged ambiguity and risk is similar to that of contemporaneous measures, with a 7% (11%) decrease (increase) in CDS spreads for a 1-standard-deviation increase in ambiguity (risk). For an average spread of 162 bps, this corresponds to a decrease (increase) of 11 (18) bps in spreads for a 1-standard-deviation increase in ambiguity (risk). The results in Columns 2 to 3 suggest that additional lags of the predictors have the same statistical significance, and similar economic magnitudes and explanatory power, although the economic impact is slightly decreasing for more distant lags. When we pool all lags together, the adjusted R^2 in Column 4 increases by about 1 percentage point, and the coefficients of all variables remain highly significant. These findings indicate that both contemporaneous and past ambiguity and risk have economically meaningful predictive power for credit spreads, but they predict spread variations in opposite directions.

4.3 Evidence on CDS exposures

In light of our findings, we examine the publicly available evidence on CDS positions. We source information on net CDS exposures from the semiannual over-the-counter (OTC) derivatives statistics published by the BIS. These data are obtained from a survey of large dealers headquartered in thirteen countries and provide information about the gross notional amounts bought and sold by different types of counterparties on a worldwide consolidated basis.[17] Although these data represent only a noisy proxy of the CDS exposures for our sample of 491 U.S. firms, they are useful for interpreting our findings.

Panel A of Table 6 reports the evolution of the total gross notional amounts of CDS contracts outstanding. We also report the market share of different counterparties as a fraction of the total gross notional amounts of CDS contracts outstanding. The survey data we use indicate that dealers account for 43% to 58% of the market at all times, consistent with the strong concentration in the CDS market (e.g., Giglio 2014; Siriwardane 2019; Eisfeldt et al. 2018). Peltonen et al. (2014) describe the CDS network as a core-periphery structure in which the 10 largest dealers take up about 71% to 77% of the overall market. Banks hold the second largest market share, peaking at 30.78% in 2009. Since 2010, their importance has reduced to 5.40% in 2016, while that of central counterparties has increased to 37.28%. Other counterparties account for less significant shares of the CDS market, even though the importance of hedge funds has been increasing in the most recent years of the sample.

Panel B of Table 6 depicts the differences between gross notional amounts of single name CDS contracts bought and sold by type of counterparty (net exposure). These values do not add up to zero as the survey-based data do not capture all positions in the global CDS market. Throughout the sample period, most counterparties purchase more CDS contracts than they sell, except for hedge funds and special purpose vehicles. It is apparent that, in early 2010, dealers reduce their single name CDS exposures and transition from being net buyers to net sellers of CDS contracts.

Dealers account for the greatest market share, so we depict their net CDS exposures by instrument type in panel C of Table 6. One will observe that dealers' evolution of net CDS exposures significantly varies across products. Their transition from net CDS buyers to net CDS sellers appears to be driven by single-name and financial CDS contracts. Dealers' exposures toward financial

[17] We focus on the difference between gross notional amounts bought and sold by different types of counterparties, reported in tables D10.1 to D10.4 from the BIS. For more information, see www.bis.org.

reference entities turn negative after the height of the GFC in the first semester of 2009 (Lehman Brothers bankruptcy), and become positive again in 2015. Dealers' transition from net buyers to net sellers of CDS contracts also starts and reverses earlier for nonfinancial reference entities than for financial reference entities. Other counterparties exhibit similar differences in net exposures across reference entities. We provide these additional statistics in the Online Appendix Table OA.7, together with visual evidence of the evolution of CDS exposures in Figures OA.3 and OA.4.

Panel D of Table 6 provides information on the dealers' net exposures, based on gross market values, toward all, as well as single-name and multiname reference entities. It illustrates that dealers are net sellers of CDSs primarily in 2011 and 2012. Similar evidence is found for the difference between positive and negative net market values of CDS contracts, as reported in panel E of Table 6.

Figure 5 uses weekly reports on the gross and net notional amounts of CDS outstanding from the Depository Trust and Clearing Corporation (DTCC) to provide additional evidence about the change in the dealers' net CDS exposure.[18] The DTCC statistics suggest that for many sectors, there is a change of net exposures by dealers around the GFC. While the aggregate order imbalance for all contracts becomes positive around the turn of the year 2012, for utilities, sovereigns, and unclassified categories, dealers begin to transition from net sellers to net buyers before 2012.

Our evidence suggests that banks and broker dealers, who capture the biggest CDS market share, are, on average, net buyers of CDS contracts (short credit risk). This is consistent with the early anecdotal evidence provided by Allen and Gale (2005) and Minton et al. (2009), as well as later evidence reported by Bongaerts et al. (2011), Peltonen et al. (2014), and Duffie et al. (2015). Our evidence is also consistent with the proprietary data used in Siriwardane (2019) and Eisfeldt et al. (2018), who show that intermediaries are, on average, net sellers of CDS contracts in 2010–2012. Further, Cetina et al. (2018) observe that they evolve from being net sellers to net buyers of CDS protection over 2013 to 2015.

[18]For our purpose, this information is less informative than is the BIS data, as DTCC began reporting positions on October 31, 2008. The weekly reports are based on the information available in the Trade Information Warehouse (TIW), a centralized global trade repository that consolidates trade reporting, post-trade processing, payment calculation, credit event processing, and central settlement. According to the DTCC, the TIW captures more than 95% of the global OTC credit derivatives market. More specifically, the TIW posts weekly gross and net notional amounts outstanding in U.S. dollar equivalents, and the number of traded contracts in aggregate, for the 1,000 most heavily traded reference entities. We use the information from Tables 2 and 3, which contain information on the gross notional amounts bought and sold by dealers for different types of underlying instruments.

4.4 Time-varying relation between ambiguity and CDS spreads

Although we find that the effect of ambiguity on credit spreads is negative, on average, the evidence from the BIS data and from other studies suggests that the net exposure of individual investors changes over time. Therefore, we examine the time-varying relation between ambiguity and credit spreads. To this end, we repeatedly estimate Equation (10) with firm-specific and aggregate control variables, using rolling regression windows of 36 months. Figure 6 plots the rolling coefficients for the sensitivity of CDS spreads to ambiguity, together with 95% confidence intervals. The dates on the x-axis correspond to the starting month of each regression window. Figure 6 reveals that there is time variation in the magnitude of the ambiguity coefficient. In particular, the ambiguity coefficient becomes more negative at the beginning of the GFC. The sensitivity of CDS spreads to ambiguity then flips to a positive sign for the first time in February 2008, peaks at an estimated value of 1.04 in September 2009, and then becomes negative again in March 2009, until the end of the sample period in October 2014. It is difficult to pinpoint the precise month of the sign flip, as the regressions are based on a 36-month rolling window. Nevertheless, the findings suggest that the positive impact of ambiguity on CDS spreads is primarily in 2009–2011.

Next, we test the time variation of the sensitivity of CDS spreads to ambiguity by interacting ambiguity with a categorical variable (*macrocrisis*), which takes the value one during the GFC, and is zero otherwise. The GFC is defined according to the NBER-defined recession dates (between December 2007 and June 2009). Kelly et al. (2016) suggest that the impact of idiosyncratic and industry-wide jump risk on the CDS spreads of large financial institutions may have changed during the GFC because of sector-wide government guarantees. To account for this possibility, we add interaction terms between industry and month fixed effects.

Table 7 reports the coefficients of these regression tests. The results in Column 1 suggest that accounting for unobserved time-varying risk at the industry level does not significantly alter the magnitude of the ambiguity coefficient compared to the estimate reported in Column 8 of Table 4. The findings for the negative and significant interaction term between *macrocrisis* and ambiguity reported in Column 2 suggest that the impact of ambiguity on credit spreads was amplified during the GFC. To refine the analysis, we add interaction terms between ambiguity and indicator variables that capture different 24-month periods; that is, the indicators are one during a consecutive 24-month period, and they are zero otherwise. These regressions estimate the evolution of the

sensitivity of CDS spreads to ambiguity, like those regression results reported graphically in Figure 6. The negative and significant coefficients in Columns 3 to 8 are confined to 2008–2009, whereas the total impact becomes slightly positive in 2009–2010 and more strongly positive in 2010–2011, before it becomes gradually more negative again over 2011–2012 and 2012–2013.

4.5 Industry effects

Net CDS exposures may be different not only over time but also across industries. Therefore, in Table 8, we examine whether the impact of ambiguity on CDS spreads is different across industries. We report only the key coefficients of interest from the main regression in Equation (10). To explore the cross-industry variation, in this regression, we add an interaction term between ambiguity and a dummy variable that is equal to one for a specific industry, and zero otherwise. We use the 12-industry classification of Fama and French (1997). This classification ranges from the nondurable goods industry (NDG) in Column 1 to financial firms (FIN) in Column 11, and a catchall group for nonclassified other firms (OTH) in Column 12.

The coefficients reported in the first row of panel A of Table 8 can be interpreted as the average sensitivity of CDS spreads to ambiguity for all industries excluding the industry captured by the interaction term. This coefficient is significant across all 12 industries. The interaction terms between ambiguity and each industry indicator confirm significant variation across industries. First, the sum of the two coefficients (unconditional plus interaction term) is negative for all firms, except for the category business equipment (BUS), for which the joint impact from the unconditional coefficient on ambiguity and the interaction term is positive. The overall effect is negative but significantly smaller than the average coefficient for nondurable goods firms (NDG), chemical firms (CHM), and health care firms (HCA). On the other hand, the aggregate effect is significantly more negative for financial firms (FIN).

In panels B and C of Table 8, we report the findings for the ambiguity coefficients for subsamples of each industry and for different time periods—during the NBER-defined recession months in panel B and during 2009–2010 in panel C. These regression tests may lack power because of a limited time series and limited number of firms in some industries. Nevertheless, the findings in panel B suggest that, during the NBER recession, the coefficient for ambiguity is negative and significant for five industries. In contrast, during 2009–2010, the coefficient is positive and significant for

four industries (MNF, CHM, UTL, and FIN), and significantly negative only for the energy sector (EGY). Overall, these results underscore the rich variation across industries and over time.

4.6 Interpretation of the empirical findings

We interpret the evidence through the lens of our model. Our interpretation centers around Proposition 2, which suggests that the sign of the impact of ambiguity on CDS spreads depends on the net credit risk exposure of the marginal investor. Investors' preferences are not identifiable based on publicly available data, so we assume that preferences for ambiguity and risk remain unchanged, implying that relative ambiguity and risk aversion remain constant over time. To relate CDS exposures to the empirical findings, two additional assumptions are needed.

First, net credit risk exposure is not identifiable based on publicly available data, so we assume that net CDS demand, defined as the difference between positive and negative gross notional amounts outstanding, is positively correlated with net credit risk exposure for our sample of 491 U.S. reference entities. Such an assumption could be consistent with segmented CDS markets, as proposed by Siriwardane (2019).

Second, we assume that dealers are the marginal price setters. Thus, by our model, dealers will dictate the sign of the impact of ambiguity on CDS spreads. Hence, all else equal, they are less risk averse or more ambiguity averse than nondealers. While the identity of the marginal price setters in the CDS market is unknown, several studies suggest that financial intermediaries have pricing power for multiple asset classes (Adrian et al. 2014; He et al. 2017), which is especially important for assets that are heavily intermediated, such as CDSs (Haddad and Muir 2018). The assumption that dealers are marginal price setters is also consistent with the CDS market structure in which dealers provide liquidity to customers (Riggs et al. 2018; Collin-Dufresne et al. 2019). Investor demand thus interacts with the dealers' willingness to trade CDS contracts.

The above intuition is similar to that in the literature on the demand-based option pricing (Bollen and Whaley 2004; Garleanu et al. 2009). These studies suggest that market makers set prices to absorb the exogeneous buy-sell order imbalances in options from end-customers. As market makers are net sellers of put options, they demand a volatility markup, which leads to the steepness of the option-implied volatility smile. Garleanu et al. (2009) formalize this argument by showing that the option's price increase is proportional to the variance of the unhedgeable part of

the option. While these studies find that option market makers are net sellers of put options to customers, we find that dealers are on average buyers of CDS contracts. Chen et al. (2018) examine the equilibrium implications of demand and supply shocks in the market for deep out-of-the-money (DOTM) put options. Their finding of a negative relation between net demand for crash insurance and option expensiveness, as measured by the variance risk premium, suggests that supply shocks dominate prices more often than demand shocks.

We find a negative relation between ambiguity and CDS spreads. Assuming that the dealers set prices to absorb the net CDS demand, by our model, the negative sign of the relation between ambiguity and CDS spreads is consistent with the evidence that dealers are net buyers of CDS contracts on average. The sign flip after the GFC is also consistent with dealers who become net CDS sellers between 2009 and 2011. The change in dealers' CDS exposures is reminiscent of the change in dealers' exposure toward DOTM put options, documented by Chen et al. (2018). While Bollen and Whaley (2004), and Garleanu et al. (2009) find that dealers are primarily net sellers of DOTM put options from 1995 to 2000 and from 1996 to 2001, respectively, Chen et al. (2018) document that they become net buyers of crash insurance following times of distress (see their Figures 1 and 5). While the BIS and DTCC data represent only a noisy proxy of the CDS exposures for our sample of 491 U.S. firms, they provide supportive evidence for the implications advocated by our model.

Instead of dealers, prices also could be set by banks, insurance companies, or nonfinancial corporations. Based on that assumption, their net buying positions also would be consistent with the unconditional negative impact of ambiguity on CDS spreads. However, if the relative preference ranking does not change such that the marginal investor remains the same, their positions are inconsistent with the changing relation between ambiguity and CDS spreads after the GFC. The positions of hedge funds and special purpose vehicles, who are net sellers of CDS contracts, can be reconciled with the sign flip. Yet, as they are mostly net CDS sellers, their positions are inconsistent with the unconditionally negative coefficient estimated for the relation between ambiguity and CDS spreads.

Alternative interpretations also may be possible if the relative aversion to ambiguity or risk does not stay constant over time. For example, dealers could become price takers after the crisis if they become more risk averse and/or less ambiguity averse than nondealers. In this case, the

positive coefficient estimate, when the sign of the relation between ambiguity and CDS spreads flips, would be consistent with the interpretation that hedge funds or SPVs replace dealers as price setters, as they are net CDS sellers around that time. The evidence is, however, inconsistent with other nondealers assuming the role of marginal investors, as they are primarily net buyers of CDS contracts.

4.7 Discussion

We find that, on average, ambiguity and CDS spreads are negatively related. This finding may seem at odds with Boyarchenko (2012), who shows that, for financial firms, ambiguity amplified CDS spreads during the GFC. A similar seemingly contradictory result is found in related work by Liu et al. (2005) and Drechsler (2013), who show that uncertainty about rare events can increase the expensiveness of out-of-the-money put options. Through the lens of the Merton (1974) model, 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. Thus, the higher the value of the put option, the lower the price of the risky bond, and the greater the credit spread. The result of a positive effect of ambiguity on credit spreads depends on the perspective of an investor who considers a drop in the value of the underlying asset to be unfavorable. However, as discussed above, a drop in asset value may be considered favorable if the investor has a short position in the asset.

Liu et al. (2005), Boyarchenko (2012), and Drechsler (2013) implicitly assume that investors invest in assets that have a positive net supply. This implies that the "bad" states are left-tail events. As discussed in relation to Figure 1, in such a scenario, an ambiguity-averse investor attributes a higher probability to the default state (and a lower probability to the no-default state), which increases the value of the put options. Thus, the results of Liu et al. (2005) and Drechsler (2013) could be obtained in our framework when the marginal investor is net long credit risk. The net credit risk exposure depends on the net demand for CDS contracts and the net aggregate position (long and short) in the underlying corporate bond. Section OA.2 of the Online Appendix shows that our predictions are also valid for a joint position in CDSs and the underlying bonds.

Conceptually, in Liu et al. (2005), Boyarchenko (2012), and Drechsler (2013), it is assumed that ambiguity-averse investors price assets based on the worst case scenario (max-min expected utility with multiple priors (MEU), Gilboa and Schmeidler, 1989). In the MEU framework, preferences

for ambiguity are outcome dependent and, therefore, risk dependent. This makes it challenging to separate ambiguity from risk. In contrast, in the EUUP framework, preferences for ambiguity are outcome independent. Thereby, it suggests a measure of ambiguity that is independent of risk, enabling the examination of the independent effects of ambiguity and risk on CDS spreads.[19]

In our model, the relation between ambiguity and CDS spreads depends on the net credit exposure of the marginal price setter. The key ingredient for this implication is investor heterogeneity. By our model, dealers dictate the sign of the impact of ambiguity on CDS spreads when they are less risk averse or more ambiguity averse than end-users. Similarly, Bongaerts et al. (2011) show that the sign of the impact of liquidity risk on assets in zero net supply depends on the (heterogeneous) investors' net nontraded risk exposure, and is determined by the more aggressive investors (in terms of wealth or risk aversion) with shorter investment horizons.

Information heterogeneity among investors has been suggested to be a source of option trading volume, and, thereby, a contributor to the expensiveness of out-of-the-money put options (Buraschi and Jiltsov 2006; Asea and Ncube 1998). Grossman and Zhou (1996), Benninga and Mayshar (2000), Bates (2008), Weinbaum (2009), Li (2013), and Feng et al. (2018) illustrate how heterogeneous preferences may lead to an increase in the prices of out-of-the-money put options and steeper implied volatility skews. Back (1993) shows that asymmetric information may lead to the inability to price options by no-arbitrage. Chen et al. (2018) show how differential risk-bearing capacity for disaster risk generates trade in DOTM options.

5 Robustness Tests and Additional Analyses

Next, we conduct several robustness tests by exploring the sensitivity of our results to alternative explanations suggested in the literature. In addition, we provide an analysis of the relation of ambiguity and risk to the slope of the term structure of CDS spreads.

[19] In Drechsler (2013), the theoretical derivation of the variance of equity returns increases in ambiguity, which is caused by enlarging the size of the set of priors, such that the worst prior changes. Because the variance of returns is computed using this new (even worse) prior, it increases risk. In our framework, as the variance of returns is computed using expected probabilities, a higher ambiguity may affect the variance of returns positively, negatively, or not at all, depending on the changes in the expected probabilities of each outcome.

5.1 Distance-to-default

Bharath and Shumway (2008) show that a "naïve" probability of default outperforms the distance-to-default measure implied by Merton (1974).[20] To control for the probability of default, we introduce the naïve distance-to-default measure into the main regression test alongside ambiguity. Column 1 of Table 9 shows that, even though the naïve 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.

5.2 Jump risk

As previously discussed, Kelly et al. (2016) suggest that the nature of idiosyncratic jump risk may have changed during the GFC, in particular for large financial institutions. To control for this effect, for each firm in our sample, we compute the number of monthly stock price jumps using 5-minute intraday returns, following the methodology of Lee and Mykland (2008). The results in Column 2 of Table 9 confirm a positive association between stock price jumps and CDS spreads, but our conclusions regarding ambiguity are qualitatively and quantitatively unaffected.

Following Zhang et al. (2009), we examine the impact of the following alternative measures of risk and jump risk, computed using high-frequency stock price data, on CDS spreads: the volatility premium, computed as the difference between the average implied volatility and the realized volatility in the preceding month; the historical moments of firm-specific equity returns (mean, variance, skewness, and kurtosis), computed for the 1-year horizon from historical daily equity returns; jump intensity (JI); jump volatility (JV); positive jump size (JP); and negative (JN) jump size. When we introduce these measures alongside ambiguity, our results in Column 3 of Table 9 confirm the results in Table 4 of Zhang et al. (2009). In particular, we find that jump intensity, jump variance, and negative (positive) jumps are positively (negatively) associated with the CDS spread levels. Furthermore, the historical mean and kurtosis (skewness) are positively (negatively) associated with the spread levels. While these results are consistent with previous

[20] The naïve probability of default is computed as $\pi_{\text{naïve}} = \mathcal{N}(-DD_{\text{naïve}})$, with $DD_{\text{naïve}} = \frac{ln(E+F/F)+(r_{i,t-1}-0.5 \text{ naïve } \sigma_V^2)T}{\text{naïve } \sigma_V \sqrt{T}}$, where F is the sum of debt in current liabilities plus one-half of long-term debt; E is the market value of the firm; naïve $\sigma_V = \frac{E}{E+F}\sigma_E + \frac{\text{naïve } D}{E+F}(0.05 + 0.25 \times \sigma_E)$; naïve$_D = 0.05 + 0.25 \times \sigma_E$; Equity volatility σ_E is the annualized percentage standard deviation of returns estimated from the prior year stock return data for each month; and $r_{i,t-1}$ is the firm's stock return over the previous year.

evidence on the relation between CDS spreads and high-frequency equity volatility and jump risk, none of these alternative sources of uncertainty explain our findings that ambiguity is negatively associated with CDS spread levels. The regression coefficient for ambiguity in Column 3 of Table 9 remains highly statistically significant and negative, with a similar economic magnitude.

5.3 Accounting information

In the accounting literature, accounting variables may explain heterogeneity in the level and dynamics of CDS spreads (Augustin et al., 2014). We verify these findings by controlling for 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 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 on a quarterly basis. The results in Column 4 of Table 9 suggest that market-to-book ratio and return on assets are negatively correlated with 5-year CDS spreads, while return on equity and the dividend payout ratio are statistically insignificant. Importantly, none of these lower frequency components account for the explanatory power of ambiguity and risk.

5.4 Firm-specific equity returns

Debt and equity prices are jointly determined in the Merton (1974) model. As the equity return should locally capture most of the variation in CDS spread returns, 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 5 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.

5.5 Equity liquidity

Das and Hanouna (2009) observe that CDS spreads respond to equity market liquidity and link this to capital structure arbitrage, suggesting that an improvement in equity liquidity facilitates greater arbitrage trading activity in CDS contracts. To measure equity illiquidity, we compute the Amihud (2002) price impact measure, which reflects the average price change per unit of trading

volume over a given period. The result in Column 6 of Table 9 shows that CDS spreads are indeed higher for greater equity illiquidity. However, this does not significantly affect the significance and magnitude of the coefficient for ambiguity. In unreported results, we draw similar conclusions when we measure equity illiquidity using effective bid-ask spreads of the stock price.

5.6 Industry heterogeneity

Several studies have deployed industry fixed effects to absorb time-invariant heterogeneity in credit spreads specific to individual industries (e.g., Campbell and Taksler, 2003; Bai and Wu, 2016). We use Fama and French's (1997) 12-industry classification and generate an indicator variable for each industry. The results in Column 7 of Table 9 confirm that absorbing time-invariant industry heterogeneity through fixed effects does not alter any of our previous conclusions about the economic significance and negative relation between CDS spreads and ambiguity.

5.7 Variation of ambiguity measurement

To construct our ambiguity measure, we assume that intrady returns are normally distributed, and therefore fully characterized by the first and the second moments of the return distribution. For robustness, we explore alternative parametric assumptions of the intraday return distribution, allowing for skewness, kurtosis, or both. First, we compute ambiguity assuming that intraday returns follow a Laplace distribution. To eliminate jump effects, we also compute both measures of ambiguity (normal and leptokurtic) by truncating 5-minute intraday returns larger than 1%. Second, we compute ambiguity nonparametrically by constructing the statistical histograms of the intraday return distributions. Third, we measure ambiguity assuming a normal distribution for the daily histograms, where the mean and variance are computed from daily open, close, high, and low prices (Garman and Klass, 1980).

We use the regression specification in Equation (10), and Table 10 reports the results. The regression coefficient of ambiguity is negative and significant for all specifications, with similar adjusted R^2 statistics. The economic significance varies moderately across different measurements of ambiguity. Recall that, for the measurement of ambiguity using normally distributed intraday returns, a 1-standard-deviation change in ambiguity is associated with approximately a 6% change in CDS spreads. Allowing for a fat-tailed distribution increases the economic significance of ambi-

guity on spreads to an 8% change in CDS spreads for a 1-standard-deviation change in ambiguity. The variations that truncate returns above at 1% produce similar results.

The economic significance weakens for the statistical distribution, as 1-standard-deviation change in ambiguity results in a 1.2% change in spreads. The reason might be that, in this measurement, many empty histogram bins are not extrapolated, as compared to the case when we use a parametric distribution. These variations in the measurement of ambiguity suggest that the significance of our results is not tied to a specific parametric assumption of the intraday return distribution.

In this study, ambiguity and risk are computed using high-frequency 5-minute returns. As an alternative, we compute both measures using daily return data. For ambiguity, we compute the first and second moments of the daily return distributions using daily open, close, high and low prices, following the Garman and Klass (1980) method. For risk, for each month, we compute the variance of the daily returns adjusted to nonsynchronous trading (Scholes and Williams, 1977). The results in Column 6 of Table 10 show that both ambiguity and risk are significant at the 1% level, and explain CDS spreads with a negative and positive sign, respectively. The crude ambiguity measurement that relies solely on open-close-high-low prices to parameterize the daily normal return distribution produces a relative impact of 3% in spreads for a 1-standard-deviation change.

Finally, we examine robustness to the measurement of ambiguity when we choose different bin sizes for the intraday return distributions and when we use intraday returns at different frequencies. In addition to our benchmark with 162 bins, we examine grids of 82 and 322 bins. Moreover, for each grid, we examine intraday returns sampled at 30-second, 5-minute, and 10-minute intervals. Alongside each variation in the measurement of ambiguity, we include a measure of risk computed using the same frequency returns. Online Appendix Table OA.8 reports the findings of these regression tests. In these tests, ambiguity (risk) is consistently negatively (positively) and significantly related to CDS spreads.

5.8 Alternative proxies for ambiguity

The main benefit of the EUUP framework is that it implies a risk-independent measure of ambiguity. Next, we examine how other suggested proxies for ambiguity proposed in the literature relate to the measure of ambiguity we employ. We consider the following proxies: the monthly variance

of the daily mean equity return, the monthly variance of the daily variance of the equity return (both computed using intraday 5-minute returns), and the dispersion of analyst GDP forecasts. In that spirit, we consider a firm-specific analyst earnings forecast dispersion as a firm-specific proxy of ambiguity. To further mitigate concerns that our measure of ambiguity may confound with realized skewness and kurtosis, we control for these higher moments of the probability distribution. In addition, we control for option-implied variance, skewness, and kurtosis, computed using the method in Bakshi et al. (2003) and described in Feunou et al. (2018).[21,22]

The findings reported in Table 11 indicate that skewness, the volatility of the mean, volatility of volatility, risk-neutral variance and skewness are independently significant predictors of CDS spreads. The regression coefficients for most of these variables also remain significant in a specification that includes all variables together. Notably, the regression coefficient for our measure of ambiguity is unaffected by the inclusion of these alternative proxies.

5.9 Aggregate ambiguity and risk

We further examine whether aggregate market measures of ambiguity and risk are relevant determinants of CDS spreads. We proxy the market risk and ambiguity using 5-minute returns on the S&P 500 Index. The estimation method is identical as for the firm-specific measures of ambiguity and risk. Then we augment the empirical model in Equation (10) to account for ambiguity and risk of the S&P 500. In addition, we introduce known macroeconomic factors: the constant maturity 2-year Treasury rate, the monthly return on the S&P 500 Index, the VIX, 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. Table 12 reports the findings. In the table the standard errors are clustered by firm and time to correct for both serial and cross-sectional correlation in the residuals.

Columns 1 to 4 of Table 12 report the univariate regression results. Firm-specific ambiguity appears to have a greater explanatory power than aggregate market ambiguity (R^2 of 20.2% vs.

[21] We thank Ricardo Lopez Aliouchkin for sharing the risk-neutral estimates of variance, skewness, and kurtosis with us.

[22] Table OA.3 in the Online Appendix provides the pairwise Pearson correlation coefficients between the different proxies for ambiguity that we consider. Our measure of ambiguity is weakly correlated with these proxies. Specifically, the correlation with ambiguity is 0.03 for skewness, 0.13 for kurtosis, -0.29 for the volatility of the mean, -0.04 for the volatility of volatility, -0.02 for analyst dispersion, -0.36 for risk-neutral variance, -0.19 for risk-neutral skewness, and 0.23 for risk-neutral kurtosis.

5.2%) and a similar economic impact. While the coefficient of -6.85 indicates a 24% decrease in the level of spreads for a 1-standard-deviation change in firm-specific ambiguity, the coefficient -2.59 indicates a 23% decrease. For the average firm, this corresponds to a decrease of 39 and 37 bps for a 1-standard-deviation increase in firm-specific and market ambiguities, respectively. Firm-specific risk has a larger explanatory power (R^2 of 17.3% vs. 3.7%) and a larger economic impact than market risk, as they are associated with a 30% and 22% increase in the CDS spreads for a 1-standard-deviation change, respectively.

Introducing all four variables in the regression in Column 5 produces results in which neither firm-specific nor market ambiguity loses its significance. These results are qualitatively unchanged in Column 6 when we introduce all firm-specific controls into the regression, as well as 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 negative, which may be due to a multicollinearity problem with market risk, which also switches sign. The empirical model fits the data well, with an R^2 of 62% in Column 6, which is slightly lower than 67%, obtained in the specification with time fixed effects in Column 8 of Table 4. The coefficient on firm-specific ambiguity in Column 6 equals -2.07, which corresponds to an 8% decrease in spreads for a 1-standard-deviation change in ambiguity, or, alternatively, to a 13-bps decrease for the average firm in the sample. This is an economically meaningful impact, and similar to previous alternative specifications that include all the controls (e.g., Column 8 in Table 4).

5.10 Slope regressions

Duffie and Lando (2001) 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, the flatter could be the slope of the term structure of credit spreads. We test this conjecture by regressing the slope, measured as the difference between the

10-year and 1-year CDS spreads, on ambiguity, risk, and all previously used control factors:[23]

$$\ln\left(Slope_{j,t}\right) = \alpha + \beta_A \cdot Ambiguity_{j,t} + \beta_R \cdot Risk_{j,t} + \delta^\top \cdot X_{j,t} + \zeta_j + \theta_t + \varepsilon_{j,t}. \tag{12}$$

Table 13 reports the results using double-clustered standard errors. Table OA.4 of the Online Appendix reports qualitatively similar results using percentage changes in the slope of the term structure of CDS spreads.

The results in Column 1 of Table 13 confirm the conjecture that a rise in ambiguity flattens the slope of the term structure. Quantitatively, the magnitude of the univariate regression coefficient indicates a 12% decrease in the slope for a 1-standard-deviation increase in ambiguity, corresponding to an 11-bps flattening of the slope, given a mean slope of 94 bps. The explanatory power of this univariate result is about 2%, which is weaker than for the level of CDS spreads. The economic impact of risk on the slope is a bit higher than for ambiguity, as a 1-standard-deviation increase in risk is associated with a 16-bps (17%) steepening of the slope in Column 2 for the univariate regression, although the fit of that model is weaker. Introducing ambiguity and risk together in the regression for Column 3 only slightly changes the magnitude of the regression coefficients, and both remain significant. We next introduce in Column 4 firm-specific controls and time fixed effects to control for unobserved common macroeconomic factors. Ambiguity and risk maintain their statistical significance. When we add firm fixed effects to absorb time-invariant heterogeneity 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 weaker economic impact: a 1-standard-deviation increase in ambiguity is associated with a 3% decrease in the difference between the 10-year and the 1-year CDS spreads.

6 Conclusion

We examine the impact of ambiguity and risk on the level and the changes of CDS spreads. While ambiguity reflects uncertainty about the *probabilities* of future outcomes, risk reflects uncertainty about the *realizations* of these outcomes. Motivated by a decision theory framework that incorporates independent preferences for ambiguity and risk, we estimate ambiguity separately from risk

[23] We use the natural logarithm of the slope in the specification to minimize the impact of some extreme outliers in the sample. Thus, we only use those firm-months with a positive slope, which corresponds to approximately 96% of the 50,057 available observations for the slope.

using high-frequency stock price information. We find that higher ambiguity is negatively associated with CDS spread levels, while higher risk is positively associated with CDS spread levels. The finding of a negative relation between ambiguity and CDS spreads suggests that the price setters in the CDS market are net short credit risk; that is, they are CDS buyers. We gain this intuition from a static general equilibrium model in which heterogeneous investors in the CDS market value these assets in zero net supply using independent preferences for ambiguity and risk.

The impact of both dimensions of uncertainty are economically significant, as a 1-standard-deviation increase in ambiguity (risk) leads to a 6% decrease (12% increase) in the CDS spread levels. For the average firm in the sample, this indicates a change of 10 (20) bps for a 1-standard-deviation change in ambiguity (risk). Our empirical models fit the data well compared with previous studies, reaching an explanatory power of up to 67% for CDS spread levels, and up to 33% for CDS spread changes.

Our analysis focuses on CDS contracts. The results should provide, however, insights that are more broadly applicable to the pricing of other assets in zero net supply and other types of insurance claims. We leave a detailed empirical analysis of such applications for future research.

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A.1 Proofs

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 $Y = N - V_L$ is the payoff of the CDS in the default state. Recall that, in our reduced-form representation, an increase in risk corresponds to an increase in the mean-preserving spread between firm values in the solvency and default states; i.e., $\Delta = V_H - V_L$. As the payoff of the CDS in the solvency state is zero, the impact of risk on CDS spreads is equivalent to the impact of an increase in Y on CDS spreads. The first-order condition (FOC) of the maximization problem of the buyer in Equation (3) can be written as:

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

The first-order condition of the maximization problem of the seller in Equation (4) can be written as:

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

The partial differentials of the buyer's FOC in Equation (A.1) 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 differentials of the seller's FOC in Equation (A.2) 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 (A.1) and (A.2) can then be written as:

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

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,

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

which, since $\Delta \propto Y$, implies that:

$$\frac{\partial p}{\partial \Delta} > 0.$$

■

Proof of Proposition 2. Using the notation of the proof of Proposition 1, the FOC of the maximization problem of the buyer in Equation (3) can be written as:

$$F^B\left(p,h,\mho^2\right) \;=\; \frac{\mathrm{Q}(DF)\mathrm{U}'\left(D\right)Y}{\mathrm{Q}(DF)\mathrm{U}'\left(D\right)+\left[1-\mathrm{Q}(DF)\right]\mathrm{U}'\left(C\right)}-p \;=\; 0. \tag{A.3}$$

The FOC of the maximization problem of the seller in Equation (4) can be written as:

$$F^S\left(p,h,\mho^2\right) \;=\; \frac{\left[1-\mathrm{Q}(SL)\right]\mathrm{U}'\left(B\right)Y}{\left[1-\mathrm{Q}(SL)\right]\mathrm{U}'\left(B\right)+\mathrm{Q}(SL)\mathrm{U}'\left(A\right)}-p \;=\; 0. \tag{A.4}$$

The partial differentials of the buyer's FOC in Equation (A.3) with respect to $\mho^2$ is:

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

The partial differentials of the seller's FOC in Equation (A.4) with respect to $\mho^2$ is:

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

The total differential of the system in Equations (A.3) and (A.4) can then be written as:

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

By Equation (A.3), $J<0$. 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,

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

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

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

when $l\frac{\mathrm{U}''(B)}{\mathrm{U}'(B)}\frac{\Upsilon''(DF)}{\Upsilon'(DF)}\mathrm{E}\left[\mathrm{P}\left(DF\right)\right]-k\frac{\mathrm{U}''(D)}{\mathrm{U}'(D)}\frac{\Upsilon''(SL)}{\Upsilon'(SL)}\mathrm{E}\left[\mathrm{P}\left(SL\right)\right]>0$ 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: Studies on the Determinants of Corporate Credit and CDS Spreads

In this table, we summarize the key literature on the determinants of credit and CDS spreads, 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 in addition to the equity volatility of the firm. In Tang and Yan (2010), equity volatility is replaced with cash flow volatility. The column *Firm IV/IV skew/VRP* is checked if any of these three variables is used in the regressions. Aggregate controls may 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, or, in some cases, time indicator variables. The categorical dummies may include, among others, indicator variables for sector and industry, maturity, the cheapest-to-deliver option, as well as restructuring clauses.

	Model		Determinants of Credit and CDS Spreads																	
Study	Levels	Changes	Equity Return	ST or LT Interest Rate	Yield Curve Slope	Leverage	Firm $\mathbb{P}$-Equity Volatility	Firm IV/IV skew/VRP	Ratings	Distance-to-Default	Firm Jump risk	VIX/Aggregate IV	Firm Liquidity	Accounting Inform.	Firm Size	Aggreg. Controls	Indicators	Dealer Capital	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)	✓			✓	✓	✓	✓	✓			✓		✓		✓				
Galil et al. (2014)	✓	✓	✓	✓	✓	✓	✓	✓			✓				✓				
Bai and Wu (2016)	✓	✓				✓	✓	✓		✓			✓	✓					
Siriwardane (2019)		✓	✓	✓	✓			✓		✓	✓	✓			✓	✓	✓		
The current study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	

Table 2: Summary Statistics

This table presents summary statistics for the firm-specific and macroeconomic variables. The sample period is January 2001 to October 2014. The sample includes 491 firms with a minimum of 24 months of continuous information on the 5-year senior unsecured CDS spread with the modified restructuring clause (*CDS5y*), the monthly standard deviation of outcome probabilities ($\sqrt{Ambiguity}$), the monthly standard deviation of daily returns computed using intraday five minute 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 $billion, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The table reports the aggregate market return, the aggregate market risk and ambiguity based on the S&P 500 Index (*SP500Ret*, $\sqrt{SP500Risk}$, 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 U.S. 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.

	Mean	*Std*	*Min*	*Med*	*Max*	*Obs*	*N*
CDS5y	1.62	3.06	0.02	0.79	95.67	53,356	491
$\sqrt{Ambiguity}$	20.11	8.59	2.30	19.25	98.14	53,356	491
$\sqrt{Risk}$	8.21	5.43	0.61	6.73	95.62	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
$\sqrt{SP500Ambiguity}$	38.64	13.04	8.40	39.54	65.94	53,356	491
$\sqrt{SP500Risk}$	4.94	3.24	1.63	4.27	25.92	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
r2	2.05	1.62	0.21	1.71	5.12	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: the 5-year senior unsecured CDS spread with the modified restructuring clause (*CDS5y*), the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*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 $billion, 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&P 500 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 the 2-year constant-maturity Treasury yields (*TSSlope*), and the difference between the BofA Merrill Lynch U.S. High Yield BBB (BB) and AAA (BBB) effective yields (*BBB_AAA* and *BB_BBB*). The sample includes 491 U.S. firms with 53,356 monthly CDS spread observations from January 2001 to 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	0.56	-0.33	1.00												
r2	-0.14	0.04	-0.07	1.00											
Leverage	0.24	-0.04	0.11	-0.03	1.00										
Rating	0.50	-0.32	0.24	-0.06	0.32	1.00									
Liquidity	-0.12	0.10	-0.05	0.41	-0.01	-0.13	1.00								
Size	-0.17	0.22	-0.11	-0.02	-0.16	-0.54	0.07	1.00							
SP500Ambiguity	-0.15	0.52	-0.32	0.12	-0.04	0.03	0.13	0.06	1.00						
SP500Risk	0.15	-0.31	0.53	-0.10	0.03	-0.00	-0.05	-0.03	-0.50	1.00					
SP500Return	-0.02	0.17	-0.21	-0.08	-0.01	0.02	-0.03	0.01	0.29	-0.47	1.00				
VIX	0.22	-0.46	0.50	-0.29	0.05	-0.00	-0.19	-0.05	-0.76	0.82	-0.35	1.00			
TSSlope	0.12	-0.13	0.09	-0.83	0.05	0.01	-0.43	-0.01	-0.26	0.15	0.03	0.35	1.00		
BBB_AAA	0.25	-0.36	0.35	-0.55	0.05	0.03	-0.32	-0.04	-0.60	0.47	-0.08	0.80	0.51	1.00	
BB_BBB	0.23	-0.43	0.44	-0.30	0.05	0.01	-0.19	-0.06	-0.71	0.68	-0.24	0.92	0.34	0.83	1.00

Table 4: Determinants of CDS Spread Levels

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*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 $billion, 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 sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Ambiguity	-11.6208***		-9.0698***		-4.7086***			-1.6714***
	(0.7888)		(0.6957)		(0.5138)			(0.2661)
Risk		20.5059***	14.8745***		9.5776***			5.3356***
		(2.9215)	(2.2145)		(1.1226)			(0.5450)
Leverage				1.1532***	1.1914***		1.7949***	1.7114***
				(0.2344)	(0.2112)		(0.2714)	(0.2666)
Rating				0.2447***	0.2097***		0.1906***	0.1730***
				(0.0078)	(0.0074)		(0.0088)	(0.0087)
Liquidity				-0.0391***	-0.0352***		0.0238***	0.0236***
				(0.0047)	(0.0043)		(0.0037)	(0.0036)
Size				0.0005	0.0006*		-0.0045***	-0.0042***
				(0.0004)	(0.0004)		(0.0009)	(0.0009)
Constant	-4.1929***	-4.9471***	-4.4589***	-6.8430***	-6.4502***	-4.6971***	-6.3990***	-6.3068***
	(0.0615)	(0.0532)	(0.0615)	(0.0971)	(0.0998)	(0.0644)	(0.0973)	(0.0960)
OBSERVATIONS	53,356	53,356	53,356	53,356	53,356	53,356	53,356	53,356
TIME FE	NO	NO	NO	NO	NO	YES	YES	YES
FIRM FE	NO	NO	NO	NO	NO	YES	YES	YES
CLUSTER FIRM	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.202	0.173	0.283	0.583	0.666	0.506	0.646	0.665

Table 5: Predictive Regressions of CDS Spread Levels

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly lagged variance of the outcome probabilities (*Ambiguity*), the monthly lagged variance of intraday five minute equity returns (*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 $billion, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
$Ambiguity_{t-1}$	-1.7284***			-0.9558***
	(0.2715)			(0.1564)
$Risk_{t-1}$	5.0396***			3.2706***
	(0.5227)			(0.3233)
$Ambiguity_{t-2}$		-1.7126***		-0.7724***
		(0.2734)		(0.1276)
$Risk_{t-2}$		4.6297***		1.5071***
		(0.5166)		(0.2452)
$Ambiguity_{t-3}$			-1.6414***	-0.8846***
			(0.2651)	(0.1415)
$Risk_{t-3}$			4.2943***	1.8864***
			(0.5129)	(0.2745)
Constant	-6.3151***	-6.3662***	-6.4718***	-6.4394***
	(0.0967)	(0.1000)	(0.0994)	(0.1004)
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	YES	YES	YES	YES
Adj. R^2	0.665	0.664	0.664	0.673

Table 6: Evidence on CDS Positions

In this table, we present statistics on the gross notional amounts of CDS outstanding by type of counterparty based on the semi-annual OTC derivatives statistics reported by the Bank for International Settlements (Tables D10.1 to D10.4). The sampling frequency is bi-annual from 2004H2 to 2016H2. The information is based on surveys from large dealers from 13 countries. Statistics are reported on a worldwide consolidated basis and include positions of foreign affiliates, but they exclude intragroup positions. In Panel A, we report the total gross notional amounts of CDS outstanding by type of counterparty (in $billion), and the market share (in %) of Dealers, Central Counterparties, Banks, Insurance and Financial Guaranty Firms, Special Purpose Vehicles, Hedge Funds, Non-Financial Corporations, and Residual Financial Institutions. In the remaining panels, we focus on the statistics for reporting dealers. In Panel B, we report the difference between total gross notional amounts of CDS bought and sold for all CDS contracts (ALL), single-name CDS contracts (SN), multi-name CDS contracts (MN), investment-grade CDS contracts (IG), speculative-grade CDS contracts (SG), CDS contracts on financial firms (FIN), CDS contracts on non-financial firms ($NON-FIN$), CDS contracts on sovereign reference entities (SOV). In Panel C, we report the difference between the positive and the negative gross market values of CDS contracts for all CDS contracts as well as single-name and multi-name CDS contracts. Gross market values do not account for netting between positive and negative market values with the same counterparty. In Panel D, we report the difference between the positive and the negative net market values for all CDS contracts, which do take into account netting between positive and negative market values in CDS contracts with the same counterparty.

	05-H1	06-H1	07-H1	08-H1	09-H1	10-H1	11-H1	12-H1	13-H1	14-H1	15-H1	16-H1
Panel A: Market Shares												
Total Notional ($bill.)	10,211	20,352	42,581	57,403	36,098	30,261	32,409	26,930	24,349	19,462	14,594	11,767
Dealers (%)	47.52	52.12	54.76	57.77	53.18	52.13	53.53	58.47	56.38	49.02	44.56	43.32
CP (%)	–	–	–	–	–	9.80	17.09	19.34	22.79	26.70	30.87	37.28
Banks (%)	15.84	24.69	22.53	23.84	30.78	26.36	18.86	10.84	9.10	10.49	8.42	5.40
IFG (%)	1.11	1.46	0.78	0.69	1.07	0.90	1.11	1.03	0.95	1.01	1.23	1.35
SPV (%)	1.05	0.38	0.25	0.19	0.30	1.72	1.63	1.70	1.53	1.39	1.27	1.30
HF (%)	2.52	0.71	0.57	0.67	0.35	2.18	2.97	3.74	4.42	5.71	5.40	4.66
NFC (%)	4.63	3.57	2.07	1.65	4.21	2.79	0.73	0.69	0.79	1.04	1.41	1.30
R (%)	4.69	17.07	19.06	15.20	10.11	4.12	4.08	4.18	4.05	4.63	6.85	5.38
Panel B: Single-Names Gross Bought - Gross Sold ($billion)												
Dealers	43	113	463	132	150	4	-130	-53	11	-73	4	12
CP	–	–	–	–	–	17	12	2	1	85	11	3
Banks	-17	52	236	325	178	142	180	173	128	116	95	104
IFG	23	52	65	50	47	33	67	35	23	48	19	18
SPV	-9	-42	-117	-526	-455	-237	-106	-81	-60	-102	-61	-22
HF	-24	-12	0	34	20	-101	-200	-172	-162	-131	-105	-101
NFC	1	49	8	229	86	31	28	47	7	33	34	16
R	26	-65	-268	50	-8	4	33	59	34	74	56	36
Panel C: Gross Notional Amounts of CDS Bought - Sold for Dealers ($billion)												
ALL	8	123	-60	482	102	4	-156	-74	-35	-51	18	60
SN	43	113	463	132	150	4	-130	-53	11	-73	4	12
MN	-35	9	-523	349	-48	-1	-25	-21	-46	23	14	48
IG	-69	132	316	81	37	-2	72	32	-2	0	104	94
SG	-1	3	-5	19	20	12	197	8	11	-12	-22	-13
FIN	-13	-34	32	1	-104	-172	-86	-102	-77	-89	7	16
NON-FIN	-54	-30	-17	-118	29	47	86	-5	36	1	49	-24
SOV	-9	14	179	-10	-11	-26	-11	-3	-7	9	7	0
Panel D: Gross Positive - Gross Negative Market Values for Dealers ($billion)												
ALL	3	-1	7	37	20	5	-1	-6	0	2	1	1
SN	2	1	6	42	10	5	3	-2	0	1	0	-2
MN	1	-1	1	-5	10	0	-4	-3	0	1	1	2
Panel E: Net Positive - Net Negative Market Values for Dealers ($billion)												
ALL	–	–	–	–	–	–	-6	-18	2	5	3	2

Table 7: Crisis Effects

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*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 $billion, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The regression tests include categorical variables that are equal to one during the NBER recession months from December 2007 to June 2009 (*macrocrisis*), in 2007-2008 (*ind0708*), in 2008-2009 (*ind0809*), in 2009-2010 (*ind0910*), in 2010-2011 (*ind1011*), in 2011-2012 (*ind1112*), in 2012-2013 (*ind1213*), and are zero otherwise. The constant and all firm controls are omitted. The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are double-clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) *CDS5y*	(2) *CDS5y*	(3) *CDS5y*	(4) *CDS5y*	(5) *CDS5y*	(6) *CDS5y*	(7) *CDS5y*	(8) *CDS5y*
Ambiguity	-1.3476***	-1.3451***	-1.4739***	-1.6010***	-1.4240***	-1.6260***	-1.6455***	-1.6046***
	(0.2753)	(0.2743)	(0.2742)	(0.2795)	(0.2844)	(0.3084)	(0.3204)	(0.3237)
Ambiguity_x_macrocrisis		-2.5576**						
		(1.2632)						
Ambiguity_x_ind0708			-1.2055					
			(0.7306)					
Ambiguity_x_ind0809				-2.2857**				
				(1.0773)				
Ambiguity_x_ind0910					1.4863**			
					(0.6023)			
Ambiguity_x_ind1011						2.3742***		
						(0.5734)		
Ambiguity_x_ind1112							1.3390***	
							(0.4110)	
Ambiguity_x_ind1213								0.9747**
								(0.3934)
OBSERVATIONS	53,353	53,353	53,356	53,356	53,353	53,353	53,353	53,353
FIRM CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY*TIME FE	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER FIRM	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.879	0.879	0.867	0.867	0.880	0.880	0.880	0.880

Table 8: Industry Heterogeneity

This table presents alternative specifications of the main regression that projects the natural logarithm of monthly 5-year senior unsecured CDS spread levels on the monthly *Ambiguity* and the monthly *Risk*, and all firm-specific control variables. The specifications in Panel A, which contain firm and time fixed effects, add an interaction effect between ambiguity and an indicator variable that takes the value one if a firm belongs to one of 12 Fama and French (1997) industries, and zero otherwise: Non-durable Goods (*NDG*), Durable Goods (*DG*), Manufacturing (*MNF*), Energy (*EGY*), Chemicals (*CHM*), Business Equipment (*BUS*), Telecommunications (*TCM*), Utilities (*UTL*), Shops (*SHP*), Healthcare (*HCA*), Financials (*FIN*), Other (*OTH*). The subsample results in Panel B restrict the regression to the NBER recession dates (December 2007 to June 2009). In the subsample results in Panel C, we restrict the regression to 2009 and 2010. The specifications in Panels B and C contain firm fixed effects and aggregate controls instead of time fixed effects. The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are double-clustered by firm and by time. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Panel A: Industry Effects												
Ambiguity	-1.85***	-1.65***	-1.68***	-1.67***	-1.81***	-1.76***	-1.73***	-1.49***	-1.73***	-1.75***	-1.19***	-1.64***
	(0.32)	(0.29)	(0.30)	(0.29)	(0.31)	(0.30)	(0.28)	(0.32)	(0.31)	(0.30)	(0.27)	(0.30)
Ambiguity_x_NDG	1.51***											
	(0.48)											
Ambiguity_x_DG		-1.35										
		(1.28)										
Ambiguity_x_MNF			0.14									
			(0.57)									
Ambiguity_x_EGY				-0.11								
				(0.71)								
Ambiguity_x_CHM					1.65***							
					(0.56)							
Ambiguity_x_BUS						2.36***						
						(0.90)						
Ambiguity_x_TCM							0.69					
							(1.14)					
Ambiguity_x_UTL								-1.01				
								(0.67)				
Ambiguity_x_SHP									0.62			
									(0.53)			
Ambiguity_x_HCA										1.63***		
										(0.59)		
Ambiguity_x_FIN											-2.56***	
											(0.64)	
Ambiguity_x_OTH												-0.50
												(0.84)
Panel B: Sub-sample Results by Industry for Dec2007-Jun2009												
Industry	NDG	DG	MNF	EGY	CHM	BUS	TCM	UTL	SHP	HCA	FIN	OTH
Ambiguity	-1.53	-2.32	-0.84	4.62	-2.30	3.00	-8.74***	-2.87*	-1.81	-1.72**	-8.44**	-9.77***
	(1.00)	(4.65)	(2.15)	(3.17)	(1.86)	(2.82)	(2.68)	(1.55)	(2.89)	(0.82)	(3.58)	(2.75)
Panel C: Sub-sample Results by Industry for Jan2009-Dec2010												
Ambiguity	1.39	0.94	2.20***	-4.28*	2.75**	0.52	0.93	1.35*	-0.53	0.89	2.12**	1.21
	(0.94)	(1.72)	(0.74)	(2.12)	(1.28)	(1.13)	(1.21)	(0.68)	(1.53)	(0.90)	(1.00)	(0.99)

Table 9: Robustness Tests - Other Controls

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*Risk*), and all firm-specific controls. In column (1), we add the default probability implied by the naïve Merton distance-to-default measure of Bharath and Shumway (2008) (π_{MERTON}) to the regression. In column (2), we include the number of jumps computed following the methodology of Lee and Mykland (2008). In column (3), we add 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*). In column (4), we add the accounting variables: market-to-book ratio (*MB*), return on assets (*ROA*), return on equity (*ROE*), the dividend payout ratio (*Dividend_Ratio*). In column (5), we include the company's monthly stock return (*Ret*). In column (6), we add the Amihud (2002) equity illiquidity measure. In column (7), we include industry fixed effects. The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Ambiguity	-1.70***	-1.81***	-1.55***	-1.37***	-1.67***	-1.70***	-1.69***
	(0.30)	(0.29)	(0.30)	(0.28)	(0.29)	(0.29)	(0.29)
Risk	3.91***	5.06***	4.60***	4.87***	5.33***	4.75***	5.32***
	(0.63)	(0.75)	(0.68)	(0.80)	(0.74)	(0.94)	(0.75)
π_{MERTON}	0.60***						
	(0.06)						
LM_jumps		0.01***					
		(0.00)					
VRP			0.06***				
			(0.01)				
ZZZ_HM			-79.06***				
			(7.34)				
ZZZ_HV			76.75***				
			(16.67)				
ZZZ_HS			-0.01				
			(0.01)				
ZZZ_HK			0.00***				
			(0.00)				
JI			0.00***				
			(0.00)				
JV			0.07**				
			(0.03)				
JP			-0.23**				
			(0.10)				
JN			0.24**				
			(0.10)				
MB				-0.22***			
				(0.03)			
ROE				0.00			
				(0.00)			
ROA				-0.99***			
				(0.25)			
Dividend_Ratio				0.44			
				(0.37)			
Ret					0.07		
					(0.05)		
Amihud						29.47*	
						(15.46)	
OBSERVATIONS	53,346	53,356	46,821	41,982	53,356	53,356	53,356
FIRM CONTROLS	YES	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	NO
INDUSTRY FE	NO	NO	NO	NO	NO	NO	YES
CLUSTER FIRM	YES	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.680	0.669	0.690	0.677	0.658	0.666	0.665

Table 10: Robustness - Variations in the Measurement of Ambiguity

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on different metrics of the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*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 $billion, 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. We compute ambiguity using the assumption that intraday returns follow a normal distribution (*Ambg_Normal*), a leptokurtic distribution (*Ambg_Laplace*), a normal distribution that truncates extreme stock returns of more than 1% in five-minute intervals (*Ambg_Normal_NoJumps*), a leptokurtic distribution that truncates extreme stock returns of more than 1% in five minute intervals (*Ambg_Laplace_NoJumps*), a statistical distribution (*Ambg_Statistical*), and a normal distribution that uses daily open and closing prices to compute the mean and standard deviation using the Garman and Klass (1980) method (*Ambg_daily*). In column (6), we measure risk using daily equity return data. The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Ambg_Normal	-1.6714***					
	(0.2931)					
Ambg_Laplace		-1.3571***				
		(0.2131)				
Ambg_Normal_NoJumps			-1.6356***			
			(0.2882)			
Ambg_Laplace_NoJumps				-1.3425***		
				(0.2124)		
Ambg_Statistical					-2.3760**	
					(1.0102)	
Ambg_daily						-2.0794***
						(0.7053)
Risk	5.3356***	5.3275***	5.3105***	5.3259***	5.2053***	1.9238***
	(0.7455)	(0.7300)	(0.7471)	(0.7317)	(0.7710)	(0.4425)
Leverage	1.7114***	1.7174***	1.7117***	1.7180***	1.6889***	1.7482***
	(0.2705)	(0.2701)	(0.2704)	(0.2701)	(0.2717)	(0.2715)
Rating	0.1730***	0.1705***	0.1732***	0.1707***	0.1783***	0.1824***
	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0093)	(0.0093)
Liquidity	0.0236***	0.0234***	0.0236***	0.0234***	0.0239***	0.0238***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Size	-0.0042***	-0.0041***	-0.0042***	-0.0041***	-0.0044***	-0.0044***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Constant	-6.3068***	-6.2773***	-6.3076***	-6.2779***	-6.3254***	-6.3506***
	(0.0960)	(0.0957)	(0.0960)	(0.0957)	(0.0983)	(0.0965)
OBSERVATIONS	53,356	53,356	53,356	53,356	53,356	53,356
TIME FE	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES
CLUSTER FIRM	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	NO	YES	YES
Adj. R^2	0.665	0.667	0.665	0.666	0.661	0.656

Table 11: Robustness Tests - Other Proxies for Ambiguity

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*Risk*), and all firm-specific controls as described in the main regressions. We control for other proxies of ambiguity used in the literature and other measures that may be confounded with ambiguity: realized skewness computed using intraday five-minute returns (*Skewness*), realized kurtosis computed using intraday five-minute returns (*Kurtosis*), the monthly variance of the daily mean equity returns computed using intraday five-minute returns (*Vol_of_Mean*), the monthly variance of the daily equity return variances computed using intraday five-minute returns (*Vol_of_Vol*), analyst earnings forecast dispersion (*Analyst_Disp*), and risk-neutral variance (ℚ-*IV*), risk-neutral skewness (ℚ-*Skewness*), and risk-neutral kurtosis (ℚ-*Kurtosis*), as computed in Bakshi et al. (2003). All variables are defined at the monthly frequency, except *Analyst_Disp*, which is measured at the quarterly frequency. The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are double clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Ambiguity	-1.67***	-1.68***	-1.68***	-1.66***	-1.66***	-1.78***	-1.84***	-1.87***	-1.67***	-1.88***
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.31)	(0.32)	(0.33)	(0.29)	(0.32)
Risk	5.35***	5.30***	4.24***	6.70***	5.32***	2.07**	6.06***	5.94***	5.56***	2.74***
	(0.75)	(0.74)	(0.80)	(0.93)	(0.74)	(0.82)	(0.97)	(0.94)	(0.94)	(0.84)
Leverage	1.71***	1.71***	1.71***	1.69***	1.71***	1.39***	1.43***	1.35***	1.69***	1.33***
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.32)	(0.32)	(0.34)	(0.27)	(0.33)
Rating	0.17***	0.17***	0.17***	0.17***	0.17***	0.16***	0.16***	0.16***	0.17***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Liquidity	0.02***	0.02***	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***	0.02***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Size	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Skewness	0.03***								0.03***	0.02*
	(0.01)								(0.01)	(0.01)
Kurtosis		0.43							0.35	0.12
		(0.28)							(0.28)	(0.31)
Vol_of_Mean			0.21**						0.21**	0.14
			(0.08)						(0.08)	(0.11)
Vol_of_Vol				-14.28***					-14.11***	-7.54***
				(4.69)					(4.66)	(2.40)
Analyst_Disp					0.00				-0.00	0.00***
					(0.00)				(0.00)	(0.00)
ℚ-*IV*						3.66***				3.15***
						(0.84)				(0.80)
ℚ-*Skewness*							-0.02**			-0.01
							(0.01)			(0.01)
ℚ-*Kurtosis*								0.00		0.00
								(0.00)		(0.00)
OBSERVATIONS	53,356	53,356	53,356	53,352	53,323	33,668	33,668	31,741	53,319	31,559
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
CLUSTER FIRM	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.665	0.665	0.665	0.667	0.666	0.671	0.666	0.667	0.668	0.675

Table 12: Determinants of CDS Spread Levels - Aggregate Controls

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*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&P 500 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 U.S. High Yield BBB (BB) and AAA (BBB) effective yields (*BBB_AAA* and *BB_BBB*). The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Ambiguity	-6.8443***				-3.3589***	-2.0657***
	(0.4295)				(0.4882)	(0.2661)
Risk		12.3505***			8.9229***	5.1238***
		(0.7103)			(0.6291)	(0.5420)
SP500Ambiguity			-2.5887***		-1.2747***	-0.2363***
			(0.0783)		(0.1168)	(0.0546)
SP500Risk				55.5299***	-1.8223	-9.2021***
				(1.6368)	(1.9947)	(1.9007)
Leverage						2.1198***
						(0.2699)
Rating						0.1592***
						(0.0083)
Liquidity						-0.0003
						(0.0025)
Size						-0.0039***
						(0.0008)
r2						-0.1376***
						(0.0096)
SP500Return						-0.4829***
						(0.0429)
TSSlope						-0.0312**
						(0.0131)
VIX						-0.2377**
						(0.1015)
BBB_AAA						0.2788***
						(0.0137)
BB_BBB						0.0268***
						(0.0099)
Constant	-4.4212***	-4.8681***	-4.3180***	-4.8565***	-4.4588***	-6.4347***
	(0.0205)	(0.0069)	(0.0130)	(0.0032)	(0.0157)	(0.1028)
OBSERVATIONS	53,356	53,356	53,356	53,356	53,356	53,356
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	YES	YES	YES	YES	YES	YES
Adj. R^2	0.202	0.173	0.052	0.037	0.238	0.620

Table 13: Determinants of CDS Slope Levels

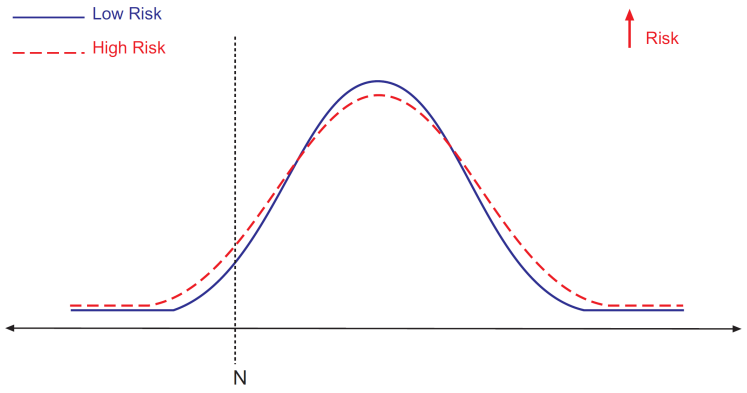
This table presents the results from the regression of the natural logarithm of the monthly slope, i.e., the difference between the 10-year and the 1-year senior unsecured CDS spread levels (*slope*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*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 $billion, measured as the number of shares outstanding times the stock price at the beginning of the month (*Size*). The sample includes 491 U.S. CDS firms for the period January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	*Slope*	*Slope*	*Slope*	*Slope*	*Slope*
Ambiguity	-3.0632***		-2.4874***	-1.9472***	-0.7331***
	(0.6645)		(0.6427)	(0.2557)	(0.2180)
Risk		7.3453***	4.5020***	1.6382**	-0.6213
		(2.3455)	(1.7475)	(0.7628)	(0.8148)
Leverage				0.6237***	0.8156***
				(0.1325)	(0.2350)
Rating				0.1616***	0.1141***
				(0.0057)	(0.0097)
Liquidity				0.0137***	0.0179***
				(0.0024)	(0.0029)
Size				0.0001	-0.0038***
				(0.0003)	(0.0005)
Constant	-4.9455***	-5.1567***	-5.0096***	-6.8264***	-6.3728***
	(0.0680)	(0.0512)	(0.0709)	(0.0704)	(0.0936)
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	0.019	0.013	0.023	0.674	0.537

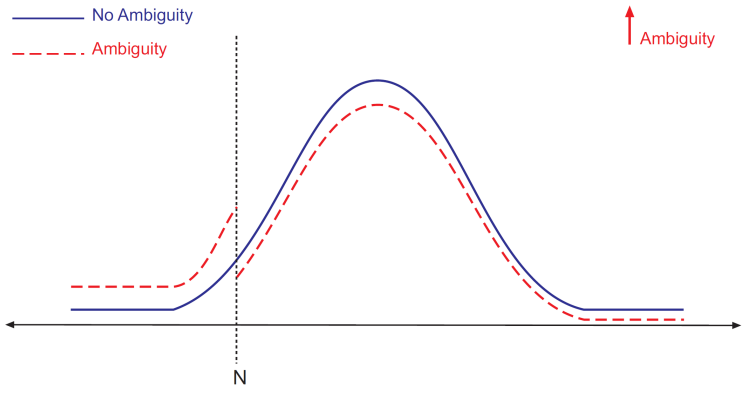
Figure 1: Ambiguity, Risk, and Perceived Outcome Probabilities

In Figure 1, we illustrate how an increase in risk and ambiguity may impact the perceived probabilities of the outcome distribution. In all graphs, the left tail of the outcome distribution represents the default state, say, when a firm's assets are insufficient to pay back the face value of debt N. In Panel a, the shift from the solid to the dashed line represents an increase in the risk. In Panels b and c, a shift from the solid to the dashed line compares the case with ambiguity to the case without ambiguity. Panel b (c) shows the perspective of an investor who is net long (short) credit risk. Investors that are net long (short) credit risk consider the default (no-default) state unfavorable. Ambiguity-averse agents overweight the probability of the unfavorable state.

(a)



(b)



(c)

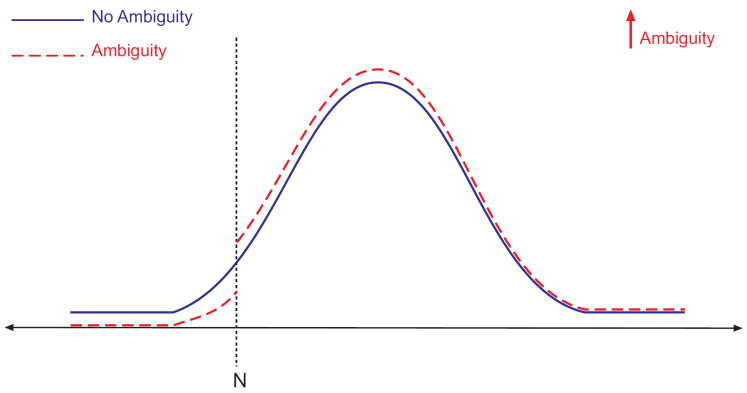
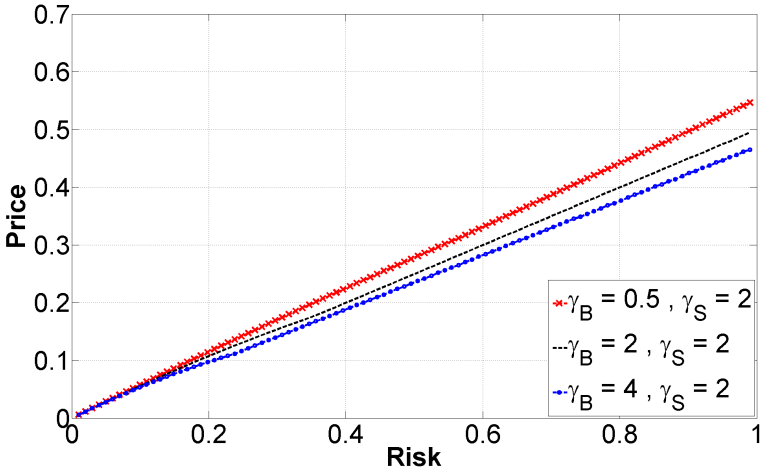


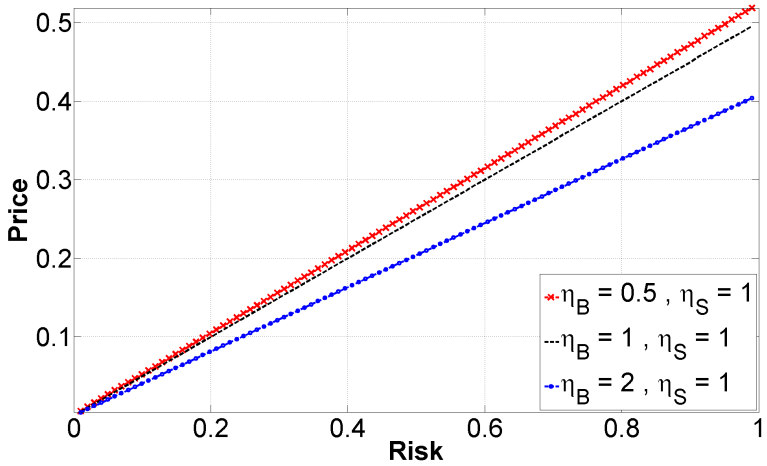
Figure 2: Ambiguity, Risk, and Credit Spreads

These graphs illustrate the relation between risk (Panels a and b) and credit spreads, as well as ambiguity (Panels c and d) and credit spreads using the model developed in Section 2, when investors exhibit constant relative risk aversion (CRRA) and constant relative ambiguity aversion (CRAA). In Panels a and c, we examine heterogeneity in the risk aversion intensity ($(\gamma_B, \gamma_S) = (0.5, 2), (2, 2), (4, 2)$), keeping ambiguity aversion for the buyer and seller equal to $\eta_B = \eta_S = 2$. In Panels b and d, we examine heterogeneity in the ambiguity aversion intensity ($(\eta_B, \eta_S) = (0.5, 1), (1, 1), (2, 1)$), keeping risk aversion for the buyer and seller equal to $\gamma_B = \gamma_S = 2$. In all graphs, we assume equal wealth $w = 2$, and face value $N = 1$. When we examine the impact of ambiguity on spreads, we keep risk constant at $\Delta = V_H - V_L = 1$, with $N - V_L = 0.5$. When we examine the impact of risk on spreads, we keep ambiguity constant at $\mho^2 = 0.01$.

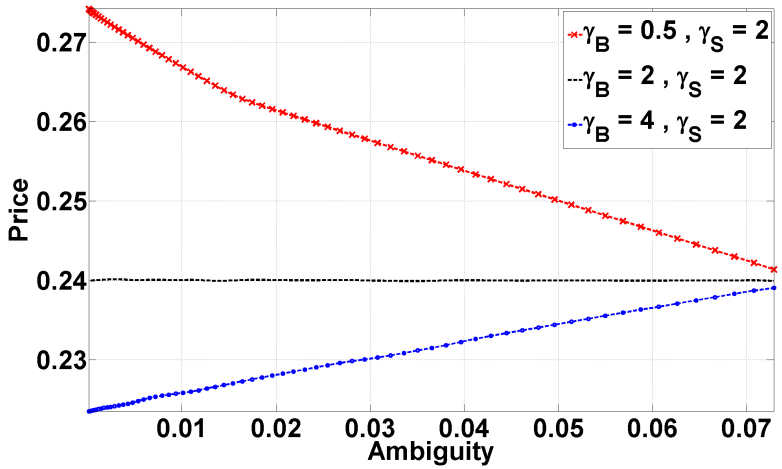
(a)



(b)



(c)



(d)

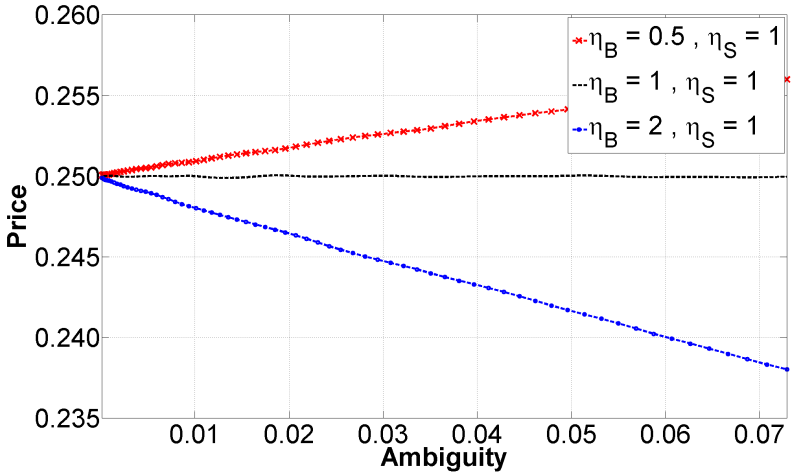


Figure 3: Ambiguity Measurement

In this figure, we provide an illustration of the computation of the ambiguity measure, which we derive for each firm-month based on intraday stock-returns sampled at a five-minute frequency from 9:30 to 16:00. Thus, we obtain up to 22 daily histograms of up to 78 intraday returns in each month. We discretize the daily return distributions into n bins of equal size $B_i = (r_{t,i}, r_{t,i-1}]$ across histograms. The height of the histogram for a particular bin is computed as the fraction of daily intraday returns observed in that bucket, and thus represents the probability of that particular bin outcome. We compute the expected probability of being in a particular bin across the daily return distributions, $\mathrm{E}[\mathrm{P}(B_i)]$, as well as the variance of these probabilities, $\mathrm{Var}[\mathrm{P}(B_i)]$. Ambiguity is then computed as $\mho^2[X] \equiv 1/\sqrt{w(1-w)}\sum_{i=1}^{n}\mathrm{E}[\mathrm{P}(B_i)]\,\mathrm{Var}[\mathrm{P}(B_i)]$, where we scale the weighted-average volatilities of probabilities to the bins' size $w = r_{j,i} - r_{j,i-1}$.

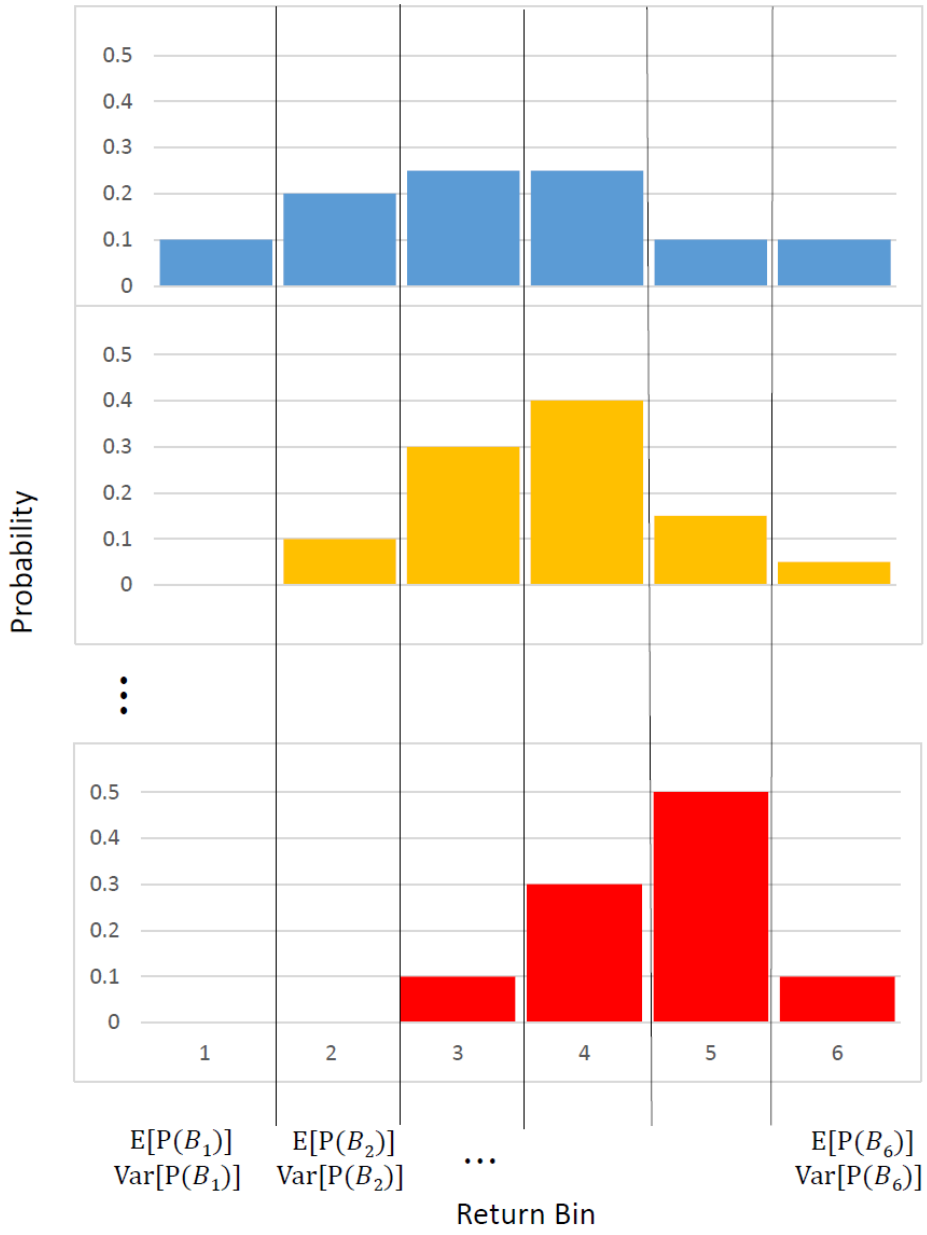
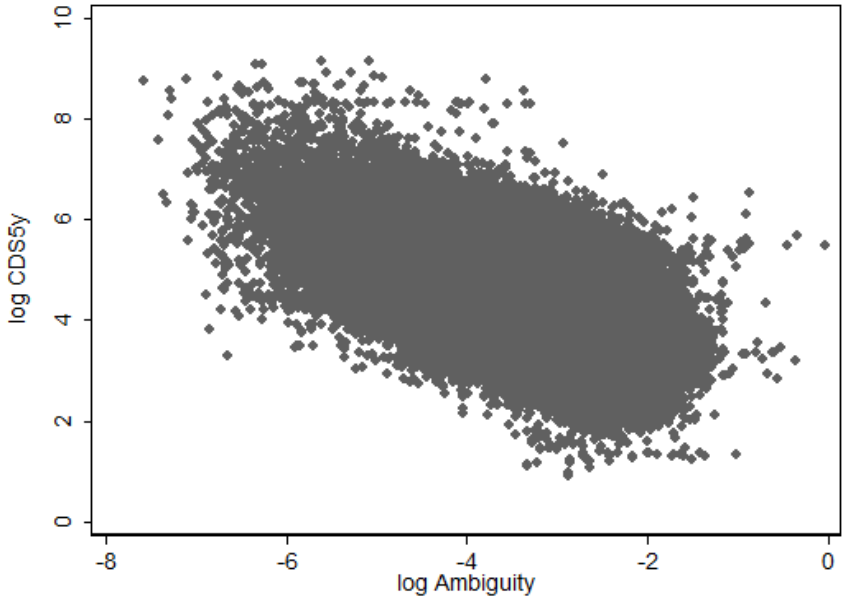


Figure 4: Scatter Plots for Risk and Ambiguity

The left graph is a scatterplot 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 is a scatterplot 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*).

(a)



(b)

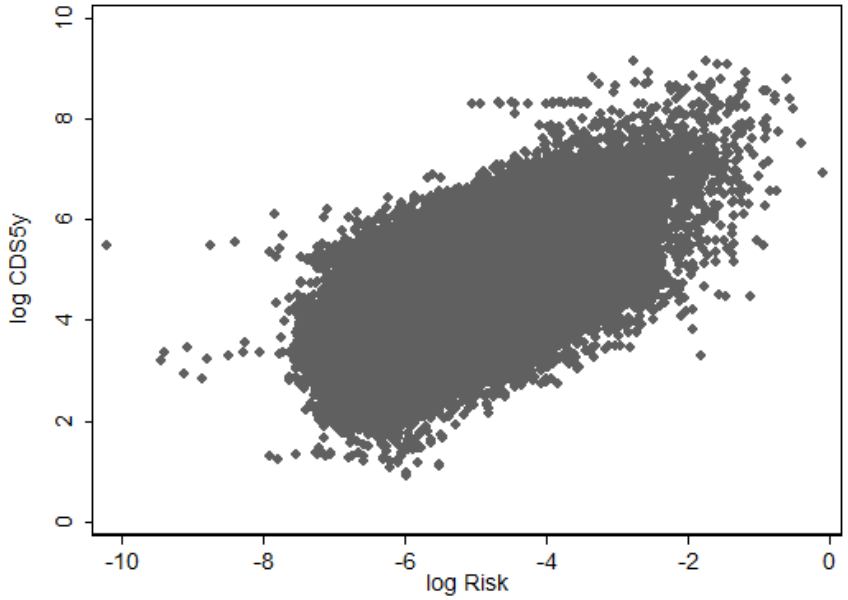


Figure 5: CDS Exposures of Dealers by Industry (DTCC)

These graphs depict, by industry, the dealers' gross notional order imbalance of CDS outstanding (in $billion), defined as the difference between the gross notional amounts of CDS outstanding bought and sold by dealers, based on all CDS contracts that are registered in the Trade Information Warehouse of the Depository Trust and Clearing Corporation (DTCC). DTCC reports the notional values as US dollar equivalents using the prevailing foreign exchange rates.

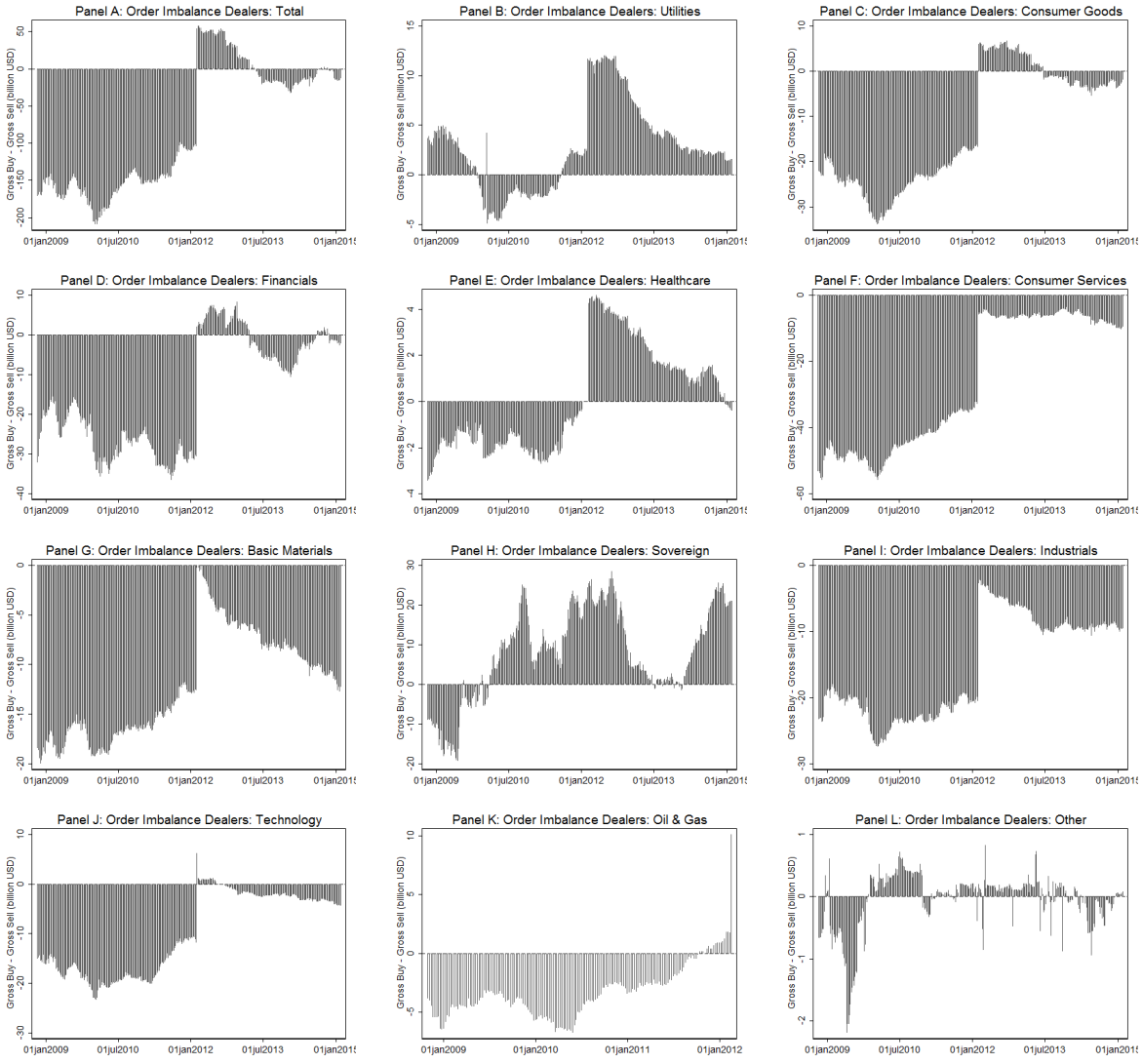
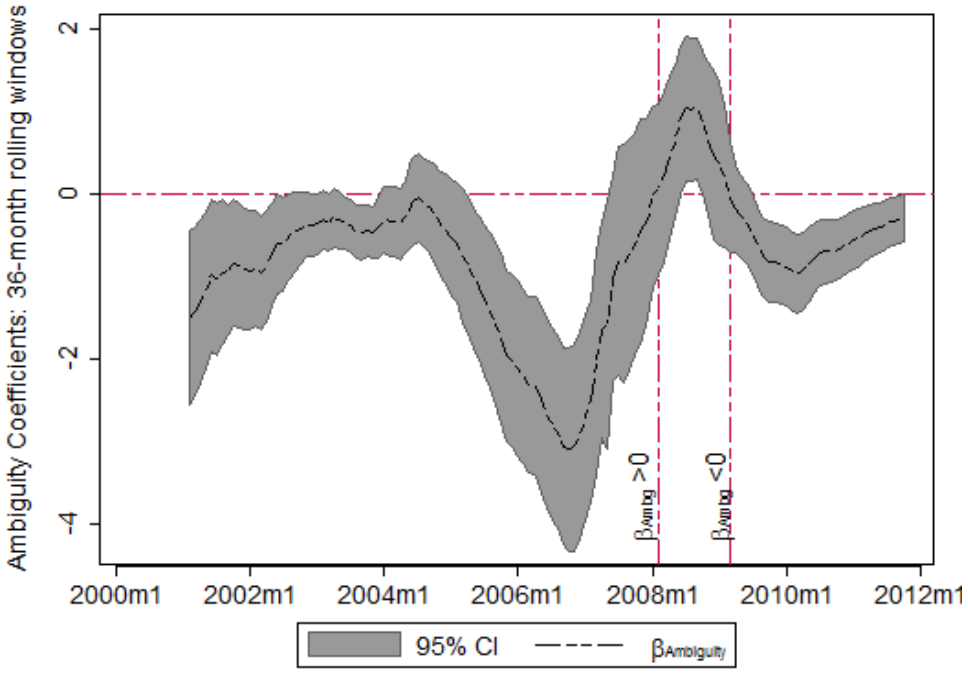


Figure 6: Time-varying Relation between Ambiguity and CDS Spreads

In this figure, we plot the sensitivity of the natural logarithm of monthly 5-year senior unsecured CDS spread levels to the monthly variance of the outcome probabilities (*Ambiguity*), computed based on rolling 36-month regression windows. Grey-shaded areas represent 95% confidence intervals. The full regression specification contains in addition the monthly variance of daily equity returns (risk), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity, the S&P's long-term issuer credit rating defined on a numerical scale from 1 for AAA to 21 for C, CDS liquidity defined as the number of dealer quotes used in the computation of the mid-market spread, and firm size in $billion, measured as the number of shares outstanding times the stock price at the beginning of the month. Aggregate controls include aggregate market ambiguity, aggregate market risk, the constant maturity 2-year Treasury rate, the monthly return on the S&P 500 Index, the CBOE S&P 500 implied volatility index, the 2-year constant-maturity Treasury yield, the difference between the 10-year and 2-year constant-maturity Treasury yields, and the difference between the BofA Merrill Lynch U.S. High Yield BBB (BB) and AAA (BBB) effective yields. The sample includes 491 U.S. firms from January 2001 to October 2014. Standard errors are clustered by firm and by time.



Ambiguity, Volatility, and Credit Risk

Online Appendix: Not for Publication

Abstract

We explore the implications of ambiguity for the pricing of credit default swaps (CDSs). A model of heterogeneous investors with independent preferences for ambiguity and risk shows that, since CDS contracts are assets in zero net supply, the net credit risk exposure of the marginal investor determines the sign of the impact of ambiguity on CDS spreads. We find that ambiguity has an economically significant negative impact on CDS spreads, on average, suggesting that the marginal investor is a net buyer of credit protection. A one standard deviation increase in ambiguity is estimated to decrease CDS spreads by approximately 6%.

Keywords: CDS, Derivatives, Heterogeneous Agents, Insurance, Knightian uncertainty, Risk aversion

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

Online Appendix

OA.1 Simple Asset Pricing Framework

To build intuition about how ambiguity and risk affect CDS spreads, in this section, we develop a simple asset pricing framework. This framework extends the derivations in Section 3.1.1 of Siriwardane (2019).

In the spirit of Duffie and Singleton (1999), in a reduced-form credit risk model, securities are subject to default risk, where this risk is driven by a hazard rate process $\Lambda_t^{\mathbb{P}}$, defined under the objective physical measure $\mathbb{P}$. This process is firm-specific. However, for simplicity, we omit firm-specific subscripts. Under the simplifying assumption that the term structure of CDS spreads is flat, the CDS spread of a given firm can be approximated by the product of the hazard rate process under the risk-neutral measure $\mathbb{Q}$ and the loss given default. That is,

$$CDS_t \quad = \quad \Lambda_t^{\mathbb{Q}} \times L, \tag{OA.1}$$

where, without loss of generality, we assume a constant loss/recovery rate, $L = 1 - R$, as is standard in the CDS pricing literature (e.g., Pan and Singleton, 2008).

In the absence of ambiguity, a firm's default risk premium, i.e., the compensation for each unit of default risk, is defined as $\Pi_t^R = \Lambda_t^{\mathbb{Q}}/\Lambda_t^{\mathbb{P}}$, suggesting that we may rewrite the CDS spread as:

$$CDS_t \quad = \quad \left(\Lambda_t^{\mathbb{Q}}/\Lambda_t^{\mathbb{P}}\right) \times \Lambda_t^{\mathbb{P}} \times L. \tag{OA.2}$$

In the presence of ambiguity, the risk adjustment is done with respect to the perceived hazard rate Λ_t^{Q}, defined over a perceived subjective probability measure Q, subject to ambiguity and aversion to ambiguity, as formally defined in Equation (2).[24] The risk premium is then defined as $\Pi_t^R = \Lambda_t^{\mathbb{Q}}/\Lambda_t^{\mathrm{Q}}$. In addition to compensation for risk, investors may require compensation for bearing ambiguity. The premium for each unit of ambiguity can be defined as $\Pi_t^A = \Lambda_t^{\mathrm{Q}}/\Lambda_t^{\mathbb{P}}$. This allows us to extend the expression of the CDS spread as follows:

$$CDS_t \quad = \quad \left(\Lambda_t^{\mathbb{Q}}/\Lambda_t^{\mathrm{Q}}\right) \times \left(\Lambda_t^{\mathrm{Q}}/\Lambda_t^{\mathbb{P}}\right) \times \Lambda_t^{\mathbb{P}} \times L. \tag{OA.3}$$

Let lowercase letters denote the natural logarithm of the variable (e.g., $cds_t = \ln(CDS_t)$,

[24] Here, $\mathbb{P}$ denotes the expected probability distribution of returns, which represents the linear aggregation of the set of first-order priors $\mathcal{P}$ using the second order prior ξ. When there is no ambiguity, or the investor is ambiguity neutral, Q and $\mathbb{P}$ are identical, and $\mathbb{P}$ corresponds to the uniquely defined objective probability distribution.

$\lambda_t = \ln(\Lambda_t)$, $\pi_t = \ln(\Pi_t)$). The previous identity then implies that

$$cds_t \quad = \quad \ell + \lambda_t^{\mathbb{P}} + \pi_t^R + \pi_t^A. \tag{OA.4}$$

Siriwardane (2019) decomposes the risk premium into a systematic component, κ_t^R, and an idiosyncratic component, ν_t^R. The systematic component can be described as a linear combination of systematic risk factor exposures,

$$\kappa_t^R \quad = \quad \sum_i \beta_i^R \theta_{i,t}^R. \tag{OA.5}$$

Similarly, the ambiguity premium can be decomposed into a systematic component, κ_t^A, and an idiosyncratic component, ν_t^A. The systematic component can similarly be described as a linear combination of independent factors,

$$\kappa_t^A \quad = \quad \sum_i \beta_i^A \theta_{i,t}^A. \tag{OA.6}$$

Thus, we have that:

$$\pi_t^R = \nu_t^R + \nu_t^R, \qquad \text{and} \qquad \pi_t^A = \kappa_t^A + \nu_t^A. \tag{OA.7}$$

Equation (OA.4) suggests that CDS spreads may be driven by the fundamental default probabilities $\lambda_t^{\mathbb{P}}$, a risk premium, and an ambiguity premium. In reduced-form credit risk models with observable covariates, $\lambda_t^{\mathbb{P}}$ is specified to depend on global-market and firm-specific state variables. In our framework, objective ambiguity and risk are two independent state variables that drive the level of CDS spreads. When investors are ambiguity averse, compensation for ambiguity is reflected by π_t^A. As we illustrate theoretically in a our equilibrium model, as well as empirically, this term may either be positive or negative, depending on whether the marginal investor is a net seller or a net buyer of CDS contracts. When investors are risk averse, additional compensation for risk is reflected by π_t^R, which is always positive. The magnitudes of π_t^A and π_t^R can be pinned down by the pricing kernel.

OA.2 Model Extensions

In this section, we derive several extensions of the static equilibrium model. We consider the case of homogeneous investors trading an asset in positive net supply, homogeneous investors trading an asset in zero net supply, heterogeneous investors trading an asset in positive net supply, and heterogeneous investors trading both assets in positive and zero net supply.

We denote the price of assets in zero net supply by p, and the price of assets in positive net supply by q. We think of CDSs (the assets in zero net supply) as contracts that are fully settled upfront. Standard CDS contracts are quoted in running spreads and are traded with fixed coupons since the implementation of the Big Bang Protocol in 2009. The difference between the running spread and the fixed coupon is settled upfront. Thus, the price of the asset in zero net supply can be viewed as entirely settled upfront, reflecting the net present value of all the expected future insurance payments linked to the credit protection. This implies that a higher credit spread is equivalent to a higher price. In contrast to the asset in zero net supply, for the asset in positive net supply (such as a bond), a lower price is equivalent to a higher yield.

OA.2.1 Homogeneous investors trading an asset in positive net supply

Consider, first, the case of an asset in positive net supply and homogeneous investors. In this case, every investor solves the following maximization problem:

$$\begin{array}{ll} \max\limits_{h} & [1-\mathrm{Q}(SL)]\,\mathrm{U}\left(w-hq+hV_L\right)+\mathrm{Q}(SL)\mathrm{U}\left(w-hq+hN\right) \\ \text{s.t.} & 0\leq h\leq \frac{w}{q} \qquad \text{and} \qquad 0<q, \end{array} \tag{OA.8}$$

where V_L is the asset's payoff in case of default, N is the asset's payoff in case of solvency, and q is the market price of the asset in positive net supply. The following proposition suggests that higher ambiguity lowers the price of the asset in positive net supply.

Proposition OA.1 *Assume an asset in positive supply and homogeneous investors, such that the boundary conditions in Equation* (OA.8) *are slack. Then the higher the firm-specific ambiguity, the lower the price of the asset.*

Proof. Denote $A=w-hq+hV_L$, $B=w-hq+hN$. The first-order condition (FOC) of the maximization problem in Equation (OA.8) implies that:

$$q \;=\; \frac{[1-\mathrm{Q}(SL)]\,\mathrm{U}'\left(A\right)V_L+\mathrm{Q}(SL)\mathrm{U}'\left(B\right)N}{[1-\mathrm{Q}(SL)]\,\mathrm{U}'\left(A\right)+\mathrm{Q}(SL)\mathrm{U}'\left(B\right)}. \tag{OA.9}$$

Differentiating q with respect to $\mho^2$ provides:

$$\frac{\partial q}{\partial \mathrm{Q}}\frac{\partial \mathrm{Q}}{\partial \mho^2} \;=\; \frac{\mathrm{U}'\left(A\right)\mathrm{U}'\left(B\right)\left(N-V_L\right)}{\left([1-\mathrm{Q}(SL)]\,\mathrm{U}'\left(A\right)+\mathrm{Q}(SL)\mathrm{U}'\left(B\right)\right)^2}\frac{\partial \mathrm{Q}}{\partial \mho^2} \;<\; 0,$$

since $\frac{\partial \mathrm{Q}}{\partial \mho^2}<0$. ■

The next proposition analyzes the effect of risk on the price of an asset in positive net supply. It shows analytically that when the investor's utility function is of the CARA class, the price of the asset decreases in risk. Intuitively, for risk averse investors, the clearing price for the asset in positive net supply must be lower when risk increases while the expected payoff remains unchanged.

Proposition OA.2 *Assume an asset in positive supply and homogeneous constant absolute risk averse investors, such that the boundary conditions in Equation* (OA.8) *are slack. Then, the higher the firm-specific risk, the lower the price of the asset.*

Proof. To identify the effect of risk in a reduced-form manner, write $V_L = 1 - \frac{\Delta}{1-\mathrm{Q}(SL)}$ and $N = 1 + \frac{\Delta}{\mathrm{Q}(SL)}$, where $\Delta \geq 0$. Increasing Δ widens the mean-preserving spread in outcomes between the solvency and default states. Thus, the total payoff in the default and solvency states can be redefined as $x \in \{A, B\}$, where $A = w - hq + h\left(1 - \frac{\Delta}{1-\mathrm{Q}(SL)}\right)$ and $B = w - hq + h\left(1 + \frac{\Delta}{\mathrm{Q}(SL)}\right)$. For a CARA utility function, a second-order Taylor expansion with respect to the payoff around the expected payoff $\mathbb{E}_{\mathrm{Q}}[x]$ provides:

$$\mathbb{E}_{\mathrm{Q}}\left[\mathrm{U}\left(x\right)\right] \;=\; \mathbb{E}_{\mathrm{Q}}\left[\frac{1-e^{-\gamma x}}{\gamma}\right] \;\approx\; \frac{1}{\gamma} - e^{-\gamma \mathbb{E}_{\mathrm{Q}}[x]}\left(\frac{1}{\gamma} + \frac{\gamma}{2}\mathbb{V}\mathrm{ar}_{\mathrm{Q}}\left[x\right]\right).$$

The FOC of the maximization of this expected utility is equal to:

$$e^{-\gamma(w+h(1-q))}\frac{2\mathrm{Q}(SL)\left(1-\mathrm{Q}(SL)\right)\left(1-q\right) - \left(\gamma h\left(2-\gamma h\left(1-q\right)\right)\right)\Delta^2}{2\mathrm{Q}(SL)\left(1-\mathrm{Q}(SL)\right)} \;=\; 0,$$

which provides:

$$q \;=\; \frac{2\mathrm{Q}(SL)\left(1-\mathrm{Q}(SL)\right) - \gamma h\left(2-\gamma h\right)\Delta^2}{\gamma^2 h^2 \Delta^2 + 2\mathrm{Q}(SL)\left(1-\mathrm{Q}(SL)\right)}.$$

Differentiating with respect to Δ provides:

$$\frac{\partial q}{\partial \Delta} \;=\; -\frac{8\gamma h \Delta \mathrm{Q}(SL)\left(1-\mathrm{Q}(SL)\right)}{\left(\gamma^2 h^2 \Delta^2 + 2\mathrm{Q}(SL)\left(1-\mathrm{Q}(SL)\right)\right)^2} \;<\; 0,$$

which completes the proof. ■

For other classes of utility functions, it is possible to show numerically a similar negative effect of risk on the asset in positive net supply.

OA.2.2 Homogeneous investors trading an asset in zero net supply

Consider the case of homogeneous investors and an asset in zero net supply. In this case, there is no trade in the CDS contract, as both investors want to buy the asset or both want to sell the

asset. Therefore, there will be no equilibrium CDS price.

OA.2.3 Heterogeneous investors trading an asset in zero and an asset in positive net supply

Our static general equilibrium model considers naked (i.e., uncovered) CDS positions only. Thus, each investor's exposure is given by the net credit risk exposure arising only from CDS contracts. However, the investor's overall credit risk exposure may be affected by the holdings of the underlying reference bond (i.e., a covered position), in which case the net credit risk exposure depends on the holdings of assets in positive and in zero net supply. We thus examine the case of heterogeneous investors who, in addition to the initial wealth endowment, are endowed with one unit of the underlying non-tradable asset, when they determine the optimal holding of CDS insurance. In this case, the maximization problem can be redefined as one in which the agent optimizes her net CDS exposure accounting for the bond holdings. As a result, the solution to the maximization problem will be equivalent to that of the naked CDS case. In particular, the joint maximization problems can be written as:

$$\begin{aligned} \max_{h} \quad & \mathrm{Q}(DF)\mathrm{U}\left(w - hp + h\left(N - V_L\right) + V_L\right) + \left[1 - \mathrm{Q}(DF)\right]\mathrm{U}\left(w - hp + N\right) \qquad \text{(OA.10)} \\ \text{s.t.} \quad & 0 \leq h \leq \tfrac{w+N}{p} \qquad \text{and} \qquad 0 < p < N - V_L \end{aligned}$$

and

$$\begin{aligned} \max_{h} \quad & \left[1 - \mathrm{Q}(SL)\right]\mathrm{U}\left(w + hp - h\left(N - V_L\right) + V_L\right) + \mathrm{Q}(SL)\mathrm{U}\left(w + hp + N\right) \qquad \text{(OA.11)} \\ \text{s.t.} \quad & 0 \leq h \leq \tfrac{w+N}{N-V_L-p} \qquad \text{and} \qquad 0 < p < N - V_L. \end{aligned}$$

The equilibrium CDS price, p, and the optimal CDS allocation, h, are immediately obtained from the FOC, as in the case with an uncovered CDS position. Recall that trade in CDS contracts and an equilibrium price exists only if there are heterogeneous investors. The effects ambiguity and risk on the CDS price, p, are obtained by the same considerations as in the proofs of Propositions 1 and 2.

OA.2.4 Heterogeneous investors trading an asset in positive net supply

Finally, consider the case of an asset in positive net supply and heterogeneous investors with respect to aversion to ambiguity and risk. The maximization problem of each investor is then given by:

$$\begin{aligned} \max_{h_i} \quad & [1 - \mathrm{Q}_i(SL)]\,\mathrm{U}_i(w - h_i q + h_i V_L) + \mathrm{Q}_i(SL)\,\mathrm{U}_i(w - h_i q + h_i N) \\ \text{s.t.} \quad & 0 \leq h_i \leq \tfrac{w}{q}, \qquad 0 < q, \qquad \text{and} \quad \textstyle\sum_i h_i = 1, \end{aligned} \tag{OA.12}$$

where q is the market price of the asset in positive net supply. The next proposition suggests that higher ambiguity is associated with a lower price of the asset in positive supply.

Proposition OA.3 *Assume an asset in positive net supply and heterogeneous investors, such that the boundary conditions in Equation* (OA.12) *are slack. Then the higher the firm-specific ambiguity, the lower the price of the asset.*

Proof. Obtained by the same considerations as those employed in the proof of Proposition OA.1, applied to each investor simultaneously. ■

Proposition OA.4 *Assume an asset in positive net supply and heterogeneous constant absolute risk averse investors, such that the boundary conditions in Equation* (OA.12) *are slack. Then, the higher the firm-specific risk, the lower the price of the asset.*

Proof. Obtained by the same considerations as those employed in the proof of Propositions OA.2, applied to each investor simultaneously. ■

Table OA.1: Data Appendix

This table presents the definitions and data sources of the main 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 intra-day return data sampled at 5-minute intervals	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 $billion	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 intra-day return data sampled at 5-minute intervals	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 OA.2: Determinants of CDS Spread Changes

This table presents the results from the regression of the percentage changes of monthly 5-year senior unsecured CDS spread levels ($\Delta CDS5y$) on the percentage changes of the monthly variance of the outcome probabilities ($\Delta Ambiguity$), the monthly variance of equity returns ($\Delta Risk$), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity ($\Delta Leverage$), 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 ($\Delta Liquidity$), and firm size in $billion, measured as the number of shares outstanding times the stock price at the beginning of the month ($\Delta Size$). The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm ($CLUSTER\ FIRM$) and by time ($CLUSTER\ TIME$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$
$\Delta Ambiguity$	-0.0724***		-0.0361***		-0.0357***			-0.0086**
	(0.0134)		(0.0088)		(0.0087)			(0.0039)
$\Delta Risk$		0.0727***	0.0497***		0.0491***			0.0332***
		(0.0131)	(0.0102)		(0.0101)			(0.0033)
$\Delta Leverage$				0.8508***	0.7239***		0.3904***	0.3742***
				(0.2950)	(0.2297)		(0.1164)	(0.1155)
$Rating$				-0.0028***	-0.0027***		-0.0139***	-0.0134***
				(0.0009)	(0.0008)		(0.0008)	(0.0008)
$\Delta Liquidity$				0.0641***	0.0552***		0.0613***	0.0590***
				(0.0226)	(0.0204)		(0.0065)	(0.0063)
$\Delta Size$				-0.0053**	-0.0053**		-0.0357***	-0.0344***
				(0.0025)	(0.0023)		(0.0028)	(0.0027)
$Constant$	0.0001	0.0000	0.0001	0.0353**	0.0349***	0.0038	0.1784***	0.1639***
	(0.0066)	(0.0067)	(0.0066)	(0.0145)	(0.0135)	(0.0140)	(0.0182)	(0.0180)
OBSERVATIONS	52,865	52,865	52,865	52,865	52,865	52,865	52,865	52,865
TIME FE	NO	NO	NO	NO	NO	YES	YES	YES
FIRM FE	NO	NO	NO	NO	NO	YES	YES	YES
CLUSTER FIRM	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.049	0.057	0.063	0.007	0.069	0.310	0.321	0.329

Table OA.3: Cross-correlations of Ambiguity Proxies

This table presents pairwise Pearson correlation coefficients between the monthly variance of the outcome probabilities (*Ambiguity*) and other proxies of ambiguity: realized skewness computed using intraday five-minute returns (*Skewness*), realized kurtosis computed using intraday five-minute returns (*Kurtosis*), the monthly variance of the daily mean equity return computed using intraday five-minute returns (*Vol_of_Mean*), the monthly variance of the daily equity return variances computed using intraday five-minute returns (*Vol_of_Vol*), analyst earnings forecast dispersion (*Analyst_Disp*), risk-neutral variance ($\mathbb{Q}$-*IV*) and risk-neutral skewness ($\mathbb{Q}$-*Skewness*) and risk-neutral kurtosis ($\mathbb{Q}$-*Kurtosis*), both computed using the method in Bakshi et al. (2003). All variables are defined at the monthly frequency, except *Analyst_Disp*, which is measured at the quarterly frequency. The sample includes 491 U.S. firms with 53,356 monthly CDS spread observations from January 2001 to October 2014.

Variables	*Ambiguity*	*Skewness*	*Kurtosis*	*Vol_of_Mean*	*Vol_of_Vol*	*Analyst_Disp*	$\mathbb{Q}$-*IV*	$\mathbb{Q}$-*Skewness*	$\mathbb{Q}$-*Kurtosis*
Ambiguity	1.00								
Skewness	0.03	1.00							
Kurtosis	0.13	0.02	1.00						
Vol_of_Mean	-0.29	-0.03	-0.02	1.00					
Vol_of_Vol	-0.04	-0.01	0.01	0.48	1.00				
Analyst_Disp	-0.02	-0.01	0.01	0.10	0.02	1.00			
$\mathbb{Q}$-*IV*	-0.36	-0.03	-0.06	0.80	0.25	0.07	1.00		
$\mathbb{Q}$-*Skewness*	-0.19	-0.04	0.10	0.02	0.00	0.01	0.02	1.00	
$\mathbb{Q}$-*Kurtosis*	0.23	0.03	-0.05	-0.09	-0.01	-0.00	-0.09	-0.80	1.00

Table OA.4: Determinants of CDS Slope Changes

This table presents the results from the regression 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 ($\Delta Slope$), on the percentage changes of the monthly variance of the outcome probabilities ($\Delta Ambiguity$), the monthly variance of equity returns ($\Delta Risk$), firm leverage defined as the total amount of outstanding debt divided by the sum of total debt and equity ($\Delta Leverage$), 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 ($\Delta Liquidity$), and firm size in $billion, measured as the number of shares outstanding times the stock price at the beginning of the month ($\Delta Size$). The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm ($CLUSTER\ FIRM$) and by time ($CLUSTER\ TIME$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	$\Delta Slope$	$\Delta Slope$	$\Delta Slope$	$\Delta Slope$	$\Delta Slope$	$\Delta Slope$	$\Delta Slope$
$\Delta Ambiguity$	-0.0266***		-0.0186***	-0.0184***	-0.0150***	-0.0185***	-0.0149***
	(0.0071)		(0.0068)	(0.0068)	(0.0046)	(0.0041)	(0.0046)
$\Delta Risk$		0.0227***	0.0107*	0.0103*	-0.0079*	0.0104***	-0.0080*
		(0.0065)	(0.0059)	(0.0060)	(0.0045)	(0.0037)	(0.0045)
$\Delta Leverage$				-0.1036	0.1261	-0.1109	0.1131
				(0.2048)	(0.1711)	(0.1748)	(0.1719)
$Rating$				0.0021**	0.0009*	0.0058***	0.0020
				(0.0009)	(0.0005)	(0.0017)	(0.0018)
$\Delta Liquidity$				0.0536***	0.0429***	0.0540***	0.0430***
				(0.0186)	(0.0130)	(0.0123)	(0.0130)
$\Delta Size$				0.0011	-0.0002	0.0030	-0.0017
				(0.0019)	(0.0011)	(0.0042)	(0.0053)
$Constant$	0.0110**	0.0110**	0.0110**	-0.0099	0.0213	-0.0454**	0.0131
	(0.0053)	(0.0053)	(0.0053)	(0.0108)	(0.0466)	(0.0202)	(0.0514)
OBSERVATIONS	46,682	46,682	46,682	46,682	46,682	46,682	46,682
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	0.002	0.002	0.003	0.058	0.003	0.058

Table OA.5: Determinants of CDS Spread Changes - Aggregate Controls

This table presents the results from the regression of the percentage changes of the natural logarithm of monthly 5-year senior unsecured CDS spread levels ($\Delta CDS5y$) on the percentage changes of the monthly variance of the outcome probabilities ($\Delta Ambiguity$), the monthly variance of equity returns ($\Delta Risk$), aggregate ambiguity ($\Delta SP500Ambiguity$), aggregate risk ($\Delta SP500Risk$), 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 ($\Delta r2$), the monthly return on the S&P 500 Index ($SP500Return$), the CBOE S&P 500 implied volatility index (ΔVIX), the difference between the 10-year and 2-year constant-maturity Treasury yields ($\Delta TSSlope$), and the difference between the BofA Merrill Lynch U.S. High Yield BBB (BB) and AAA (BBB) effective yields (ΔBBB_AAA and ΔBB_BBB). The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm ($CLUSTER\ FIRM$) and by time ($CLUSTER\ TIME$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$	$\Delta CDS5y$
$\Delta Ambiguity$	-0.0722***				-0.0174***	-0.0053**
	(0.0028)				(0.0026)	(0.0024)
$\Delta Risk$		0.0725***			0.0311***	0.0326***
		(0.0028)			(0.0027)	(0.0026)
$\Delta SP500Ambiguity$			-0.0781***		-0.0329***	-0.0180***
			(0.0026)		(0.0023)	(0.0022)
$\Delta SP500Risk$				0.0699***	0.0168***	-0.0443***
				(0.0023)	(0.0024)	(0.0033)
$\Delta Leverage$						0.4103***
						(0.1201)
$Rating$						-0.0084***
						(0.0008)
$\Delta Liquidity$						0.0615***
						(0.0060)
$\Delta Size$						-0.0149***
						(0.0023)
$\Delta r2$						-0.1135***
						(0.0079)
$SP500Return$						-0.1035***
						(0.0248)
$\Delta TSSlope$						-0.0021**
						(0.0009)
ΔVIX						0.1196***
						(0.0117)
ΔBBB_AAA						0.3101***
						(0.0096)
ΔBB_BBB						0.1734***
						(0.0069)
$Constant$	0.0001***	0.0000	0.0000	-0.0001***	0.0001***	0.1056***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0106)
OBSERVATIONS	52,865	52,865	52,865	52,865	52,865	52,865
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	0.0489	0.0565	0.0613	0.0627	0.0768	0.2390

Table OA.6: Determinants of CDS Spreads - End-of-month Spreads

This table presents the results from the regression 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 Δ*CDS5y*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of daily equity returns (*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 $billion, 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 sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Levels			Changes	
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	Δ*CDS5y*	Δ*CDS5y*	Δ*CDS5y*
Ambiguity	-1.6782***		-2.0703***	-0.0098**		-0.0067**
	(0.2908)		(0.3036)	(0.0040)		(0.0033)
Risk	5.4051***		5.1714***	0.0347***		0.0334***
	(0.7296)		(0.6881)	(0.0061)		(0.0033)
$Ambiguity_{t-1}$		-1.7125***			0.0043*	
		(0.2963)			(0.0024)	
$Risk_{t-1}$		5.0364***			0.0143***	
		(0.7814)			(0.0034)	
OBSERVATIONS	53,282	52,550	53,282	52,722	52,012	52,722
FIRM CONTROLS	ALL	ALL	ALL	ALL	ALL	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	YES	YES	YES	YES	YES	YES
Adj. R^2	0.658	0.658	0.613	0.231	0.237	0.169

Table OA.7: **CDS Positions.** In this table, we present statistics on the gross notional amounts of CDS outstanding by type of counterparty based on the semi-annual OTC derivatives statistics reported by the Bank for International Settlements (Tables D10.1 to D10.4). The sampling frequency is bi-annual from 2004H2 to 2016H2. The information is based on surveys from large dealers from 13 countries. Statistics are reported on a worldwide consolidated basis and include positions of foreign affiliates, but they exclude intragroup positions. In Panel A, we report the total gross notional amounts of CDS outstanding by type of counterparty, and the market share of Dealers, Central Counterparties, Banks, Insurance and Financial Guaranty Firms, Special Purpose Vehicles, Hedge Funds, Non-Financial Corporations, and Residual Financial Institutions. We report the difference between total gross notional amounts of CDS bought and sold for all contracts in Panel B, for single-name contracts in Panel E, for multi-name contracts in Panel G, for investment grade contracts in Panel I, for speculative grade contracts in Panel J, for financial contracts in Panel K, for non-financial contracts in Panel L, for sovereign contracts in Panel M; the difference between the positive and negative gross market values for all contracts in Panel C, for single-name contracts in Panel F, and for multi-name contracts in Panel G; the difference between the positive and negative market values for all contracts in Panel D.

	05-H1	06-H1	07-H1	08-H1	09-H1	10-H1	11-H1	12-H1	13-H1	14-H1	15-H1	16-H1
Panel A: Market Shares												
Total Notional ($bill.)	10,211	20,352	42,581	57,403	36,098	30,261	32,409	26,930	24,349	19,462	14,594	11,767
Dealers (%)	47.52	52.12	54.76	57.77	53.18	52.13	53.53	58.47	56.38	49.02	44.56	43.32
CP (%)	–	–	–	–	–	9.80	17.09	19.34	22.79	26.70	30.87	37.28
Banks (%)	15.84	24.69	22.53	23.84	30.78	26.36	18.86	10.84	9.10	10.49	8.42	5.40
IFG (%)	1.11	1.46	0.78	0.69	1.07	0.90	1.11	1.03	0.95	1.01	1.23	1.35
SPV (%)	1.05	0.38	0.25	0.19	0.30	1.72	1.63	1.70	1.53	1.39	1.27	1.30
HF (%)	2.52	0.71	0.57	0.67	0.35	2.18	2.97	3.74	4.42	5.71	5.40	4.66
NFC (%)	4.63	3.57	2.07	1.65	4.21	2.79	0.73	0.69	0.79	1.04	1.41	1.30
R (%)	4.69	17.07	19.06	15.20	10.11	4.12	4.08	4.18	4.05	4.63	6.85	5.38
Panel B: Gross Bought - Gross Sold ($billion)												
Dealers	8	123	-60	482	102	4	-156	-74	-35	-51	18	60
CP	–	–	–	–	–	10	23	-26	4	197	27	80
Banks	27	86	117	287	168	110	263	296	224	153	150	123
IFG	39	160	156	159	150	137	216	135	99	81	68	34
SPV	54	63	51	61	19	120	269	259	211	88	70	62
HF	-14	-5	15	9	9	-139	-307	-242	-191	-133	-79	-79
NFC	41	77	42	124	116	64	54	65	52	42	47	19
R	29	-7	-260	207	178	163	245	147	72	176	130	108
Panel C: GMV Positive - GMV Negative ($billion)												
Dealers	3	-1	7	37	20	5	-1	-6	0	2	1	1
CP	–	–	–	–	–	0	-1	-3	-1	-1	0	2
Banks	1	1	-2	27	24	6	13	13	4	-2	-1	0
IFG	0	0	0	17	33	28	31	11	6	3	3	3
SPV	-2	1	4	19	20	38	23	21	7	2	1	1
HF	1	0	0	4	3	-7	-7	-7	0	3	1	-3
NFC	0	3	3	23	35	8	3	5	3	2	0	0
R	1	1	2	76	94	54	22	23	11	4	3	3
Panel D: NMV Positive - NMV Negative ($billion)												
Dealers	–	–	–	–	–	–	-6	-18	2	5	3	2
CP	–	–	–	–	–	–	-1	1	0	1	0	1
Banks	–	–	–	–	–	–	12	8	1	-2	0	0

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Table OA.7 – *Continued from previous page*

	05-H1	06-H1	07-H1	08-H1	09-H1	10-H1	11-H1	12-H1	13-H1	14-H1	15-H1	16-H1
IFG	–	–	–	–	–	–	17	7	5	4	3	3
SPV	–	–	–	–	–	–	21	20	6	2	1	1
5HF	–	–	–	–	–	–	-6	-7	-1 0	0	-2	-1
NFC	–	–	–	–	–	–	3	5	3	2	0	0
R	–	–	–	–	–	–	18	23	10	4	4	2
Panel E: Single-Names Gross Bought - Gross Sold ($billion)												
Dealers	43	113	463	132	150	4	-130	-53	11	-73	4	12
CP	–	–	–	–	–	17	12	2	1	85	11	3
Banks	-17	52	236	325	178	142	180	173	128	116	95	104
IFG	23	52	65	50	47	33	67	35	23	48	19	18
SPV	-9	-42	-117	-526	-455	-237	-106	-81	-60	-102	-61	-22
HF	-24	-12	0	34	20	-101	-200	-172	-162	-131	-105	-101
NFC	1	49	8	229	86	31	28	47	7	33	34	16
R	26	-65	-268	50	-8	4	33	59	34	74	56	36
Panel F: Single-Names GMV Positive - GMV Negative ($billion)												
Dealers	2	1	6	42	10	5	3	-2	0	1	0	-2
CP	–	–	–	–	–	0	0	-2	-1	-1	0	2
Banks	2	0	0	18	24	9	10	11	4	0	-1	0
IFG	0	0	0	12	21	16	18	5	3	2	2	2
SPV	-3	0	1	3	6	11	11	7	4	2	1	0
HF	0	0	0	7	5	-4	-4	-5	0	2	1	0
NFC	-3	-2	-5	2	-13	-11	-1	0	-1	0	-1	-1
R	1	-1	-3	50	65	27	10	13	7	4	4	4
Panel G: Multi-Names Gross Bought - Gross Sold ($billion)												
Dealers	-35	9	-523	349	-48	-1	-25	-21	-46	23	14	48
CP	–	–	–	–	–	-7	12	-28	3	112	16	78
Banks	44	34	-119	-39	-11	-32	83	123	96	38	55	18
IFG	15	108	91	109	103	104	149	100	76	33	49	16
SPV	36	53	33	53	35	127	185	186	176	64	48	27
HF	9	7	15	-25	-12	-38	-107	-70	-29	-2	25	23
NFC	40	29	33	-106	30	33	26	19	45	10	13	3
R	3	58	8	157	186	159	212	88	38	102	74	72
Panel H: Multi-Names GMV Positive - GMV Negative ($billion)												
Dealers	1	-1	1	-5	10	0	-4	-3	0	1	1	2
CP	–	–	–	–	–	0	-1	-1	0	0	0	0
Banks	0	1	-2	9	0	-3	3	3	0	-2	0	0
IFG	0	0	0	5	12	11	13	6	3	1	1	1
SPV	1	1	3	16	14	27	12	14	3	0	0	1
HF	1	0	0	-3	-1	-2	-3	-2	1	1	0	-3
NFC	0	2	1	12	22	7	2	3	2	1	-1	0
R	0	2	5	27	30	28	12	10	4	0	-1	-1
Panel I: Investment Grade Gross Bought - Gross Sold ($billion)												
Dealers	-69	132	316	81	37	-2	72	32	-2	0	104	94
CP	–	–	–	–	0	-3	-19	15	6	129	35	64
Banks	12	58	17	179	147	150	203	185	136	112	122	110
IFG	24	42	46	17	10	29	70	32	33	24	24	21
SPV	47	40	29	40	18	55	83	78	76	55	21	18
HF	-32	-2	6	7	8	-95	-201	-201	-142	-115	-79	-54
NFC	-4	16	-60	-16	24	-1	9	22	40	22	18	18
R	9	-19	-185	-72	-7	30	115	113	58	85	66	59

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Table OA.7 – *Continued from previous page*

	05-H1	06-H1	07-H1	08-H1	09-H1	10-H1	11-H1	12-H1	13-H1	14-H1	15-H1	16-H1
Panel J: Speculative Grade Gross Bought - Gross Sold ($billion)												
Dealers	-1	3	-5	19	20	12	197	8	11	-12	-22	-13
CP	–	–	–	–	–	17	-22	-45	-33	14	-13	-7
Banks	0	-11	7	44	24	23	47	57	38	34	8	10
IFG	0	2	0	2	5	1	26	21	22	15	9	7
SPV	8	3	2	3	-17	-7	12	18	10	12	4	5
HF	-2	-2	1	-16	-6	-18	-49	-44	-23	-2	-6	-22
NFC	-1	-15	-9	107	-3	-3	-2	-3	0	1	6	2
R	6	-47	-18	40	-10	17	26	22	18	20	23	20
Panel K: Financials Gross Bought - Gross Sold ($billion)												
Dealers	-13	-34	32	1	-104	-172	-86	-102	-77	-89	7	16
CP	–	–	–	–	–	-1	20	47	46	119	23	1
Banks	-2	3	26	-62	35	-37	59	34	28	35	45	39
IFG	10	7	-2	-9	-30	5	27	23	14	37	7	5
SPV	20	28	21	18	23	-3	59	24	4	9	-1	-7
HF	–	–	–	–	–	–	341	24	-98	-146	-78	-9
NFC	4	8	18	144	51	32	29	25	1	20	19	0
R	-1	18	-21	8	14	9	-8	-8	2	30	60	38
Panel L: Non-Financials Gross Bought - Gross Sold ($billion)												
Dealers	-54	-30	-17	-118	29	47	86	-5	36	1	49	-24
CP	–	–	–	–	–	2	-7	-29	-48	75	6	22
Banks	4	-8	-36	44	-9	-15	109	94	58	59	58	44
IFG	16	19	22	1	39	21	70	18	16	15	14	11
SPV	13	9	0	8	2	-3	47	41	46	20	24	34
HF	-9	-12	-16	29	5	-5	-114	-112	-95	-81	-49	-59
NFC	18	12	5	14	1	0	0	17	5	8	11	10
R	16	19	21	96	19	11	26	40	36	42	19	22
Panel M: Sovereigns Gross Bought - Gross Sold ($billion)												
Dealers	-9	14	179	-10	-11	-26	-11	-3	-7	9	7	0
CP	–	–	–	–	–	0	0	0	2	-4	0	-1
Banks	-1	14	12	53	63	73	74	82	78	39	35	39
IFG	0	0	0	-1	0	2	3	1	2	0	0	1
SPV	3	1	0	0	0	26	31	22	17	8	3	4
HF	-5	-7	-8	5	5	-33	-78	-67	-49	-36	-31	-20
NFC	-2	5	20	33	2	4	3	3	3	4	6	6
R	-1	-17	77	-63	-51	-14	25	41	17	29	20	9

Table OA.8: Robustness - Variations in the Measurement of Ambiguity

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on different metrics of the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*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 $billion, 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. We compute ambiguity using the assumption that intraday returns follow a normal distribution. The measures in columns (1) to (3) [(4) to (6), (7) to (8)] include an ambiguity measure computed when the daily return distributions are grouped into 162 (82, 322) bins. Ambiguity and risk are computed using intraday returns sample at 300 (30, 600) second intervals in columns (1), (5), and (8) [(2), (4), and (7); (3), (6), and (9)]. As an example, *Ambg_162b300s* refers to ambiguity computed using 162 bins and 300 second (5-minute) returns. The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Ambg_162b300s	-1.67***								
	(0.29)								
Risk_300s	5.34***								
	(0.75)								
Ambg_162b30s		-4.83***							
		(0.69)							
Risk_30s		1.36***							
		(0.39)							
Ambg_162b600s			-0.92***						
			(0.17)						
Risk_600s			9.65***						
			(1.26)						
Ambg_82b30s				-2.23***					
				(0.31)					
Risk_30s				1.07***					
				(0.41)					
Ambg_82b300s					-1.02***				
					(0.15)				
Risk_300s					7.94***				
					(1.01)				
Ambg_82b600s						-0.71***			
						(0.11)			
Risk_600s						9.55***			
						(1.22)			
Ambg_322b30s							-6.94***		
							(1.83)		
Risk_30s							1.77***		
							(0.51)		
Ambg_322b300s								-2.10***	
								(0.61)	
Risk_300s								7.97***	
								(1.07)	
Ambg_322b600s									-1.29***
									(0.31)
Risk_600s									9.65***
									(1.29)
OBSERVATIONS	53,356	53,334	53,334	53,334	53,334	53,334	53,334	53,334	53,334
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER FIRM	YES	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.665	0.659	0.668	0.659	0.671	0.670	0.657	0.667	0.667

Table OA.9: Robustness Tests - Other Proxies for Ambiguity

This table presents the results from the regression of the natural logarithm of monthly 5-year senior unsecured CDS spread levels (*CDS5y*) on the monthly variance of the outcome probabilities (*Ambiguity*), the monthly variance of equity returns (*Risk*), and all firm-specific controls as described in the main regressions. We control for realized skewness (*Skewness*) and realized kurtosis (*Kurtosis*) computed using intraday five-minute returns in columns (1) and (2), intraday 30-second returns in columns (3) and (4), intraday 10-minute returns in columns (5) and (6). Ambiguity and risk are computed using intraday returns of matched frequency. All variables are defined at the monthly frequency. The sample includes 491 U.S. firms from January 2001 to October 2014. The standard errors reported in parentheses are double clustered by firm (*CLUSTER FIRM*) and by time (*CLUSTER TIME*). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*	*CDS5y*
Ambg_162b300s	-1.67***	-1.68***	-1.68***						
	(0.29)	(0.29)	(0.29)						
Risk_162b300s	5.35***	5.30***	5.31***						
	(0.75)	(0.74)	(0.74)						
Skew_300s	0.03***		0.03***						
	(0.01)		(0.01)						
Kurt_300s		0.43	0.42						
		(0.28)	(0.28)						
Ambg_162b30s				-4.84***	-4.87***	-4.87***			
				(0.68)	(0.68)	(0.68)			
Risk_162b30s				1.36***	1.35***	1.35***			
				(0.39)	(0.38)	(0.38)			
Skew_30s				0.01***		0.01***			
				(0.00)		(0.00)			
Kurt_30s					-0.00***	-0.00***			
					(0.00)	(0.00)			
Ambg_162b600s							-0.92***	-0.92***	-0.92***
							(0.17)	(0.17)	(0.17)
Risk_162b600s							9.65***	9.65***	9.65***
							(1.26)	(1.25)	(1.25)
Skew_600s							0.02*		0.02*
							(0.01)		(0.01)
Kurt_600s								0.01**	0.01**
								(0.00)	(0.00)
Leverage	1.71***	1.71***	1.71***	1.76***	1.76***	1.76***	1.66***	1.66***	1.66***
	(0.27)	(0.27)	(0.27)	(0.28)	(0.28)	(0.28)	(0.27)	(0.27)	(0.27)
Rating	0.17***	0.17***	0.17***	0.18***	0.18***	0.18***	0.17***	0.17***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Liquidity	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-6.31***	-6.32***	-6.32***	-6.31***	-6.27***	-6.27***	-6.31***	-6.38***	-6.38***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
OBSERVATIONS	53,356	53,356	53,356	53,334	53,334	53,334	53,334	53,334	53,334
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER FIRM	YES	YES	YES	YES	YES	YES	YES	YES	YES
CLUSTER TIME	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665	0.665

Figure OA.1: The Relation between Ambiguity, Risk, Skewness, and Kurtosis in a Discrete State Space

In this figure, we provide simulated evidence on the relation between ambiguity, and risk, skewness, and kurtosis, using a discrete state space with three events [A, B, C], each associated with a single outcome. In this simulation, there are two symmetric probability distributions, and each distribution is assigned with equal likelihood. The variance, skewness and kurtosis are computed using the expected probabilities. The distribution is calibrated to match the mean ambiguity and risk in our data, as reported in the summary statistics in Table 2 in the paper. To increase risk, skewness, and kurtosis, we increase one or more outcomes associated with the three events, while the probabilities remain unchanged. To increase ambiguity, we change the probabilities of events such that the expected probabilities remain unchanged (mean preserving spreads in probabilities), while the outcomes associated with the events remain unchanged.

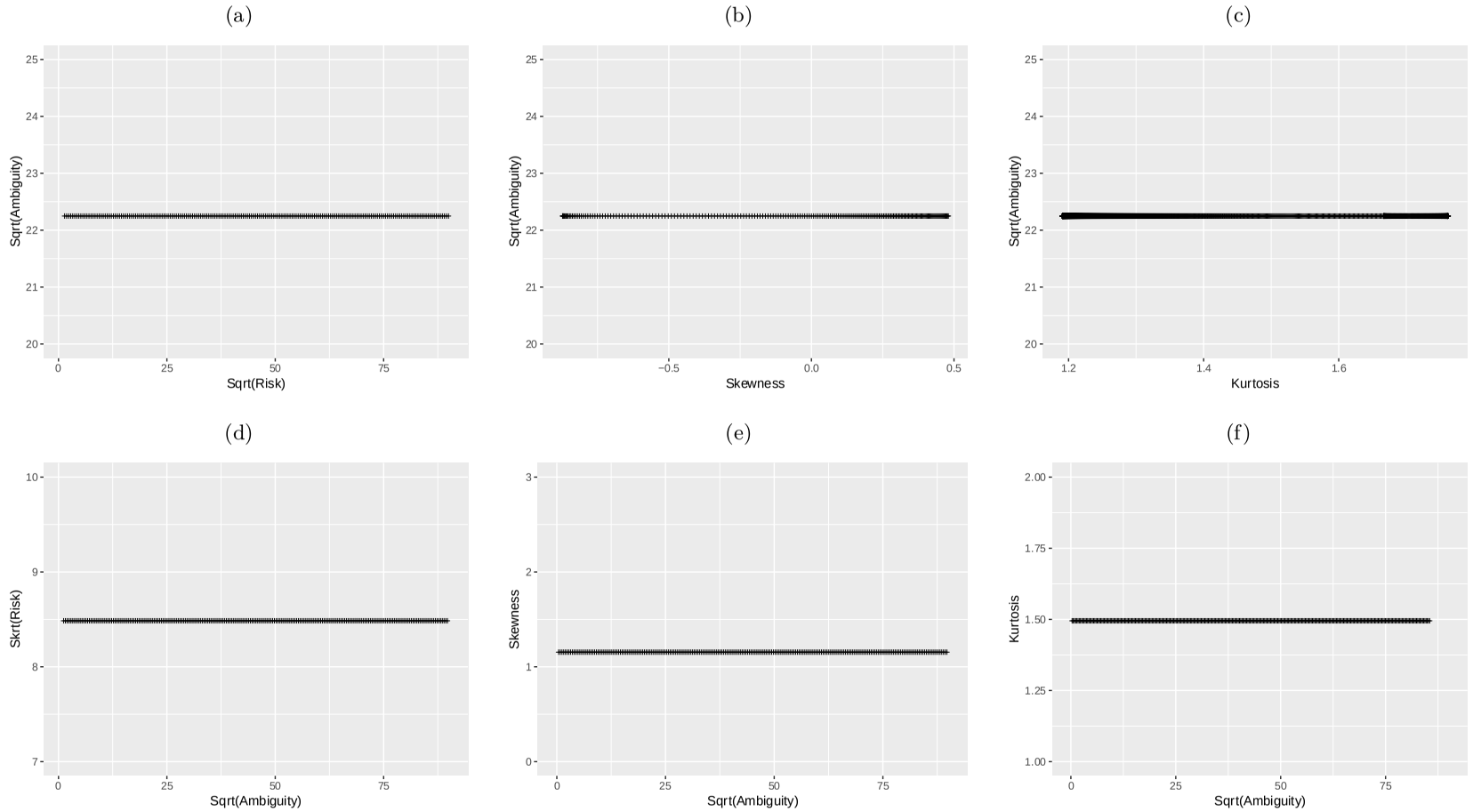


Figure OA.2: The Relation between Ambiguity, Risk, Skewness, and Kurtosis in a Continuous State Space

In this figure, we provide simulated evidence on the relation between ambiguity, and risk, skewness, and kurtosis, using a continuous state space with an infinite number of events, each associated with a single outcome. We consider two normal probability distributions with different means and standard deviations, and each distribution is assigned with equal likelihood. The variance, skewness and kurtosis are computed using the expected probabilities. The distribution is calibrated to match the mean ambiguity and risk in our data, as reported in the summary statistics in Table 2 in the paper. To increase risk, skewness, and kurtosis, we increase the standard deviation of the two distributions. To increase ambiguity, we change the mean of one of the probability distributions.

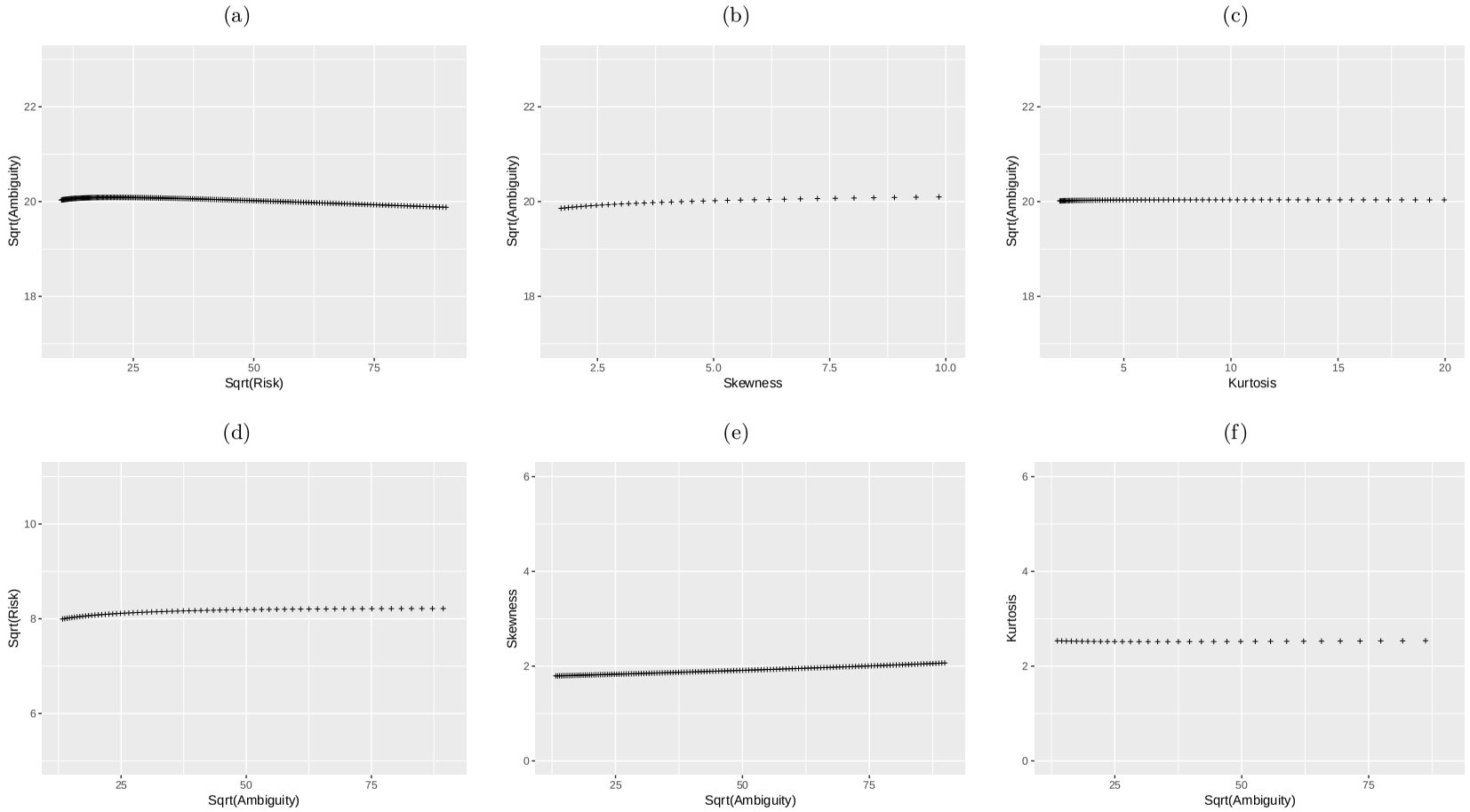
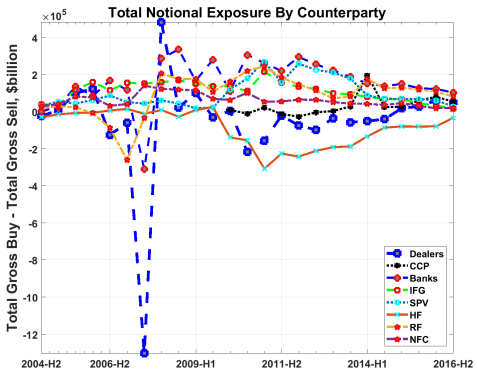


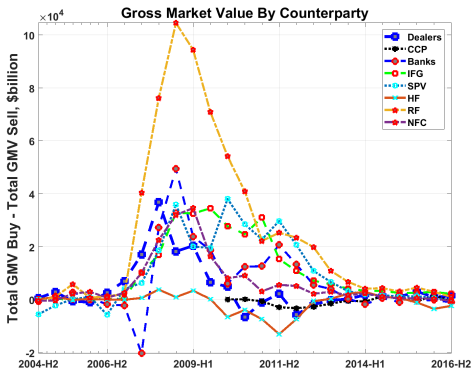
Figure OA.3: CDS Exposures by Type of Counterparty and Instruments (BIS)

These figures depict gross notional amounts of CDS contracts outstanding by type of counterparty based on the semi-annual OTC derivatives statistics reported by the Bank for International Settlements (Tables D10.1 to D10.4, see www.bis.org). The sampling frequency is bi-annual from 2004H2 to 2016H2. The information is based on survey data of large dealers from 13 countries. Statistics are reported on a worldwide consolidated basis and include positions of foreign affiliates, but they exclude intragroup positions. Panel a depicts the differences between total gross notional amounts of CDS bought and sold (exposure) by type of counterparty for all CDS contracts. Panel b depicts the difference between the positive and the negative gross market values of CDS contracts for all CDS contracts by type of counterparty. Gross market values do not account for netting between positive and negative market values with the same counterparty. Panel c (d) depicts the exposures by type of counterparty for single-name (multi-name) CDS contracts. Panel e (f) depicts the exposures by type of counterparty for financial (non-financial) reference entities.

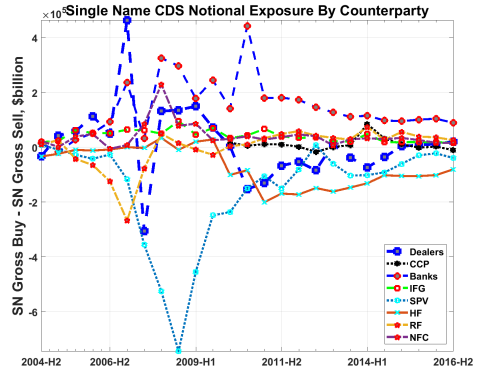
(a)



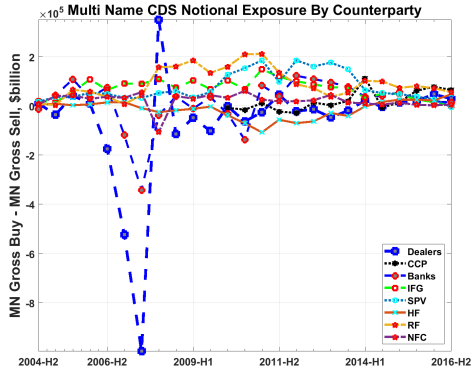
(b)



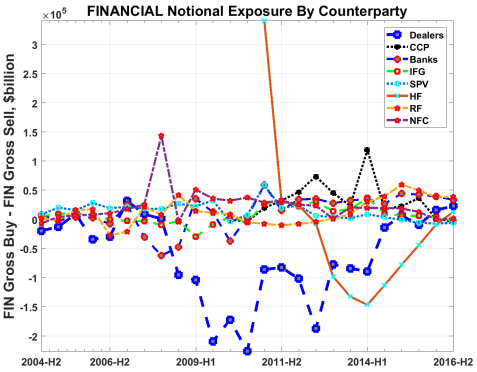
(c)



(d)



(e)



(f)

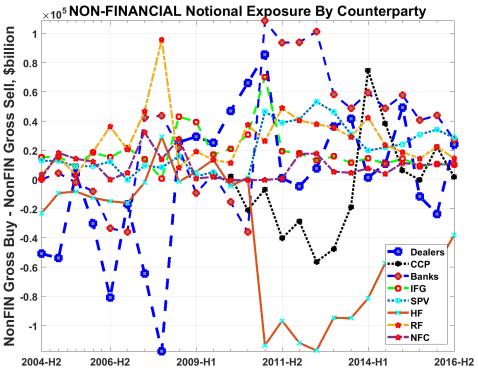
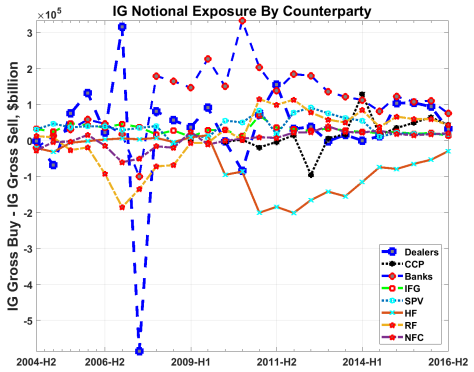


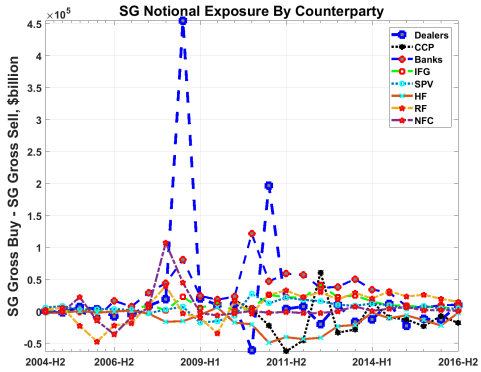
Figure OA.4: CDS Exposures by Type of Counterparty and Instruments (BIS)

These figures depict gross notional amounts of CDS contracts outstanding by type of counterparty based on the semi-annual OTC derivatives statistics reported by the Bank for International Settlements (Tables D10.1 to D10.4, see www.bis.org). The sampling frequency is bi-annual from 2004H2 to 2016H2. The information is based on survey data of large dealers from 13 countries. Statistics are reported on a worldwide consolidated basis and include positions of foreign affiliates, but they exclude intragroup positions. Panel a depicts the differences between total gross notional amounts of CDS bought and sold (exposure) by type of counterparty for investment-grade contracts. Panel b depicts the exposure by type of counterparty for speculative-grade contracts. Panel c depicts the exposures by type of counterparty for contracts with a maturity between 1 and 5 years. Panel d depicts the exposures by type of counterparty for sovereign reference entities.

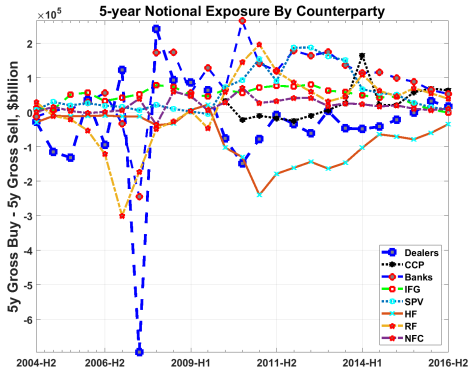
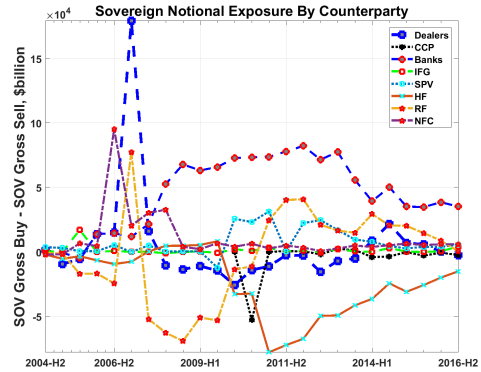
(a)



(b)



(c)



(d)