Trading, Ambiguity and Information in the Options Market

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September 2023

Abstract

We study how firm ambiguity—Knightian uncertainty—affects investor trading behavior using the options market as a laboratory. Greater ambiguity in the underlying asset negatively relates to both options open interest and options trading volume. The reduction in options trading activity is stronger for options with shorter maturities and out-of-the-money options that are hard-to-value. Greater ambiguity is also associated with a reduction in the informativeness of options trading for future stock prices, and it is associated with lower delta-hedged options returns for both puts and calls. The effect of ambiguity is distinct from and contrasts with the well-documented effect of risk, and it shares a similar economic significance. These findings illustrate that even sophisticated market participants, like options traders, are influenced by ambiguity to limit their market participation and trade less.

Keywords and Phrases: Knightian uncertainty, Options trading, Ambiguity measure, Limited participation, Portfolio inertia, Information inertia, Expected utility with uncertain probabilities.

JEL Classification Numbers: D81, D83, G11, G12

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§We thank Yakov Amihud, Patrick Augustin, Jules Van Binsbergen, Menachem Brenner, Itzhak Ben-David, Richard Herron, Hagit Levy, Dmitry Livdan, Dmitriy Muravyev, Lin Peng, Gideon Saar, Ron Shalev, Elvira Sojli, Andrea Tamoni, Jaime Zender, Dexin Zhou, and Emanuel Zur for valuable discussions and suggestions. Izhakian acknowledges hosting by the Stern School of Business, New York University.

Introduction

Market participation is critical for well-functioning financial markets and is a central feature of many asset pricing models (Campbell, 2006). Indeed, canonical consumption models predict that all individuals ought to participate in financial markets (e.g., Merton, 1975), yet many households are disengaged with financial markets, even wealthy households (e.g., Haliassos and Bertaut, 1995; Briggs et al., 2021). On the other hand, it is well appreciated that sophisticated market participants play an outsized role in shaping market outcomes (Koijen et al., 2020), such that even small changes in sophisticated participants trading behaviors may have important consequences (e.g., Jansen, 2021). Thus, it is a natural and important question to understand what drives the participation and trading decisions of sophisticated investors.

In this paper, we address this question by studying how ambiguity, or Knightian uncertainty,[1] shapes participation and trading decisions in options markets. The options market is a natural laboratory to study participation decisions of sophisticated investors because, as options are in zero net supply, changes in open interest reflect changes in options market participation. Employing firm-day measurement of ambiguity and activity in options markets, we show that greater ambiguity reduces both options market participation and options trading, particularly for difficult-to-value options contracts. Moreover, when ambiguity is high, options trading is less informed for stock prices and both writers and buyers of options earn lower delta-hedged returns. Overall, these findings imply that ambiguity is an important market force, even for options markets that are inhabited by sophisticated traders.

Turning to our empirical design, our contribution is facilitated by employing a recently developed ambiguity measure available at the firm-day level and using it to study options markets. This measure is an empirically-applicable, *risk-independent* measure of ambiguity (Izhakian and Yermack, 2017; Brenner and Izhakian, 2018; Augustin and Izhakian, 2020). This measure estimates firm-level ambiguity from intraday returns data as the volatility of return probabilities. The main advantages of this daily measure are its risk independence and its mitigation of potential confounding effects that are difficult to address using lower frequency (e.g., monthly) proxies. In contemporaneous work, Ben-Rephael et al. (2022) show that this ambiguity measure bears a strong negative relation to daily trading volume in the stock market, and it dampens the relationship

[1] Risk is the condition in which outcomes are a priori unknown, but the odds of all possible outcomes are perfectly known. Ambiguity is the condition in which the possible outcomes are a priori unknown, and the odds of these possible outcomes are either unknown or not uniquely assigned. Knight (1921) defines the concept of (Knightian) uncertainty as distinct from risk since the condition in which the set of events that may occur is a priori unknown and the odds of these events are either unknown or not unique.

between disagreement and stock trading, consistent with a valid empirical proxy for ambiguity.

In this paper, we focus on the options market instead of the underlying asset. This has three main advantages. First, options are held in zero net supply. Since options are a zero sum game, both buyers and sellers are affected by the same uncertainty when ambiguity increases.[2] Second, the rich variation in option contracts allows us to explore the effect of ambiguity along the dimensions of investment maturity and valuation as captured by strike prices. Finally, the fact that multiple option contracts are traded on the same stock allows to better control for firm unobservables.

We begin by studying how call and put options open interest (i.e., holdings that capture the extent of options market participation) relates to the firm-day ambiguity measure at the daily level. We find that high ambiguity is robustly and negatively related to participation. Specifically, a standard deviation increase in ambiguity is associated with between 0.012 and 0.015 standard deviations smaller call (or put) options open interest. Although this estimate reveals a relatively small magnitude along the participation margin, the estimate is highly statistically significant and its economic magnitude is similar to that of intraday volatility, which is known to have a tight connection to options markets. Thus, our core finding is that ambiguity reduces participation of relatively sophisticated options traders, a finding that supports predictions given by ambiguity theory (e.g., Dow and Werlang, 1992; Easley and O'Hara, 2009).

Next, we turn to investigating how ambiguity relates to trading volume. The vast majority of trading volume is driven by activities that, on net, cancel out (e.g., rebalancing and market making activities). We find that ambiguity is also negatively related to options trading volume for both calls and puts. Thus, our evidence on trading volume effects reflects an intensive margin effect, which suggests that ambiguity increases inertia of making a planned trading decision, consistent with ambiguity theory (e.g., Illeditsch, 2011; Illeditsch et al., 2021). Moreover, the estimate is opposite in sign from risk, and of comparable economic magnitude given that the connection between risk and options trading is well-established in the literature (e.g., Bandi et al., 2008).

Observing that ambiguity relates negatively to participation and trading in options markets, we use the richness of the options contracts to provide two more refined tests. Specifically, there are many options contracts available at the same time about the same firm but with different strike prices and different expiration dates. The incentives facing traders of these different contracts

[2] This argument applies in similar force for long versus short positions at the stock level. However, as an empirical matter, stock positions are dominated by long holders since the amount of short selling is small relative to outstanding shares. Note that similar to a firm's bond versus equity holders (Izhakian et al., 2022), call versus put option buyers (and sellers) may face different levels of ambiguity since they face different partitions of the state space.

may be substantially different. Following Muravyev and Ni (2020), we examine heterogeneity in the moneyness and the maturity of options contracts. Consistent with underlying theoretical mechanisms, ambiguity matters most for trading when options are difficult to value. That is, the negative effects of ambiguity on open interest and trading are driven primarily by out of the money options that are more difficult to value. The effects are also more concentrated in the options that expire in the nearer term (within 3 months). We either see the opposite pattern or no consistent pattern with risk, which contrasts with our findings on ambiguity.

Next, we turn to understanding the market implications of a reduction in participation and trading in options markets. First, we investigate how ambiguity moderates the stock price informativeness of options trading. A well-established result in the literature is that options trading, captured by the "put call ratio," is informative of future stock returns (Pan and Poteshman, 2006). We replicate this finding within our sample. Then, in a specification that interacts ambiguity with the put call ratio, we find that a standard deviation increase in ambiguity reduces the stock price informativeness of options trading by roughly 11% of the baseline effect. This return implication is much stronger than the main effect of ambiguity on stock pricing; thus, our evidence reflects an important reduction in the informativeness of options trading.

Finally, we investigate whether ambiguity relates to options returns. Specifically, we relate both ambiguity and risk to delta-hedged cumulative returns over a five-day horizon. Consistent with a classic options pricing perspective, we find a strong positive relation between risk and delta-hedged returns. In contrast, we find that ambiguity relates *negatively* to delta-hedged returns, and our estimate carries a magnitude of 20% to 50% of the economic magnitude of the estimated risk coefficient. These findings are consistent with options being less desirable, suggesting that ambiguity may play a quantitatively important role in options pricing.

Our daily measure of ambiguity is axiomatically rooted and is outcome independent.[3] As such, the measure is theoretically risk independent (Izhakian, 2017, 2020). While other proxies suggested in the literature (e.g., disagreement among analysts' forecasts, VIX, volatility-of-mean, volatility-of-volatility, skewness, and kurtosis) capture various dimensions of uncertainty, they are outcome dependent and therefore risk dependent. Indeed, we find that the correlation between the aforementioned measures and risk is highly positive, whereas the correlation of our ambiguity measure and risk is negative. For example, the correlation between risk and the volatility-of-mean

[3] The ambiguity measure applies exclusively to the probabilities of events, independently of the outcomes associated with these events. Since the measure is outcome independent, the degree of ambiguity does not change if the outcomes associated with events change while the induced partition of the state space into events remains unchanged.

is 0.71, and the correlation between risk and the volatility-of-volatility is 0.57. Moreover, in a set of robustness exercises, we observe that all of the findings regarding $AMBG$ and options trading hold when holding constant the existing proxies in the literature.

We make several contributions to the literature. First, we provide evidence that greater ambiguity dampens options trading intensity at the firm-day level. Most prior work on ambiguity and trading either uses survey data or employs market-level proxies for ambiguity.[4] In this respect, the closest existing research to this paper is Ben-Rephael et al. (2022), which shows that firm-day ambiguity relates negatively to trading in the stock market, and dampens the relation between disagreement and trading. This paper makes a distinct contribution by focusing on how ambiguity in the trading environment affects relatively sophisticated traders who trade in options markets.[5] Moreover, the fact that options are in zero net supply allows us to measure asset participation in a clean way. Besides trading intensity, we show that buyers and sellers actively reduce their positions.

Next, in studying how the trading decisions of options traders depend on ambiguity and risk, we contribute to the literature on what shapes the trading decisions of sophisticated investors. This literature has focused on the informed trades by myriad market participants, such as activists (Collin-Dufresne and Fos, 2015), insiders (Cohen et al., 2012; Augustin et al., 2019), short-sellers (Boehmer et al., 2008; Engelberg et al., 2012) and even options traders (Chakravarty et al., 2004). It is important to understand what drives sophisticated investors to trade because these investors play an outsized role in determining market outcomes (Koijen et al., 2020). At the same time, a broadly held view about sophisticated investors is that they are more immune to non-classical frictions the afflict retail traders. Indeed, much of this research shows that sophisticated investors react to the market conditions (e.g., liquidity and valuation effects) created by other, more behavioral investors (Cookson et al., 2022; Eaton et al., 2021), or that they act in a hyper-informed way with respect to the timing of news (Rogers et al., 2017), and are skilled information processors (Engelberg et al., 2012; Huang et al., 2020). In contrast to this commonly held view, our findings show that even informed and sophisticated options traders respond to ambiguity in the trading environment, and that this behavior matters for the informativeness of options trading and options pricing.

Our paper also contributes to the options literature in at least two aspects. First, we provide

[4] For example, a common proxy for market-level ambiguity is disagreement of analyst forecasts, which has been used to study equity fund flows (Antoniou et al., 2015), aggregate expected return (Anderson et al., 2009), and the term premium (Ulrich, 2013)

[5] The ambiguity measure is drawn from high-frequency trades and quotes in the TAQ database, which is derived from stock market transactions. By studying the separate options market, this paper's findings cannot be driven by omitted microstructure characteristics.

evidence on the link between ambiguity and options pricing. The vast majority of the literature on options has focused on the pricing of volatility (e.g., Bandi et al., 2008; Feunou and Okou, 2019). We show that ambiguity is an important component of options pricing, and thus, it should be taken into account. It operates in an opposite way to the effect of risk and is economically significant. Second, there is a growing interest in the effect of investment horizon (e.g., Dew-Becker and Giglio, 2016; Bandi et al., 2021; Van Binsbergen et al., 2019) and how difficult are securities to be valued (e.g., Kumar, 2009; Baker and Wurgler, 2006; Stambaugh et al., 2015) on trading behavior and pricing. Our findings on options trading show a clear role for maturity and moneyness in shaping options trader incentives. In showing the importance of these aspects of options markets, our findings add to the recent empirical evidence on horizon investments and horizon pricing. We also add to the evidence on hard-to-value securities, which are at the heart of the mispricing literature (van Binsbergen et al., 2021). We show that investors tend to close positions of hard-to-value options earlier in the presence of ambiguity.

Finally, we shed empirical light on the economic effect of ambiguity rather than aversion to it. In this respect, much of the empirical literature focuses on investors' *aversion* to ambiguity, based mostly on experiments. Typically, individuals exhibit aversion to ambiguity, preferring alternatives with clearer probabilities over the ones involving ambiguous probabilities (Ellsberg, 1961). Aversion to ambiguity has been shown to affect human decisions (Halevy, 2007; Crockett et al., 2019) and to be economically relevant, both in experimental market settings (Bossaerts et al., 2010; Ahn et al., 2014) and among business owners and managers (Chesson and Viscusi, 2003). A few studies that use trading data to capture ambiguity aversion are Williams (2014); Thimmea and Völkertb (2014); Li et al. (2016). Relating to work that focuses on ambiguity aversion, we provide direct evidence on the effect of firm level ambiguity and focus on ambiguity itself, distinct from ambiguity aversion.

1 Motivation

In this section, we provide theoretical motivation for our empirical tests, and discuss in greater detail the expected effect of ambiguity on stock options.

1.1 Ambiguity and trading behavior

A common misconception is that ambiguity and risk bear the same implications. However, ambiguity and risk are conceptually different, and might have different implications. To illustrate, consider a decision whose payoff is determined by a flip of an unbalanced coin, for which the investor does not know the odds of heads or tails. The payoff is \$100 in the case of heads, and \$0 in the case of tails. Suppose that prior to the coin being flipped, the payoff in the case of heads is suddenly changed to \$200. Since no new information about probabilities has been obtained, the investor has no reason to change the assessed probabilities or the perceived degree of ambiguity. Therefore, ambiguity is *outcome independent* up to a state space partition, since it applies exclusively to probabilities. However, the risk does increase in this example, since it is *outcome dependent*.

The literature on decision making under ambiguity has proposed different models, which are "seemingly different [...] rarely related to one another, and often expressed in drastically different formal languages" (Epstein and Schneider, 2010). However, based upon these models, the literature has derived a few complimentary theoretical predictions regarding decision makers' trading behavior in response to ambiguity.

The first prediction is that of <u>limited participation</u> − that is, *when ambiguity associated with a stock increases, the marginal investors reduce their holdings in that stock.* The idea that, for high ambiguity, investors limit their market participation or do not participate at all is supported by several studies. For example, Dow and Werlang (1992) show that for high enough ambiguity or aversion to ambiguity, investors would not participate in the market to the extent that there will be no trade. Cao et al. (2005) show that, when ambiguity dispersion is sufficiently large, investors who face high ambiguity choose not to participate in the stock market. Epstein and Schneider (2007) stress that "an increase in confidence—captured in our model by a posterior set that shrinks over time—induces a quantitatively significant trend towards stock market participation and investment." Easley and O'Hara (2009) attribute limited market participation to aversion to ambiguity. Using similar settings, Ui (2011) shows that, in a rational expectations equilibrium with high enough ambiguity or low enough risk, investors limit their market participation. Finally, using the volatility of aggregate volatility as a measure of ambiguity about market volatility, Kostopoulos et al. (2021) find that ambiguity averse investors reduce their stock market exposure when ambiguity increases.

The second prediction is that of <u>inertia</u> − that is, *when ambiguity associated with a security increases, the marginal investors become more reluctant to rebalance their holding positions and, therefore, adjust their holdings more slowly.* In an extreme case, investors even "freeze up" their trading activity, avoiding rebalancing their holdings. The idea that ambiguity causes investors to adjust their holding more slowly, perhaps for information acquisition, is supported by several studies. For example, Simonsen and Werlang (1991) introduce the concept of portfolio inertia due to ambiguity, and Epstein and Wang (1994) extend it into a more general form. Epstein and Schneider (2010) characterize the conditions for portfolio inertia. Illeditsch (2011) shows that investors' desire to hedge ambiguity leads to portfolio inertia, especially when facing surprising news. Further, Illeditsch et al. (2021) show that risk and ambiguity aversion may also lead to information inertia, consistent with low trading by households.

These two core predictions suggest that ambiguity, and aversion to it, have a direct effect on investors' trading behavior. Other theoretical work includes, Guidolin and Rinaldi (2010) who show that, for sufficiently high ambiguity, a large portion of traders withdraw from trading and market breakdowns. De Castro and Chateauneuf (2011) show that a greater aversion to ambiguity implies less trading. Easley et al. (2013) investigate the way ambiguity regarding hedge fund investment strategies affects asset prices through trading and liquidity demand.[6]

1.2 Ambiguity and options markets

The derivative market provides a natural laboratory for examining the effect of ambiguity on trading behavior. It provides a direct way to test the aforementioned theoretical predictions empirically. Furthermore, derivative securities allows the refinement of the predictions above regarding the implications of ambiguity for different cases.

Most models of decision-making under ambiguity (e.g., Schmeidler, 1989; Gilboa and Schmeidler, 1989; Bewley, 2002) assert that ambiguity-averse investors act *as if* they overweight the probabilities of bad events (events with negative payoff) and underweight the probabilities of good events (events with positive payoffs). In the perspective of option buyers out-of-the-money is a bad event, and in-the-money is a good event. In the perspective of option writers out-of-the-money is a good event, and in-the-money is a bad event. However, for both option buyers and writers, a higher ambiguity reduces the perceived expected payoff of the option (Augustin and Izhakian, 2020), which motivates both to reduce (or close) their position in the option. In contrast, when risk rises, both buyers and writers are motivated to increase (or open) positions. Buyer may be seeking to increase their hedging or, alternatively, motivated by better speculative opportunities. Writers are motivated by the higher demand and the higher premium. Since options are assets in zero-net supply, these predictions can be directly tested in the options market using options' open interest.

When ambiguity rises, trading volume in option would also decrease, as both buyers and writers decrease (or close) their positions, and less contracts are available for trade. In addition, due to

[6] A further discussion of the implications of ambiguity for trading behavior is provided in recent surveys (e.g., Epstein and Schneider, 2010; Guidolin and Rinaldi, 2013).

(portfolio and information) inertia, trading would slow down, since writers and buyers would be waiting for additional information. Concerning pricing, since the perceived expected payoff for both writers and buyer declines when ambiguity rises, writers would require a higher premium, whereas the buyers would be willing to pay a lower price. Therefore, liquidity would decline and bid-ask spread would increase. However, in the short run a counter effect might accrue, since both writers and buyers may desire to close position quickly. In this respect, other considerations may play a role in options trading behaviour. For example, option writers may be forced to close positions quickly, due to margin constraints.

Besides margin constraints, the option market introduce other aspect that may affect the relation between ambiguity trading behavior. It is well documented that out-of-the-money options are not as strongly related to their underlying assets as in-the-money options, and are therefore more complex to evaluate. For this reason, one would expect out-of-the-money options to be more sensitive to ambiguity and also to risk. Similar to the volatility (risk) process, the ambiguity—the volatility of probabilities—process is a mean-reverting process. Therefore, one would expect short maturity options to be more sensitive to ambiguity than long maturity options. Finally, the perspective of option writers and buyers regarding event classification as good or bad may depend upon their other holdings. For example, in the perspective of naked put option buyers (for speculative motives), in-the-money is a good event. In contrast, in the perspective of protective put option buyers (for hedging motives), in-the-money is a bad event. Therefore, the effect of ambiguity on trading behavior may be different, conditional upon the dominate group.

2 The data

The primary data sources for our analysis are: Intraday Trade and Quote (TAQ) data for the estimation of the daily firm-specific degree of ambiguity, risk, other uncertainty factors (including volatility-of-mean, volatility-of-volatility, skewness and kurtosis) and liquidity; OptionMetrics data for options' trading volume, open interest and liquidity measures; Center for Research in Security Prices (CRSP) data for the estimation of trading volume, number of shares outstanding, and stock prices; and I/B/E/S (IBES) data for analysts' coverage.

In this paper, we focus on exploring the effect of ambiguity on options' trading, pricing, and liquidity. Since options expected value is determined by the ambiguity and risk of the underlying asset, we measure the ambiguity, risk, and other dimension of uncertainty at the stock level.

2.1 Estimating ambiguity

To measure ambiguity, we follow recent literature's (Izhakian and Yermack, 2017; Augustin and Izhakian, 2020; Izhakian et al., 2021) implementation of the expected utility with uncertain probabilities (EUUP, Izhakian, 2017) framework. The primary motivation for using this framework is that it naturally delivers a risk-independent measure of ambiguity, denoted by $\mho^2$.[7] In particular, the degree of ambiguity can be measured by the volatility of uncertain *probabilities*, just as the degree of risk can be measured by the volatility of uncertain *outcomes*. Formally, the measure of ambiguity is defined as:

$$\mho^2 [X] \equiv \int \mathrm{E} [\varphi (x)] \operatorname{Var} [\varphi (x)] \, dx, \tag{1}$$

where $\varphi(\cdot)$ is an uncertain probability density function, and the expectation $\mathrm{E}[\cdot]$ and the variance $\operatorname{Var}[\cdot]$ are taken using the second-order probability measure ξ (i.e., probabilities of probability distributions) on a set $\mathcal{P}$ of probability measures (Izhakian, 2020). The measure of ambiguity defined in Equation (1) is distinct from aversion to ambiguity. The former is a matter of beliefs (or information) and measured from data, while the latter is a matter of subjective attitudes and endogenously determined by the empirical estimations.

To estimate the measure of ambiguity in Equation (1), we use intraday stock data from the TAQ database. We compute the degree of ambiguity for each stock each day. To this end, we elicit a set of priors for each stock each day. We assume that the intraday equity return distribution for each time interval during the day in a given day represents a single prior (probability distribution) in the set of priors and the number of priors in the set is assumed to depend on the number of time intrevals in the day. Each prior in the set is elicited from thirty-second observed intraday returns on the firm's equity, over a time interval of 1170 seconds during the trading hours.[8] Thus, a set of priors consists of 20 realized distributions, at most, over a day. By the principle of insufficient reason (Bernoulli, 1713; Laplace, 1814), each distribution is assigned an equal weight. The rest of the estimation of Equation (1) follows the methodology in Izhakian and Yermack (2017), Augustin and Izhakian (2020), and Izhakian et al. (2021), which for completeness is detailed in Appendix A. We denote the daily estimation of $\mho^2$ by $AMBG$.

[7] In the EUUP framework, a decision-maker possesses a set of priors, equipped with second-order beliefs (i.e., probabilities of probability distributions). An ambiguity-averse decision maker, in this framework, does not compound these probabilities linearly due to her aversion to ambiguity.

[8] Our findings are robust to the use of different time intervals, implying a different number of distributions per day.

2.2 Estimating risk and other moments

In our analysis, we control for risk. For consistency, we measure the daily risk using the same thirty-second returns that are used to measure the degree of ambiguity. For each stock on each time interval, we compute the variance of thirty-second intraday returns. We then measure the firm's daily degree of risk as the mean of these values over the day, normalized to daily terms.[9] We denote the daily estimation of risk by *RISK*. Note that the same variances of returns, estimated over the intraday time intervals, are used in our ambiguity and risk measures.

We estimate the other uncertainty measure similarly. In particular, we measure the volatility-of-mean (*VOM*) as the variance of the time-interval average return over the day, and the volatility-of-volatility (*VOV*) as the variance of the time-interval variance over the day. In addition, we use the thirty-second intraday returns to estimate the skewness (*SKEW*) and kurtosis (*KURT*) for each stock in each day, similarly to *RISK*.

2.3 Options trading and liquidity measures

Our main analysis focuses on the daily effect of ambiguity on trading behavior (market participation and liquidity). To this end, we use the option market as a laboratory, as it offers a cleaner setting to study such behavior (e.g., stocks are held in positive supply, and an aggregate exit from the market is not feasible). We employ several measures of option trading and liquidity extracted from OptionMetrics data. To reduce noise due to option contract expiration or unusual maturities, we only consider call and put options with maturities of 7 to 365 calendar days. To reduce noise due to extremely illiquid options, we apply the filters in Muravyev (2016), Christoffersen et al. (2018), and Muravyev and Ni (2020). In particular, we keep option contrasts with absolute delta between 0.1 to 0.9; positive open interest; and a valid bid-ask spread information. We drop contracts with bid-ask spread to midpoint ratio greater than 70%; bid-ask spread greater than \$3; and midpoints lower than \$0.10 cents.

Our first measure of market participation is based on the call and put options open interest (*COI* and *POI*, respectively), calculated as the end of the day open interest of call or put options written on the firm equity, divided by the number of its shares outstanding. Open interest allows us to directly explore whether investors reduce their options positions and limit their market participation.[10] Our second measure of market participation is based on the call and put options daily

[9] For robustness, we also apply the Scholes and Williams (1977) correction for non-synchronous trading (e.g., French et al., 1987). The findings are essentially the same.

[10] *COI* and *POI* are lagged by one day in OptionMetrics since November 28$^{\text{th}}$, 2000; therefore, we use OptionMetrics reported values from the next trading day.

volume (*CVOL* and *PVOL*, respectively), calculated as the total daily trading volume of call or put options written on the firm equity, divided by the number of its shares outstanding. Option volume allows us to explore how quickly investors rebalance their option positions. To measure option liquidity, we use the call and put options' bid-ask spread (*CBAS* and *PBAS*, respectively), based on the end of day bid and ask quotes, divided by the bid-ask spread midpoint.

We control for several additional variables, commonly used in the literature, including the natural logarithm of firm size (*LnSize*), the natural logarithm of firm book-to-market ratio (*LnBM*), institutional holdings (*InstHold*), daily stock return (*RET*), cumulative 21-day returns (*CumRet*), the natural logarithm of one plus the number of analysts covering the firm (*LnNumEst*), and the natural logarithm of one over the stock average price ($\ln \frac{1}{AvePrc}$).

In addition, we also report statistics and correlations for the stock (the underlying asset) trading volume (*SVOL*), measured by the daily share trading volume divided by the number of shares outstanding. We obtain trading volumes and the number of shares outstanding from CRSP daily data. Finally, we consider the relation between *AMBG*, stock return predictability, and option pricing. Table B.1 details all the variables employed in our analysis.

2.4 Summary statistics

Our main sample consists of 6,766,488 day-firm observations from January 2002 to December 2018 (4,253 trading days) of 4,757 unique firms. It includes all common stocks with Share Code 10 and 11 and a daily price greater than or equal to \$5 (Amihud, 2002). Estimating our main variable of interest, *AMBG*, for every stock and day, requires a minimal number of intraday observations, as detailed in Appendix A. Therefore, our sample starts in January 2002.[11]

Table 1 reports the summary statistics of the pooled sample. Panel A reports statistics for the stock variables. The average (median) firm size is $8,408.14$ ($1,899.96$) million dollars, and the average (median) daily turnover (*SVOL*) is 1.193% (0.805%) of the outstanding shares.

[Table 1]

Panel B reports statistics for the option variables. The average (median) number of call and put options is 15.30 (9.00) and 15.55 (9.00), respectively. The call and put options' average (median) open interest is 0.794% (0.29%) and 0.656% (0.194%) of the outstanding shares, respectively. The average (median) daily trading volume of call and put options is 0.05% (0.005%) and 0.036%

[11] For the period prior to 2002, there is only a very small number of firms that have the sufficient information required to estimate the daily ambiguity measure.

(0.002%) of the outstanding shares, respectively. The trading volume and open interest of call options is higher than that of put options, indicating that call options are more activity traded relative to put options, perhaps due to speculative motives. Finally, the call and put options' average (median) percentage bid-ask spread is 14.05% (11.28%) and 13.02% (10.26%) of the spread midpoint.

Table 2 reports the cross correlations. Panel A reports the univariate correlations between *AMBG*, *RISK*, and the main variables analyzed in the paper. The correlation between *AMBG* and *RISK* is -0.28, implying that, on average, ambiguity is lower on days with high volatility. Note that, as detailed in Appendix A, to estimate ambiguity, we assume that returns are normally distributed. In this class of continuous parametric probability distributions, a change in the parameter of the distribution σ modifies the partition of the state space (Papoulis and Pillai, 2002); thereby, changes the degree of ambiguity. Clearly, a change in σ changes risk.[12] To account for this relation, in all our regression tests, alongside *AMBG*, we control for *RISK* to ensure that our findings are not driven by the correlation between these two uncertainty measures.

[Table 2]

Panel A of Table 2 reveals that *AMBG* is negatively correlated with option trading volume and open interest. *AMBG* is also negatively correlated with stock (the underlying asset) turnover (*SVOL*). Overall, the correlation matrix indicates that an increase in ambiguity is contemporaneously associated with a lower trading activity for both options and the underlying asset, whereas an increase in risk is contemporaneously associated with a higher trading activity.

A few earlier studies use higher distribution moments as proxies for uncertainty. Panel B (Panel C) of Table 2 reports the univariate (multivariate) correlation between *AMBG* and these proxies, providing important insights. Panel B shows that *AMBG* is negatively correlated with *VOM* and *VOV*, with a correlation of -0.18 and -0.08, respectively. At a first glance, one might find these findings surprising, since the variation in the underlying distributions should be positively correlated with the variation in mean and precision of the distribution. However, the strong positive correlation between *RISK* and *VOM* and *VOV* (0.71 and 0.56, respectively) suggests that the relation between *AMBG* and these two proxies is dominated by the latent variable *RISK*. Note that *VOM* and *VOV* are strongly related to *RISK*, since as *RISK* they are outcome dependent.

[12]To see the intuition for the negative relation between ambiguity and risk in this case, suppose that σ increases to infinity. In that case, risk becomes infinite and the degree of ambiguity tends to zero, since all the normal distributions in the set of possible distributions converge to a uniform distribution, implying no uncertainty about the probabilities (i.e., no ambiguity is present).

A subsequent analysis in Columns 2-4 of Panel C reveals that once *RISK* is controlled for, the relation between *AMBG* and *VOM* and *VOV*, becomes positive as expected. Column 5 indicates that kurtosis is also positively correlated with *AMBG*, while skewness is negatively correlated with *AMBG*. We control for all these measures in our analysis. Further, the analysis below shows that *VOM* and *VOV* deliver similar findings to those of *RISK*.

3 Participation and trading in options markets

In this section, we seek to understand the empirical relation between ambiguity and participation in options markets, as well as the relation between ambiguity and trading in options markets (conditional on participation). We expect ambiguity to discourage both participation and trading in options markets, but for different reasons. On the extensive margin, we expect that ambiguity's tendency to shake investor confidence, thereby to decrease participation in options markets (e.g., Easley and O'Hara, 2009). However, even conditional on holding an option contract, ambiguity tends economic agents toward inertia, which would tend to decrease trading volume (Epstein and Schneider, 2010; Illeditsch, 2011).

To evaluate the participation margin, we estimate how ambiguity (*AMBG*) relates to open interest on options, while treating calls and puts separately. If stock options open interest increases for a firm, this is a clear indication of greater participation. Unlike stocks, options are assets in zero net supply. Therefore, greater open interest implies more participation. To evaluate the intensive margin effect on trading, we examine options trading volume directly. As an empirical matter, trading volume reflects mostly trades among active participants (not changes in participation) because trading volume vastly exceeds changes to option open interest on any given day. Thus, variation in trading volume is mostly driven by decisions to buy and sell by traders who, on net, have already decided to participate in the options market.

3.1 Option open interest

We investigate how *AMBG* relates to participation in the options market by relating it to open interest in a firm's option's contracts at the firm-day level in the following specification:

$$OpenInterest_{j,t+i} = \alpha + \beta \cdot AMBG_{j,t} + \gamma \cdot RISK_{j,t} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{j,t}, \quad (2)$$

where the dependent variable, *Open Interest*$_{j,t+i}$, is the open interest in options contracts relating to firm j held on date $t+i$, where i is the number of forward days. We estimate this specification separately for each $i = 0, \ldots, 5$ to illustrate the short run dynamics of open interest. We also estimate the specification separately for call options and for put options to highlight asymmetries driven by optimism or pessimism about the underlying stock.

The main coefficient of interest is β, which is the coefficient estimate on *AMBG*. To distinguish *AMBG* from underlying riskiness of the stock, persistence of past options participation decisions and other explanations, we include *RISK* and other notable controls in the specification. The vector of controls (*CONTROLS*) includes log firm size (*LnSize*), log book-to-market ratio (*LnBM*), cumulative stock returns (*CumRet*), log of one plus the number of analysts' estimates (*LnNumEst*), institutional holdings (*InstHold*), and log one over average price ($\ln \frac{1}{AvePrc}$), as well as the 21-trading-day trailing average of the dependent variable (Open-Interest), *AMBG* and *RISK*, which account for their persistence. To reduce the effect of outlier observations, all raw variables are trimmed at the top and bottom 0.1% of their sample distribution. We also include firm and date fixed effects across all specifications, and we double cluster standard errors by firm and date to account for persistence over time and common shocks affecting many firms at the same time.

By controlling for *RISK*, we also provide a natural benchmark comparison for the coefficient on *AMBG* to be estimated within the same regression. Prior work has found that *RISK* is strongly and positively related to trading in options markets. Thus, this makes *RISK* a natural control variable to include, while also serving as a useful quantitative benchmark.

[Table 3]

Table 3 reports the findings from estimating Equation (2). Panel A reports findings for call option open interest for trading days t to $t + 5$, and Panel B reports the analogous findings for put options. Across all specifications, *AMBG* exhibits a negative and statistically significant relation to option open interest. For call options, a standard deviation increase in ambiguity on date t is associated with a reduction in call option open interest of 0.012 standard deviations. As we consider a longer time lag, the magnitude on the *AMBG* coefficient estimate increases to -0.014. In contrast, the coefficient on *RISK* is much smaller and statistically and economically insignificant by day t+5. Turning to the relation to put option open interest, we observe a similarly strong and significant negative relation between *AMBG* and put option open interest that, like the coefficient estimates in Columns 1 through 5, increases slightly with the time horizon. The coefficient estimates for *RISK*, exhibit similar economic magnitudes to those of *AMBG* and are in the opposite sign.

Our estimated coefficients on *AMBG* reveal a decrease in options market participation that is similar in magnitude for call options and put options. This decrease in participation in options markets is well predicted by theory (Cao et al., 2005; Easley and O'Hara, 2009), and it contrasts with the pattern of coefficient estimates for $RISK$.[13] By contrast to our findings on relation between $AMBG$ and open interest, $RISK$ seems to motivate participation, especially in put options.

As a complement to our main analysis, we estimate a vector autoregression (VAR) model to more fully identify the dynamics of the relations of ambiguity and risk to open interest (again, separately for call options and put options). The VAR we consider includes five lags for ambiguity, risk, and open interest, governed by the following equations:

$$
\begin{aligned}
OI_{j,t} &= \alpha_1 + \sum_{i=1}^{5} \beta_{1,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{1,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{1,i} \cdot OI_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{1,j,t}; \\
AMBG_{j,t} &= \alpha_2 + \sum_{i=1}^{5} \beta_{2,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{2,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{2,i} \cdot OI_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{2,j,t}; \\
RISK_{j,t} &= \alpha_3 + \sum_{i=1}^{5} \beta_{3,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{3,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{3,i} \cdot OI_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{3,j,t},
\end{aligned}
$$

where $CONTROLS$ is the same vector of control variables we include in our regression specifications above, measured at date t.

[Figure 1]

The VAR specification allows for nonlinear dynamics and feedback between ambiguity and risk. Despite this different in richness, the VAR delivers similar qualitative findings to our main specifications. Specifically, Panels A and B of Figure 1 present the impulse response function for a standard deviation increase in ambiguity at date t. Consistent with our regression evidence, higher ambiguity is negatively related to participation in options markets, and this effect accumulates over time. Panels C and D present the impulse response functions for $RISK$, showing that risk is positively related to both put and call open interest with a similar accumulation of the effect as the time horizon lengthens.

Overall, we find robust evidence that ambiguity is negatively related to options markets open interest. The economic magnitude of this reduction in option market open interest is comparable to the analogous effect of risk; it is also opposite in sign. This latter finding highlights a sharp economic distinction between ambiguity and risk in options markets. Unlike risk, which encourages options market participation, ambiguity discourages participation in options markets.

[13] Our findings are also in line with prior study by Izhakian and Yermack (2017), who show that higher expected ambiguity motivates the early exercise of options by executives.

3.2 Options trading volume

Having established that $AMBG$ exhibits a significant and negative relation to participation in options markets, we now turn our attention to understanding the intensive margin decision to trade options. Since trading volume in options markets vastly exceeds changes to open interest, trading volume in calls and puts mostly reflects these intensive margin decisions.

Thus, we estimate how options trading volume relates to $AMBG$ and $RISK$ by estimating a specification like the one we used for open interest, but replacing the dependent variable with options trading volume:

$$OptionVolume_{j,t+i} = \alpha + \beta \cdot AMBG_{j,t} + \gamma \cdot RISK_{j,t} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{j,t}, \qquad (3)$$

where the dependent variable, $Option\ Volume_{j,t+i}$. is the trading volume on call options (or put options, separately) on day $t+i$ for options linked to firm j. As in the tests with open interest as the dependent variable, we estimate the relation between $AMBG$ and trading volume at date $t+i$ until five trading days later (trading day $t+5$). In addition, we consider how $RISK$ relates to options trading volume as a benchmark for the estimated economic magnitudes.

[Table 4]

Table 4 presents the findings from estimating this specification for call trading volume (Panel A) and for put trading volume (Panel B). A standard deviation increase in $AMBG$ is associated with a 0.04 standard deviation reduction in call trading volume contemporaneously. The estimated magnitude reduces as we consider longer time lags between $AMBG$ and call trading volume. At a five-day lag (day t+5), a standard deviation increase in $AMBG$ is associated with only a 0.016 standard deviation decrease in call trading volume. These estimated magnitudes are opposite in sign from the magnitude on the within-day volatility term, $RISK$, and roughly one-third its magnitude: a standard deviation increase in $RISK$ is associated with 0.137 standard deviations more call trading volume. This comparison to $RISK$ highlights that, although equity market volatility stimulates trading in options markets (positive coefficient estimate on $RISK$), $AMBG$ discourages trading. This negative estimate parallels our analogous specification for open interest. However, trading volume mostly reflects trading decisions that are conditional on participation in the options market. In this way, the estimated reduction in trading volume likely reflects a reluctance of existing options traders to trade, not the decision to participate in options markets at all.

Panel B of Table 4 presents a similar pattern for put trading volume for both the coefficient estimates on *AMBG* and *RISK*. Among other things, the similarity in the findings for calls and puts rules out any alternative explanation that predicts a directional movement in options markets.

As a complement to this main analysis, we present evidence from a vector autoregression (VAR) that relates *AMBG* and *RISK* to trading volume of puts (and separately calls). The VAR we estimate follows the same structure as the one we employed in the analysis of options open interest with five lags of *AMBG*, *RISK*, and trading volume in the system of equations.

[Figure 2]

In Figure 2, the impulse response confirms the intuition from the main regression analysis. Notably, Panels A and B illustrate that an increase in ambiguity generates a reduction in both put and call option trading volume that converges relatively quickly to a steady state. By contrast, an increase in risk leads to an increase in both call and put options trading volume, as is illustrated in the impulse responses in Panels C and D.

Overall, the findings on trading volume suggest that ambiguity reduces trading volume in options markets, above and beyond the market participation effects on options market open interest. These findings are consistent with models of ambiguity that predict that ambiguity leads to greater inertia in risky and ambiguous decision making (e.g., Illeditsch, 2011; Illeditsch et al., 2021).

3.3 Heterogeneity by option characteristics

We now exploit the richness of the option contracts to provide a series of more refined tests. Namely, at any given date, there are many different options available that are linked to the same underlying firm. As these options differ on their expiration date and strike price, the incentives facing options traders can be quite different for different options relating to the same underlying security. The literature on options has identified several characteristics that capture the incentives of options traders − most notably, the moneyness of the option (or its *delta*) and the maturity of the option (measured by the time to expiration). We consider heterogeneity in options trading activity by each of these characteristics.

To operationalize the heterogeneity tests in this section, we note that the full underlying data set is at the option contract $\times$ firm $\times$ date level, and the tests in the previous section collapsed this data set to the firm $\times$ date level. We collapse to the group $\times$ firm $\times$ date level for groups of options contracts that share the same moneyness characteristics or maturity characteristics. For each characteristic, we split the sample into three groups. We estimate specifications of the form:

$$\begin{aligned} DepVariable_{j,t+i,g} \quad = \quad & \alpha + \sum_{g=2}^{3} \alpha_g GroupDum_{j,t,g} + \sum_{g=1}^{3} \beta_g \cdot AMBG_{j,t} \times GroupDum_{j,t,g} + \\ & \sum_{g=1}^{3} \gamma_g \cdot RISK_{j,t} \times GroupDum_{j,t,g} + \delta \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{j,t}, \end{aligned} \tag{4}$$

where $DepVariable$ is either $OpenInterest$ or $OptionVolume$, aggregated to the stock-day-group level. The coefficients of interest are the β_g coefficient estimates on the $AMBG\times$ $GroupDum$ terms, which captures how trading activity of options in group g relates to ambiguity at the firm-day level. The degree to which these coefficient estimates are different captures how important the grouping (by moneyness or maturity) is for explaining the heterogeneity in the relation of $AMBG$ to option trading activity. As in the main specifications, we include firm and date fixed effects, and the full set of $CONTROLS$ that we include in the main specifications. The standard errors are clustered by firm and date, which in this specification additionally accounts for cross-correlations within-firm, across options, as well as the usual accounting for serial correlation and common shocks.[14]

3.3.1 Moneyness

An important characteristic of an option is the option's *delta* or Δ, which describes the sensitivity of the option price to the underlying stock price. The Δ is signed, with put options taking on negative values and call options taking on positive values. To place put options and call options on the same footing, we consider delta's absolute value $|\Delta|$ for grouping options by their sensitivity to the underlying stock price. We refer to this sensitivity to the underlying price as *moneyness*, following Muravyev and Ni (2020), and we group options into three groups: "out of the money" ($0.1 \leq |\Delta| \leq 0.4$), "at the money" ($0.4 < |\Delta| < 0.6$), and "in the money" ($0.6 \leq |\Delta| \leq 0.9$).

We present the full estimates of Equation (4) for date t through date $t+5$, separately for call options and put options in Table B.3. The findings of the open interest are reported in Panel A of Table B.3. As in the main tests, the coefficient estimates on $AMBG$ and $RISK$ strengthen slightly from date t to date $t+5$. To summarize the heterogeneity by moneyness, we present plots of these coefficient estimates as of date $t+5$ for each of the three grouped terms for both $AMBG$, and as an instructive benchmark, $RISK$ (both separately for calls and puts). Panel A of Figure 3 indicates that most of the negative relation between $AMBG$ and open interest is driven by out-of-

[14] An alternative strategy to this stacked specification would be to estimate the original specification in Equation (2) separately by group. Such a specification would allow the fixed effects and controls to take on different values by group. We obtain qualitatively similar findings if we estimate such a split-sample specification.

the-money options and at-the-money options ($0.1 \leq |\Delta| \leq 0.4$ and $0.4 < |\Delta| < 0.6$, respectively). In comparison to in-the-money options, these options are more difficult to value, and thus, are more sensitive to the ambiguity in the trading environment. Further, we see a similar pattern for both call and put options, which reinforces our interpretation.

[Figure 3]

By contrast, Panel B of Figure 3 shows that the positive and significant relation between *RISK* and open interest is driven by the impact of *RISK* on in-the-money options only. Apart from the directional difference in the relation to open interest, this difference in the subsample that drives the *RISK* term's relation provides further evidence on the distinction between *AMBG* and *RISK*.

Turning to our evidence on trading volume, we note that the dynamics of the results on trading are distinct because trading volume is not cumulative over the date t to $t + 5$ horizon, whereas open interest is. As in the open interest tests, the full heterogeneity results for trading volume are presented in the Panel B of Table B.3. Because the effect of *AMBG* and *RISK* on date t is the strongest, we present plots based on the date t relation to more clearly highlight heterogeneity in the moneyness of the options. Panels C and D of Figure 3 present these plots. In Panel C, we see heterogeneity in the relation of *AMBG* to open interest that is driven by the out-of-the-money options (for both calls and puts). Similar to the participation margin, as ambiguity increases, it tends to discourage trading in lower *delta* options that are more difficult to value (and generally more sensitive to changes in probabilistic assessments). By contrast, in Panel D, we see little heterogeneity in the *RISK* term, either for calls or puts, consistent with the theme that *AMBG* and *RISK* capture distinct economic phenomena related to options markets.

3.3.2 Maturity

Following Muravyev and Ni (2020), we conduct a similar analysis by splitting the option sample into whether they expire soon (< *3 months*), at an intermediate horizon (*between 3 and 6 months*), or at a long horizon (> *6 months*). Given this grouping by different option maturities, we estimate analogous specifications to our moneyness heterogeneity tests for both open interest and trading volume. The full estimates are presented in Table B.4. We summarize the heterogeneity in the estimated impact of *AMBG* and *RISK* in Figure 4. Given the cumulative nature of the open interest variable and the short-lived impacts for trading volume, the impact on open interest is considered as of date $t + 5$, and on trading volume as of date t. Panels A through D of Figure 4 present these estimates, with separate panels for *AMBG* and *RISK*.

[Figure 4]

Panels A and B of Figure 4 present the heterogeneity by maturity of the estimated relation of $AMBG$ and open interest as of date $t+5$. Consistent with the intuition that near-term expiring options are more sensitive to frictions in the trading environment, we see that most of the negative relation between $AMBG$ and option open interest is driven by the shorter maturity options (i.e., those expiring within 3 months of date t). Longer-term options do not exhibit a meaningful relation between $AMBG$ and option open interest. By contrast, the heterogeneity in the estimated coefficient of $RISK$ with respect to maturity is not meaningful, and it is not consistent across call versus put options.

Panels C and D of Figure 4 present the analogous results on heterogeneity by maturity of the estimated impact of $AMBG$ and $RISK$ on options trading volume as of date t. Similar to the findings on open interest, the negative relation between $AMBG$ and trading volume is driven mostly by a reduction in the trading of shorter maturity options. One rationale for the greater responsiveness of the shorter-term-maturity options to $AMBG$ is that the ambiguity measured today is arguably more relevant to the trading decisions regarding options with nearer-in-time expiration dates. Overall, these findings across heterogeneity on maturity support the view that the differences in responsiveness of trading activity to maturity are driven by ambiguity-induced frictions to participating in the options market.

4 Return predictability

Thus far, we have focused on the relation between $AMBG$, market participation, and trading. In this section, we examine the relation between $AMBG$ and two aspects of returns: stock return predictability and option pricing. First, we extend existing literature showing that trading in the option market has predictive power for stock returns (e.g., Pan and Poteshman, 2006) by exploring how $AMBG$ affects the relation between options trading and stock return predictability. Second, we explore the effect of $AMBG$ on option return.

4.1 Stock return predictability

It is well established that options trading contains information about future stock prices (Pan and Poteshman, 2006). Given our findings that ambiguity dampens options market trading, a natural question is how this affects the informativeness of options trading for stock returns. Therefore, we consider how $AMBG$ interacts with the informativeness of the direction of trading in options markets. We focus on two measures to link information from the option market and stock returns.

The first measure is a variant of Pan and Poteshman (2006)'s put-call ratio. The second is the implied volatility spread by Cremers and Weinbaum (2010).

Using unique data and methodology, Pan and Poteshman (2006) construct put-call ratio from option volume initiated by buyers who open *new* positions (volume-based put-call ratio). They find that stocks with low put-call ratio outperform stocks with high put-call ratio by more than 40 basis points on the next day and more than 1% over the next week. We build on these findings using information available in the OptionMetrics data. It is not possible within OptionMetrics to distinguish the opening of new positions from the closing of old positions or market making activities that zero out. Therefore, we use changes in open interest to construct the put-call ratio. This approach reduces the noise in constructing an informative volume-based put-call ratio because open interest changes more closely reflect position initiations than trading volume changes.[15] Specifically, we calculate the put-call ratio as the aggregate open interest of put options divided by the sum of the aggregate open interest of put and call options, $PC\_RATIO = P/(C+P)$. Changes in the put-call ratio (ΔPC_RATIO) are taken as the difference between PC_RATIO on day t and PC_RATIO on day t-1.

Cremers and Weinbaum (2010) construct an implied volatility spread measure that captures the difference between call and put implied volatilities for call and put options with the same strike price and maturity. They find that stocks with relatively expensive calls outperform stocks with relatively expensive puts by 50 basis points per week. We follow their methodology and aggregate the information at the stock level using the average call and put open-interest as the weight. While they focus on weekly aggregates, we construct daily spread measures. We denote the measure as *IVS*.

To examine the relation between ambiguity, option information measures ($OPTINFO$), and return predictability, we estimate the following specification:

$$\begin{aligned} DGTWRET_{j,t+1:t+k} &= \alpha + \beta_1 \cdot AMBG_{j,t} + \beta_2 \cdot RISK_{j,t} + \beta_3 \cdot OPTINFO_{j,t} + \\ &\quad \beta_4 \cdot OPTINFO_{j,t} \times AMBG_{j,t} + \beta_5 \cdot OPTINFO_{j,t} \times RISK_{j,t} + \\ &\quad \Gamma \cdot CONTROLS_{j,t} + \theta_t + \epsilon_{j,t}, \end{aligned} \tag{5}$$

where the dependent variable $DGTWRET$ is the DGTW-adjusted cumulative stock returns of

[15] Indeed, when we repeats the analysis conducted in this subsection using volume-based put-call ratio (instead of open-interest based), we find a negative but weak relation between the volume-based put-call ratio and subsequent stock returns, which amounts to -2 basis points after 10 trading days. We report these findings in Table B.7 for reference.

firm j from day $t+1$ to $t+10$ (Daniel et al., 1997), and $OPTINFO$ is either trading day t's changes in put-call open interest ratio (ΔPC_RATIO) or trading day t's implied volatility spread (IVS). For example, in the case of ΔPC_RATIO, this specification regresses returns on ΔPC_RATIO, ambiguity ($AMBG$), risk ($RISK$), and the interactions $\Delta PC\_RATIO \times AMBG$ and $\Delta PC\_RATIO \times RISK$. We estimate specifications that consider next-day DGTW returns, and cumulative returns at five-day and ten-day horizons.

Given conventional practice, we include date fixed effects but exclude firm fixed effects from the return based analysis. Results including firm fixed effects are reported in Table B.8. We double cluster standard errors by firm and calendar date to account for serial correlation and correlation within overlapping multiperiod return windows.

Our empirical tests build up to this full specification that include all interaction terms. We start with regressing DGTW returns on $RISK$ and $AMBG$ and the option information measures. This specification provide an estimate of the benchmark relation between $RISK$, $AMBG$ and future stock returns and gives an empirical validation that Pan and Poteshman (2006) and Cremers and Weinbaum (2010) finding holds within our sample, measurement strategy and specification. We then sequentially include the interactions $\Delta PC\_RATIO \times AMBG$ and $\Delta PC\_RATIO \times RISK$. These specifications allow us to quantify the importance of $AMBG$ and $RISK$ in moderating the informativeness of options trading for stock market returns.

[Table 5]

The findings from estimating Equation (5) with ΔPC_RATIO are reported in Panel A of Table 5. To allow for a natural interpretation of the cumulative returns, we present these returns in percentage point units. However, ΔPC_RATIO, $RISK$, and $AMBG$ are all presented in standardized units. Thus, the coefficient estimates for the main effects in the table are a percentage point change in DGTW-adjusted returns for a standard deviation increase in the variable of interest.

Our base specifications (Columns 1, 4, and 7) imply that $AMBG$ exhibit weak stock market predictability. At the one-day horizon, a standard deviation in $AMBG$ is associated with an increase of only 0.5 basis points, which is economically small. The stock return predictability increases somewhat at longer holding periods. For five-day returns, a standard deviation increase in $AMBG$ is associated with returns increasing by 1.6 basis points. For ten-day returns, a standard deviation increase in $AMBG$ is associated with an increase of 2.3 basis points. Though small in magnitude, these findings can be consistent with a risk-based explanation, where $AMBG$ command a premium in the cross-section of stock returns. The results for $RISK$ across the different horizons are mixed consistent with prior evidence.

We also find a strong relation between ΔPC_RATIO and subsequent stock returns, consistent with Pan and Poteshman's (2006) findings. A standard deviation increase in ΔPC_RATIO is associated with roughly 31 to 36 basis points increase of DGTW-adjusted return over the next one to ten trading days. Despite the noise in using OptionMetrics data, we obtain an estimated magnitude that is comparable with Pan and Poteshman's (2006) estimates of 40 basis points for next day return, though smaller than their finding of 100 basis points over a similar horizon.[16] Moreover, in our specification, most of the return predictability occurs on date $t + 1$ with non-significant returns related to the put-call ratio in future periods. Panel A of Figure 5 illustrates the return patterns over time.

[Figure 5]

Next, in Columns 2, 5 and 8, we consider the interaction between $AMBG$ and ΔPC_RATIO. Consistent with $AMBG$ being an important factor for participation and trading, we find that $AMBG$ has a positive and significant interaction with ΔPC_RATIO. In particular, a standard deviation increase in $AMBG$ is associated with a reduction in the informativeness of ΔPC_RATIO for stock returns by 3.4 to 4.6 basis points for the one to ten day horizon. The effect amounts to approximately 12.8% of ΔPC_RATIO main effect. Including the interaction with $RISK$ (Columns 3, 6, and 9) slightly reduces this effect. By comparison to this interaction with $AMBG$, we find that the interaction effect of $RISK$ is only around 4.2% of ΔPC_RATIO main effect. The magnitude of the interactive effect for $AMBG$ is stronger than ambiguity's main effect; particularly, at the one-day horizon − in Column 3, the main effect of $AMBG$ is 0.5 basis points, whereas its interaction with ΔPC_RATIO is 3.4 basis points. The main effect of $AMBG$ is similar whether we include the interaction in the specification or not. Thus, this interactive effect is unlikely to reflect any direct effect of $AMBG$ on stock return predictability. Taken together, these findings suggest that ambiguity leads to a reduction in option trading informativeness for stock market returns.[17]

[16] We consider standard deviation changes in our specification, whereas Pan and Poteshman's (2006) result corresponds to a long-short quintile approach. A standard deviation change is consistent with a movement from the 16th percentile to the 84th percentile of a normal distribution. Thus, our estimated magnitudes are roughly comparable to the quintile approach.

[17] The dynamic nature of the main effect of $AMBG$ versus the interactive effect also supports this interpretation. Notably, the interactive effect is immediately seen in the one-day returns with a slightly larger magnitude by day 10. This contrasts with the main effect, which is very small at the one-day horizon but gradually emerges over the 10-day window. The immediate nature of the interactive effect more closely resembles the main effect of ΔPC_RATIO, which is linked only to trading in options markets.

Next, in Panel B of Table 5 we report the results using Cremers and Weinbaum (2010)'s measure. Columns 1, 4, and 7 confirm the positive return predictability of *IVS* in the cross-section of stock returns. Specifically, a on standard deviation increase in *IVS* is associated with 6.2 to 8.3 basis points. We use daily measures, while Cremers and Weinbaum (2010) use weekly aggregates. Multiplying the coefficient estimates by 5 provides comparable magnitudes to those reported in Cremers and Weinbaum (2010).

Columns 2, 5, and 8 further indicate that *AMBG* has a negative and significant interaction with *IVS*. In particular, a standard deviation increase in *AMBG* is associated with a reduction in the informativeness of *IVS* for stock returns by 0.7 to 2.7 basis points for the one to ten day horizon. The effect amounts to approximately 37% of *IVS* main effect. Interestingly, including the interaction with *RISK* (Columns 3, 6, and 9) attenuates this effect, where it amounts to 23%. The interaction effect of *RISK* seem more important in the case of *IVS* then ΔPC_RATIO, where the effect of *RISK* amounts to 37.7% at the ten day horizon.

Overall, Table 5 indicates that *AMBG* play an important and consistent role in shaping how information flows from the options to the stock market. In particular, an increase in *AMBG* results in lower informativeness of stock prices.

4.2 Option returns

Establishing the importance of *AMBG* for return predictability, we turn to examine how *AMBG* relates to option returns. Given the sensitivity of options to the underlying asset, we follow the convention of reporting results based on delta-hedged returns. In particular, we calculate the options' end of day prices based on the midpoint between the end of day best bid and best ask quotes ($OptionPRC_t$). The option's daily delta-hedged return is then calculated as $[(OptionPRC_t - OptionPRC_{t-1}) - \Delta_{t-1}(StockPRC_t - StockPRC_{t-1})]/OptionPRC_{t-1}$. To aggregate options at the firm level, we form value-weighted portfolios using day t-1 open interest dollar value as the weight, separately for puts versus calls. We fix day $t-1$ open interest dollar value to allow for a natural buy and hold interpretation.

To estimate the impact of *AMBG* on options returns, we estimate the following specification:

$$CumulativeReturns_{j,t:t+k} = \alpha + \beta \cdot AMBG_{j,t} + \gamma \cdot RISK_{j,t} + \Gamma \cdot CONTROLS_{j,t} + \theta_t + \epsilon_{j,t}, \quad (6)$$

where the dependent variable *Cumulative Returns*$_{j,t:t+k}$ is either the delta-hedged cumulative returns on call options (value weighted) from date t to $t+k$, or the analogous cumulative returns term for put options. To analyze dynamics in the returns, we estimate this specification separately for dates t to $t+5$. We employ the same controls as in the open interest and trading volume regressions. As in Table 5 we exclude the firm fixed effects. We also double cluster by calendar date and firm, which accounts flexibly for serial correlation (e.g., overlapping return windows).

[Table 6]

The findings from estimating Equation (6) are reported in Table 6. The results including firm fixed effects are reported in Table B.9. To allow for a natural interpretation of the cumulative returns, we present the dependent variable in percentage units, as we did for stock returns. *RISK* exhibits a positive relation to both the call and put option returns, as expected from a classic option pricing perspective (e.g., Black and Scholes, 1973). At date t, a standard deviation increase in *RISK* is associated with 31.1 (31.4) basis points increase in call (put) option return, and by the end of day t+5 *RISK* is associated with 65.2 (68) basis points increase in call (put) option return.[18]

In contrast to *RISK*, *AMBG* is *negatively* related to delta-hedged option returns with an estimated magnitude that is sizeable relative to the estimated magnitude for *RISK*. On day t, a standard deviation increase in *AMBG* is associated with 13.8 (18.5) basis points reduction in call (put) option returns. After five days *AMBG* is associated with 18.5 (36) basis points reduction in call (put) option return. Panels B and C of Figure 5 present plots of the dynamics of the delta-hedged return effects. For both *AMBG* and *RISK*, most of the return is accrued on the first few days, quickly converging to no additional effect.

Viewed at a high level, these findings on option returns provide a complementary perspective on the results on participation and trading in options markets. Our findings suggest that high ambiguity reduces options trading, while also decreasing option returns. From an economic perspective, given that options are a zero sum game, these findings jointly point to the interpretation that the option is less desirable when *AMBG* increases, which is a natural consequence of heightened ambiguity. Theoretically, though taking different approaches to model decision-making under ambiguity (e.g., Gilboa and Schmeidler, 1989; Schmeidler, 1989; Wakker and Tversky, 1993), a joint concept of these models is that, in the presence of ambiguity, ambiguity-averse investors act *as if* they overweight the probabilities of unfavorable outcomes and underweight the probabilities

[18] Notably, Cao and Han (2013) document a negative relation between risk and option returns. Importantly, they look at a monthly *RISK* measure and predict the options return over the subsequent month. Consistent with these findings in Table B.10 we report the coefficient estimates of *RISK* and *AMBG* based on their 21-day rolling averages, and recover a negative relation between *AvgRISK* and subsequent options returns.The effect is much smaller than the contemptuous effect of *RISK* on options returns.

of favorable outcomes. All else equal, such a weighting lowers the perceived expected value of the option for both buyers and writers.

5 Robustness and extensions

In this section, we present robustness and extensions to the main findings on options trading and returns.

5.1 *AMBG* and stock options bid-ask spread

First, we consider the relation on $AMBG$ to options liquidity, measured by the options' bid-ask spread. One possible mechanism that could explain the findings is that periods of high ambiguity correspond with greater illiquidity, which discourages trading in the options market. To evaluate this possibility, we estimate how the options' bid-ask spread depends on $AMBG$ and $RISK$ in a panel regression of the same structure as Equation (2), but with the bid-ask spread as the dependent variable. To this end, we use the options' end of day percentage bid-ask spread (relative to the midpoint, BAS).

[Table 7]

Table 7 reports the finding from estimating this specification. For both put and call options, we obtain a small and non-significant estimated coefficient on $AMBG$ as of date t. On subsequent days, the coefficient estimate on $AMBG$ increases, and becomes statistically significant while remaining relatively small. These findings are inconsistent with liquidity effects driving the differences in trading volume. In fact, the response of trading volume to ambiguity may, in part, be responsible for the non-significant result as of date t. As both writers and buyers of the contracts have a mutual incentive to the reduce (close) their positions as ambiguity rises, open interest reduces while liquidity remains constant. In contrast, during subsequent days $AMBG$ has a positive effect on the BAS as the spreads widen.[19] This finding is consistent with the view portrayed by our options returns results: as ambiguity rises, writers require a higher premium due to a lower perceived expected payoff, while at the same time, buyers offer a lower price for the same reason. Widening spreads is a natural consequence of these market conditions (e.g., Glosten and Milgrom, 1985).

The findings for $RISK$ contrast with our main findings on $AMBG$. For call options, $RISK$ exhibits a positive relation to the BAS on day t and the subsequent trading days, where the effect attenuates over time. For put options, we find a similar pattern, which is slightly weaker relative

[19] We confirm this finding in a set of unreported findings showing a decrease in the BAS on day t for out-of-the-money options and options with a short maturity. In contrast, we find an increase in BAS for the other options.

to the call options. The positive relation of risk to bid-ask spread (negative effect on liquidity) is also expected and consistent with prior evidence (e.g., Hameed et al., 2010).

5.2 Options trading around news days

In this section, we consider whether the options market participation and trading effects we observe in our main tests also hold around notable firm-specific news events when information comes out about the underlying security. To this end, we repeat the analysis for days t and $t+5$ around firm earnings announcement days, and unscheduled news disclosures (proxied by 8-K filing days).

[Table 8]

Panel A of Table 8 presents the findings on open interest while Panel B presents the findings on options trading volume. Interestingly, we find a consistent amplification of the *AMBG* coefficient estimate for unscheduled news (8-K disclosure dates) for both open interest and trading volume. A standard deviation increase in *AMBG*, implies a reduction in open interest of 0.017 standard deviations (for both calls and puts). This is notably stronger coefficient estimate than the estimates from the main table, which range form -0.012 to -0.015. The trading volume analysis imply a proportionate amplification of the *AMBG* coefficient estimates. For earnings announcement days, we see a weakening of the relation between *AMBG* and call option open interest, but a strengthening of the relation of *AMBG* and put option open interest.

At a high level, the findings from Table 8 imply that the negative relation between ambiguity and options trading is present on identifiable firm news days, implying that public information arrival does not render insignificant the effects of *AMBG* in options markets.

5.3 Subsample analysis by firm size and time period

In this subsection, we repeat our main analysis for subsamples by firm size and subperiods. To conduct the analysis by firm size, we classify firms into tercile subsamples by their market capitalization, and establish dummy variables accordingly. We then interact these dummy variables with *AMBG* and *RISK*, analogous to the heterogeneity specification in Equation (4).

Table B.11 in Appendix B reports the findings. Panel A of reveals an interesting difference between *AMBG* and *RISK*. In particular, the effect of *RISK* on options open interest is more significant for larger firms (3^{rd} tercile). In contrast, the effect of *AMBG* is uniformly present across all terciles. Turning to the effect of *AMBG* and *RISK* on options trading volume, Panel B reveals that the effect of both *AMBG* and *RISK* on trading volume is stronger for larger firms.

Next, we explore whether different time periods affect investors' reaction to ambiguity and risk. We divide our sample into three equal-length subperiods: 2002-2006, 2007-2012, and 2013-2018. Similar to the firm-size heterogeneity, we define dummy variables for each subperiod, and estimate a specification that interacts *AMBG* and *RISK* with these indicator variables.

Table B.12 in Appendix B reports the findings. Similar to the findings reported in Table B.11, *AMBG* presents consistent coefficient estimates across the three subperiods for both options open interest (Panel A) and options trading volume (Panel B). *RISK* also presents consistent coefficient estimates, except for call options open interest where the coefficients change sign across the subperiods.

5.4 Uncertainty factors, dispersion in analyst forecasts and market conditions

In this section, we explore the robustness of our main findings, reported in Tables 3, 4 and 6, by extending our empirical investigation in several ways. First, we explore how the *AMBG* coefficient estimates change when we exclude *RISK* or when we include *RISK* together with other uncertainty proxies. These proxies include skewness (*SKEW*), kurtosis (*KURT*), the volatility-of-mean returns (*VOM*), and the volatility-of-volatility of returns (*VOV*). Second, *VOM* and *VOV* and dispersion of analyst forecasts (*DAF*) are often used as proxies for ambiguity. Thus, we contrast *AMBG* with *VOV*, *VOM*, and *DAF* and explore their directional predictions and economic significance.[20] Third, to differentiate firm-specific shocks in *AMBG* from any market-wide shocks in risk or ambiguity, we include the changes in market volatility (ΔVIX) and changes in market ambiguity ($\Delta MktAMBG$) as additional control variables in our regression specifications. Importantly, across all the tests, our *AMBG* estimates remain intact.

We start by including all other uncertainty factors in our regressions test, alongside *AMBG* and *RISK*. Table B.13 in Appendix B reports the findings. Specifically, we report findings for open interest (Panel A), trading volume (Panel B), and cumulative delta-hedged returns (Panel C). To ease the comparison, in all the tests we include the "Base" findings from our main tables. Across all panels and specifications, the findings indicate that excluding all uncertainty proxies or including all of them does not alter our findings with respect to *AMBG*. These findings are consistent with

[20] Our measure of ambiguity $\mho^2$ is broader than *VOM* and *VOV* as it accounts for both, as well as for the volatility of all higher moments of the probability distribution (e.g., skewness and kurtosis) through the variance of probabilities. Furthermore, $\mho^2$ solves some major issues that arise from the use of only the volatility-of-mean or the volatility-of-volatility as proxies for ambiguity. For example, two securities could have a constant mean, but different degrees of ambiguity, or two securities could have constant volatility but different degrees of ambiguity. Second, as opposed to the volatility-of-mean, volatility-of-volatility, and dispersion of analyst forecasts, the measure $\mho^2$ is outcome and risk independent, as it does not depend upon the magnitudes of outcomes, but only upon their probabilities.

the fact that all these uncertainty factors do not explain more than 9% of the variation in *AMBG* (Panel C of Table 2). They are also consistent with the fact that all the other uncertainty factors are outcome dependent and therefore risk dependent, while ambiguity is outcome independent.

Next, we contrast *AMBG* with *VOM* and *VOV*, where we replace *RISK* with *VOM* and *VOV*. The findings of these tests are reported in Table B.14 in Appendix B. Similar to Table B.13, we report findings for open interest (Panel A), trading volume (Panel B), and cumulative delta-hedged returns (Panel C). Given our previous findings, it is not surprising that controlling for *VOV* or *VOM* does not alter our *AMBG* coefficient estimates. Since *VOM* and *VOV* are often used as proxies for ambiguity, the directional relation and economic significance of *VOM* and *VOV* is of interest. Starting with *VOM*, we find that across all panels *VOM* coefficient estimates are in the opposite sign of *AMBG* and consistent with the predictions of *RISK*. The economic magnitude is also comparable to *AMBG*. The finding of *VOV* are also consistent with those of *RISK*, except for open interest, where *VOV* shows a negative relation. However, the economic significance is very small compared to *AMBG*. Overall, the findings in Table B.14 demonstrate that the effect of *VOM* and *VOV* is qualitatively similar to that of *RISK*. This is not surprising given that Panel B of Table 2 reveals that the correlations of *VOM* and *VOV* with *RISK* are very high.

Next, we contrast *AMBG* with *DAF*. Table B.15 in Appendix B reports the fidings. Notably, the correlation between *AMBG* and *DAF* is virtually zero as reported in Panel B of Table 2. Thus, it is not surprising that controlling for *DAF* does not alter our findings regarding *AMBG*. What is striking is that higher dispersion in analyst forecasts (updated at a monthly frequency) predicts an increase in open interest and an increase in trading volume. This positive relation is inconsistent with *DAF*'s interpretation as an ambiguity measure. However, it is consistent with *DAF* being a measure of difference-of-opinions or disagreement across analysts. If analyst disagreement correlates with overall disagreement, this is consistent with Cookson and Niessner (2020) who find that higher disagreement is associated with higher trading volume. Moreover, in the options setting, higher disagreement is also associated with more contracts being opened. Finally, in contrast to the findings of *AMBG* and *RISK*, *DAF* has no prediction power for option returns.

In our last set of tests, we explore the robustness of our findings to the inclusion of market risk and market ambiguity. We use the *VIX* as market risk measure, and the ambiguity of the S&P500 index as market ambiguity measure. To capture shocks in these variables, we use the changes in $VIX(\Delta VIX)$ and changes in $MktAMBG(\Delta MktAMBG)$. Since these variables are constructed at the daily level, we replace the day fixed effects with day-of-the-week fixed effects. Overall, the

AMBG coefficient estimates are similar to those reported in our main tables. The only exception is the effect on the delta-hedge returns, where the magnitudes seem to be larger for both *AMBG* and *RISK*. Finally, changes in *MktAMBG* have no significant effect on options open interest, trading volume, or option returns. And, changes in market volatility have a consistent and significant sizeable effect only for option returns.

6 Conclusion

Ambiguity has long been recognized as a theoretical mechanism that can lead to non-participation in financial markets and inertia that inhibits trading (e.g., Easley and O'Hara, 2009; Illeditsch, 2011; Illeditsch et al., 2020). However, to date, empirical support for these theoretical consequences of ambiguity is sparse. This paper fills this important gap between theory and empirics. Specifically, we employ a newly developed daily measure of firm-level ambiguity and options market outcomes to show that both non-participation and inertia are *empirically* important outcomes of ambiguity. Beyond showing empirical support for these classic mechanisms, our findings highlight the ambiguity's importance for trading decisions by relatively sophisticated traders who inhabit options markets.

The reduction in options trading due to ambiguity also tends to reduce the informativeness of options trading (Pan and Poteshman, 2006), which is an important downstream implication of ambiguity's limited participation and inertia effects. Further, we note that greater ambiguity tends to lead to negative and non-reverting delta-hedged option returns for both puts and calls. These option return effects are of comparable economic magnitude to the impact of volatility on options returns. Given the central role volatility plays in options pricing (e.g., Black and Scholes, 1973), our findings suggest that ambiguity ought to also be considered in the pricing of options, given the striking economic magnitudes we find.

A consistent feature of our findings is that the estimated impacts of ambiguity are distinct from those of risk with comparable economic magnitudes. Given this quantitative importance of ambiguity for trading decisions, we anticipate that future work on ambiguity's effects the trading environment will continue to be fruitful. As recent work by Giglio et al. (2021) has articulated, there are many open questions in how investors update their beliefs and trade upon existing belief differences. Since ambiguity impedes acting upon one's beliefs, the linkages between ambiguity, beliefs, and trading decisions is a natural path forward for future research.

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Figure 1: Impulse response functions of call and put open interest

This figure plots the impulse responses of call and put open interest to a one-standard-deviation shock to $AMBG$ and $RISK$. For each call and put open interest (OI), it estimates a daily vector autoregression (VAR) system of OI, $AMBG$, and $RISK$, with five lags of each variable. All variables are defined in Table B.1, where $AMBG$, $RISK$, and OI are trimmed at the top and bottom 0.1% of their sample distribution. All regression tests include the full set of firm control variables together with firm fixed effects and date fixed effects. The VAR system takes the following form

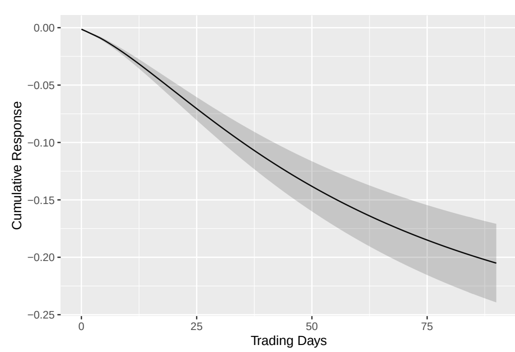
$$OI_{j,t} = \alpha_1 + \sum_{i=1}^{5} \beta_{1,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{1,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{1,i} \cdot OI_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{1,j,t};$$

$$AMBG_{j,t} = \alpha_2 + \sum_{i=1}^{5} \beta_{2,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{2,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{2,i} \cdot OI_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{2,j,t};$$

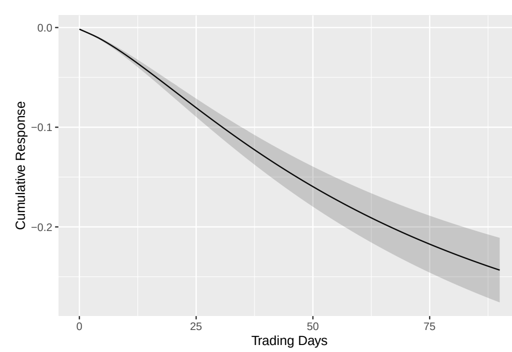
$$RISK_{j,t} = \alpha_3 + \sum_{i=1}^{5} \beta_{3,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{3,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{3,i} \cdot OI_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{3,j,t}.$$

The estimated coefficients of this system are reported in Table B.2. This figure includes two pairs of graphs, one for $AMBG$ and one for $RISK$Each pair plots the cumulative response of DEP to a one-standard-deviation shock to $AMBG$ (upper graphs) and to $RISK$ (lower graph). To estimate the effect of $AMBG$ ($RISK$) on DEP, the Cholesky order is set to be $RISK$, $AMBG$, DEP ($AMBG$, $RISK$, DEP). Each graph depicts the response in the subsequent $0, \ldots, 90$ trading days, listed on the x-axis. The solid line depicts the variable response and the dashed gray lines depict the 95% confidence intervals.

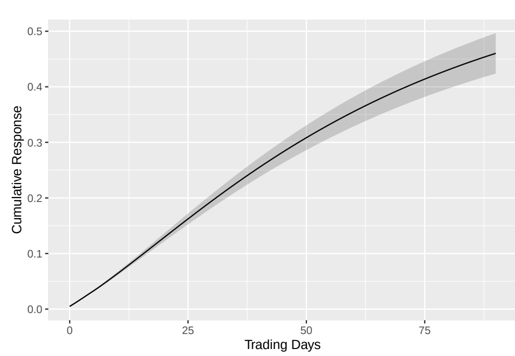
Panel A: Response of call option open interest to firm ambiguity



Panel B: Response of put option open interest to firm ambiguity



Panel C: Response of call option open interest to firm risk



Panel D: Response of put option open interest to firm risk

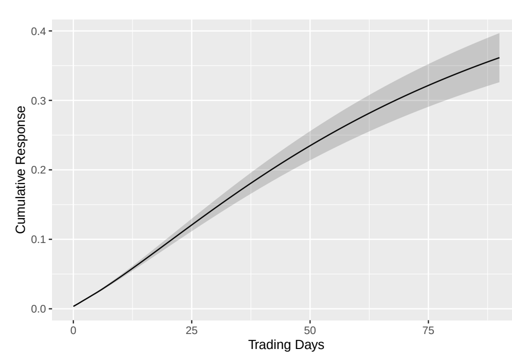


Figure 2: Impulse Response Functions of call and put trading volume

This figure plots the impulse responses of call and put trading volume to a one-standard-deviation shock to $AMBG$ and $RISK$. For each call and put trading volume (VOL), it estimates a daily vector autoregression (VAR) system of VOL, $AMBG$, and $RISK$, with five lags of each variable. All variables are defined in Table B.1, where $AMBG$, $RISK$, and VOL are trimmed at the top and bottom 0.1% of their sample distribution. All regression tests include the full set of firm control variables together with firm fixed effects and date fixed effects. The VAR system takes the following form

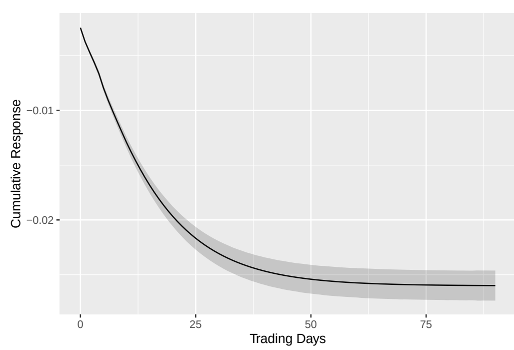
$$VOL_{j,t} = \alpha_1 + \sum_{i=1}^{5} \beta_{1,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{1,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{1,i} \cdot VOL_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{1,j,t};$$

$$AMBG_{j,t} = \alpha_2 + \sum_{i=1}^{5} \beta_{2,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{2,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{2,i} \cdot VOL_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{2,j,t};$$

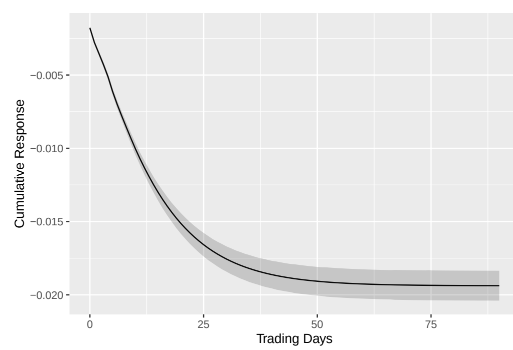
$$RISK_{j,t} = \alpha_3 + \sum_{i=1}^{5} \beta_{3,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{3,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{3,i} \cdot VOL_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{3,j,t}.$$

The estimated coefficients of this system are reported in Table B.2. This figure includes two pairs of graphs, one for $AMBG$ and one for $RISK$Each pair plots the cumulative response of DEP to a one-standard-deviation shock to $AMBG$ (upper graphs) and to $RISK$ (lower graph). To estimate the effect of $AMBG$ ($RISK$) on DEP, the Cholesky order is set to be $RISK$, $AMBG$, DEP ($AMBG$, $RISK$, DEP). Each graph depicts the response in the subsequent $0, \ldots, 90$ trading days, listed on the x-axis. The solid line depicts the variable response and the dashed gray lines depict the 95% confidence intervals.

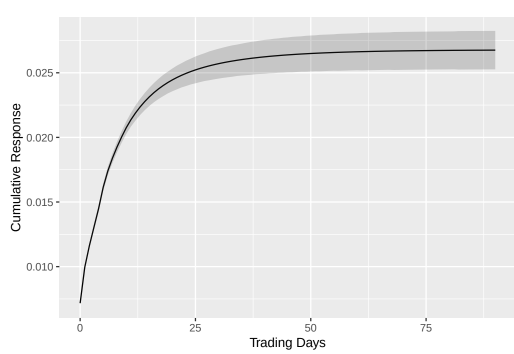
Panel A: Response of call option volume to firm ambiguity



Panel B: Response of put option volume to firm ambiguity



Panel C: Response of call option volume to firm risk



Panel D: Response of put option volume to firm risk

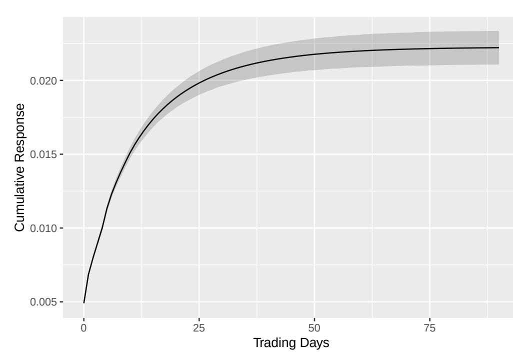
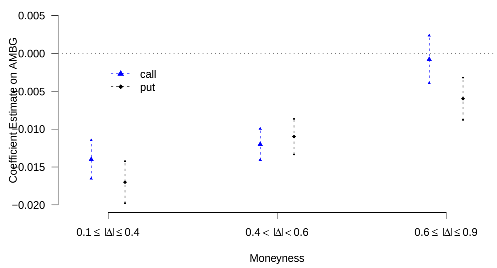


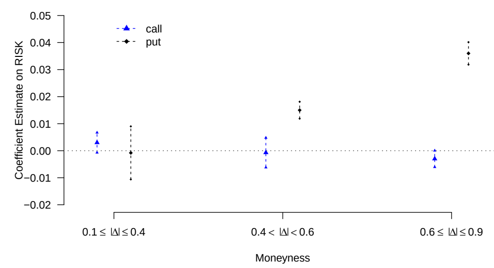
Figure 3: The effect of *AMBG* and *RISK* on options' open interest and trading volume based on moneyness

This figure plots the coefficient estimates of *AMBG* and *RISK* from daily panel regressions, in which call and put stock option open interest or trading volume on trading day $t, \dots, t+5$ are regressed on trading day t's ambiguity (*AMBG*), risk (*RISK*), and other firm characteristics based on moneyness. In particular, for each firm and day we aggregate options open interest (Graphs A-B) or trading volume (Graphs C- D) based on contract moneyness. The moneyness groups are defined as $0.1 <= |\Delta| <= 0.40$, $0.40 < |\Delta| < 0.60$, and $0.60 < |\Delta| <= 0.90$, respectively. To estimate the coefficients we stack each firm daily measures in the same regression and interact *AMBG* and *RISK* with dummy variables based on the three defined moneyness groups.The regression results are reported in Table B.3. The graphs below plot the regressions' coefficient estimates of open interest (trading volume) from trading day $t+5$ (t) together with their 95% confidence intervals.

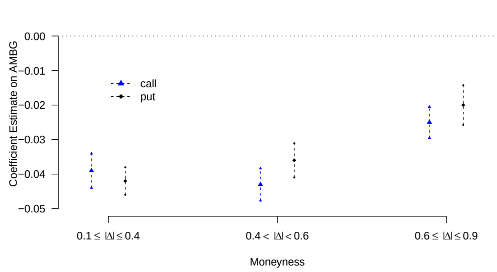
Panel A: *AMBG* and open interest



Panel B: *RISK* and open interest



Panel C: *AMBG* and trading volume



Panel D: *RISK* and trading volume

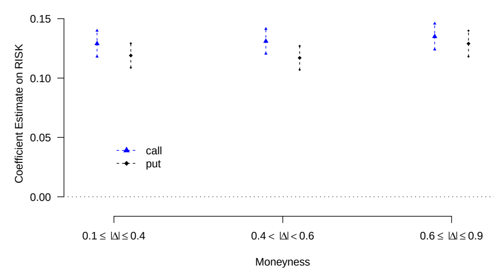
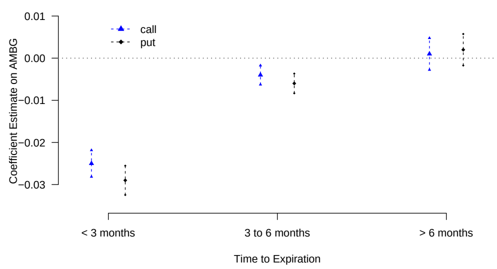


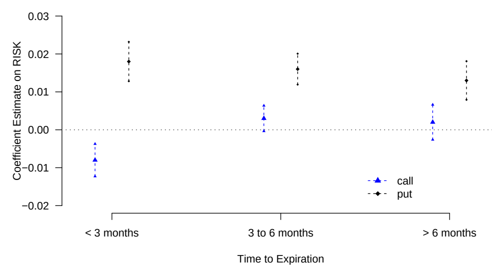
Figure 4: The effect of *AMBG* and *RISK* on options' open interest and trading volume based on maturity

This figure plots the coefficient estimates of *AMBG* and *RISK* from daily panel regressions, in which call and put stock option open interest or trading volume on trading day $t, \dots, t+5$ are regressed on trading day t's ambiguity (*AMBG*), risk (*RISK*), and other firm characteristics based on maturity. In particular, for each firm and day we aggregate options open interest (Graphs A-B) or trading volume (Graphs C-D) based on contract maturity. The maturity groups are defined as *Maturity <= 3 months*, *3 < Maturity <= 6 months*, and *6 < Maturity <= 12 months*, respectively. To estimate the coefficients we stack each firm daily measures in the same regression and interact *AMBG* and *RISK* with dummy variables based on the three defined maturity groups.The regression results are reported in Table B.4. The graphs below plot the regressions' coefficient estimates of open interest (trading volume) from trading day t+5 (t) together with their 95% confidence intervals.

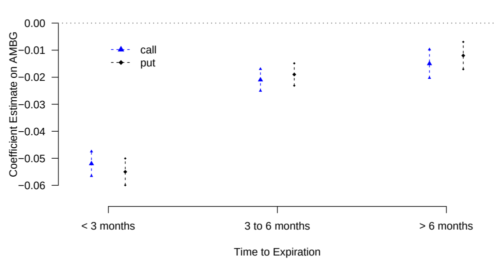
Panel A: *AMBG* and open interest



Panel B: *RISK* and open interest



Panel C: *AMBG* and trading volume



Panel D: *RISK* and trading volume

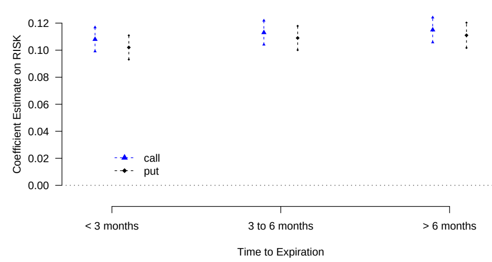
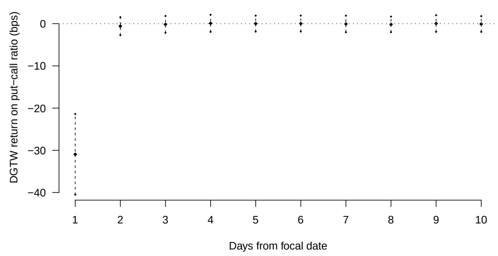


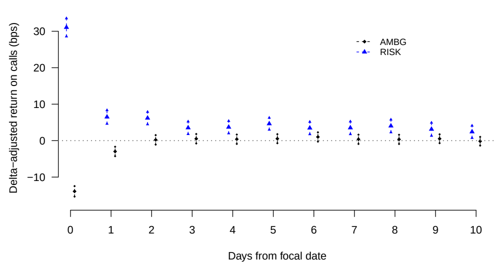
Figure 5: The dynamics of non-cumulative daily stock and option returns

This figure plots coefficient estimates of ΔPC_RATIO based on Equation (5) (Panel A) and the coefficient estimates of $AMBG$ and $RISK$ based on Equation (6) (Panels B and C) using non-cumulative daily returns. Panel A plots results from daily DGTW adjusted stock returns from day t+1 to t+10 together with their 95% confidence intervals. Similarly, Panels B and C plot results from daily delta-hedged option returns from day t to t+10. In all panels the focal date is day t.

Panel A: DGTW adjusted stock returns



Panel B: Call option delta-hedged returns



Panel C: Put option delta-hedged returns

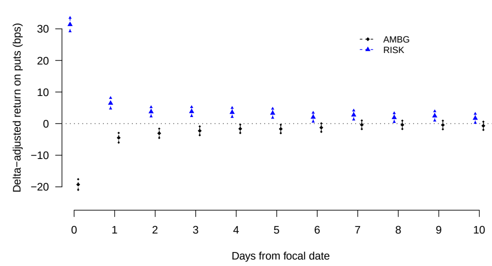


Table 1: Summary statistics

This table reports the summary statistics of the variables employed in the statistical analysis. All variables are defined in Table B.1. All panels reports the sample's mean Std. Dev. and median together with the number of firm-day observations. Panel A reports the statistics of the main stock variables. For ease of presentation, *AMBG* and *RISK* are multiplied by 10,000, *VOV* is multiplied by 1 million, and *VOM*, stock turnover (*SVOL*), and *CumRet* are multiplied by 100. Panel B reports statistics regarding the number of unique call and put option contracts and the trading variables of interest. All variables are trimmed at the top and bottom 0.1% of their sample distribution. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics.

Panel A: Main stock variables

	Mean	Std. Dev.	Median	Obs.
AMBG	60.615	84.185	32.202	6,766,488
RISK	9.897	9.242	6.951	6,766,488
VOV	1.399	2.389	0.520	6,766,488
VOM	1.921	2.000	1.270	6,766,488
DAF	0.068	0.463	0.020	6,766,488
SKEW	-0.002	0.281	-0.002	6,766,488
KURT	4.834	0.941	4.745	6,766,488
Size in Millions	8408.142	26830.731	1899.955	6,766,488
Book-to-Market	0.536	0.515	0.426	6,766,488
Number of Analysts	10.524	6.869	9.000	6,762,750
InstHold	0.692	0.201	0.727	6,412,098
SVOL	1.193	1.669	0.805	6,766,488
ES	0.318	2.117	0.096	6,766,488
$\frac{1}{AvePrc}$	0.047	0.039	0.034	6,766,488
CumRet	1.386	12.946	1.097	6,766,488

Panel B: Main option variables

	Mean	Std. Dev.	Median	Obs.
# Call Options	15.302	20.829	9.000	6,128,675
# Put Options	15.551	21.236	9.000	6,050,752
COI	0.794	1.644	0.290	6,123,752
POI	0.656	1.616	0.194	6,045,825
CVOL	0.050	0.205	0.005	6,124,603
PVOL	0.036	0.169	0.002	6,046,688
CBAS	14.054	10.233	11.275	4,738,569
PBAS	13.020	9.809	10.258	4,081,344
CRET	-0.349	7.686	-0.490	6,112,183
PRET	-0.338	7.480	-0.409	6,032,070

Table 2: Correlations

This table reports the sample correlations between *AMBG* and other variables of interest. The sample period is from January 2002 to December 2018.All variables are defined in Table B.1. Panel A reports the correlation matrix between *AMBG*, *RISK*, and the main variables of interest. Panel B reports the correlation matrix between *AMBG*, *RISK*, and other uncertainty variables. Finally, Panel C reports the partial correlations from daily panel regressions of *AMBG* on other uncertainty proxies. To capture within firm variation the variables in all panels are de-meaned. Consequently, the $AdjR^2$ in Panel C captures the variance explained by the independent variables. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.All variables are defined in Table B.1. All variables are trimmed at the top and bottom 0.1% of their sample distribution. The sample period is from January 2002 to December 2018. The institutional investors' net trading data is from January 2002 to December 2015, taken from ANcerno. The options trading data is taken from OptionMetrics.

Panel A: Main variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) *AMBG*	1.00						
(2) *RISK*	-0.28	1.00					
(3) *COI*	-0.00	-0.02	1.00				
(4) *POI*	-0.03	0.03	0.65	1.00			
(5) *CVOL*	-0.02	0.03	0.40	0.29	1.00		
(6) *PVOL*	-0.03	0.04	0.29	0.36	0.56	1.00	
(7) *SVOL*	-0.05	0.11	0.18	0.18	0.46	0.40	1.00

Panel B: Ambiguity and other uncertainty factors - univariate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) *AMBG*	1.00						
(2) *RISK*	-0.28	1.00					
(3) *VOM*	-0.18	0.71	1.00				
(4) *VOV*	-0.08	0.57	0.40	1.00			
(5) *SKEW*	-0.01	0.01	0.00	0.00	1.00		
(6) *KURT*	0.16	-0.40	-0.29	-0.18	-0.00	1.00	
(7) *DAF*	-0.01	0.02	0.01	-0.00	-0.00	-0.03	1.00

Panel C: Ambiguity and other uncertainty factors - multivariate

	(1)	(2)	(3)	(4)	(5)	(6)
	t	t	t	t	t	t
RISK	-2.979***	-3.677***	-3.258***	-3.961***	-3.735***	-3.735***
	(-50.22)	(-50.05)	(-60.95)	(-59.34)	(-49.35)	(-49.34)
VOV		4.046***		4.051***	3.919***	3.921***
		(43.40)		(43.70)	(40.17)	(40.17)
VOM			1.591***	1.616***	1.658***	1.658***
			(14.69)	(14.49)	(14.66)	(14.66)
SKEW					-1.997***	-1.997***
					(-9.46)	(-9.46)
KURT					4.093***	4.097***
					(10.94)	(10.96)
DAF						0.427
						(1.17)
Firm FEs	YES	YES	YES	YES	YES	YES
Firm Cluster	YES	YES	YES	YES	YES	YES
Day Cluster	YES	YES	YES	YES	YES	YES
Observations	6,766,486	6,766,486	6,766,486	6,766,486	6,766,486	6,766,486
AdjR^2	0.077	0.085	0.077	0.086	0.088	0.088

Table 3: Call and put options' open interest

This table reports the findings from daily panel regressions, in which call and put stock option open interest on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), risk ($RISK$), and other firm characteristics. Call and put open interest measures are reported in Panel A and B, respectively. The regressions with the full set of controls are reported in Table B.5. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG(AvgAMBG)$ and $RISK(AvgRISK)$. This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Call open interest

	COI(Z)				
	(1)	(2)	(3)	(4)	(5)
	t	t+1	t+2	t+3	t+5
AMBG(Z)	-0.012***	-0.012***	-0.013***	-0.013***	-0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	-0.004***	-0.003**	-0.001	-0.001	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES
Observations	5,871,968	5,872,005	5,872,150	5,872,179	5,872,223
AdjR^2	0.837	0.837	0.840	0.839	0.839

Panel B: Put open interest

	POI(Z)				
	(1)	(2)	(3)	(4)	(5)
	t	t+1	t+2	t+3	t+5
AMBG(Z)	-0.014***	-0.014***	-0.014***	-0.014***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.015***	0.016***	0.017***	0.017***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES
Observations	5,791,506	5,791,552	5,791,681	5,791,760	5,791,788
AdjR^2	0.846	0.846	0.848	0.847	0.845

Table 4: Call and put options' trading volume

This table reports the findings from daily panel regressions, in which stock option trading volume measures on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), risk ($RISK$), and other firm characteristics. Call and put trading volume measures are reported in Panels A and B, respectively. The regressions with the full set of controls are reported in Table B.6. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG(AvgAMBG)$ and $RISK(AvgRISK)$. This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. Firm and date fixed effects are included in each specification. (Z) stands for a Z-Score adjustment. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Call trading volume

	CVOL(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5
AMBG(Z)	-0.040***	-0.023***	-0.018***	-0.017***	-0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.137***	0.058***	0.033***	0.026***	0.020***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES
Observations	6,008,137	5,940,699	5,924,982	5,910,826	5,884,918
AdjR^2	0.400	0.409	0.408	0.404	0.395

Panel B: Put trading volume

	PVOL(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5
AMBG(Z)	-0.039***	-0.023***	-0.018***	-0.015***	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.132***	0.059***	0.037***	0.029***	0.024***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES
Observations	5,922,273	5,857,357	5,841,742	5,828,234	5,802,097
AdjR^2	0.369	0.373	0.371	0.367	0.359

Table 5: Option based measures and stock return predictability

This table reports the findings from daily panel regressions, in which DGTW adjusted cumulative stock returns from trading day $t+1,\ldots,t+10$ are regressed on trading day t's option based measures, ambiguity ($AMBG$), risk ($RISK$), the interaction of these measures with $AMBG$ and $RISK$ controlling for other firm characteristics. In Panel A we use the changes in put-call open interest ratio (ΔPC_RATIO), where ΔPC_RATIO is calculated as the difference between the open interest of P/(C+P) on day t and t-1. In panel B we use Cremers and Weinbaum (2010)'s implied volatility spread measure (IVS), which captures the difference between call and put implied volatilities for call and put options with the same strike price and maturity. The stock level measure is the open-interest weighted average across all pairs. Columns 1-3, 4-6 and 7-9 report results for cumulative returns based on one, five and ten trading days, respectively. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG$($AvgAMBG$) and $RISK$($AvgRISK$). This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: The put-call open interest ratio

	$DGTW_t1$			$DGTW_t5$			$DGTW_t10$		
	(1) t+1	(2) t+1	(3) t+1	(4) t+1_t+5	(5) t+1_t+5	(6) t+1_t+5	(7) t+1_t+10	(8) t+1_t+10	(9) t+1_t+10
$AMBG(Z)$	0.005**	0.005**	0.005**	0.016***	0.016***	0.016***	0.023***	0.022***	0.022***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z)$	0.002	0.002	0.002	0.003	0.003	0.003	-0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta PC\_RATIO(Z)$	-0.309***	-0.304***	-0.304***	-0.352***	-0.346***	-0.345***	-0.365***	-0.358***	-0.357***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta PC\_RATIO(Z)\times AMBG(Z)$		0.034***	0.031***		0.044***	0.036***		0.046***	0.038***
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
$\Delta PC\_RATIO(Z)\times RISK(Z)$			-0.005			-0.014***			-0.015***
			(0.00)			(0.00)			(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	NO	NO	NO	NO	NO	NO	NO
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,822,503	5,822,503	5,822,503	5,820,028	5,820,028	5,820,028	5,817,898	5,817,898	5,817,898
AdjR^2	0.026	0.026	0.026	0.008	0.009	0.009	0.006	0.006	0.006

Panel B: The implied volatility spread measure

	$DGTW_t1$			$DGTW_t5$			$DGTW_t10$		
	(1) t+1	(2) t+1	(3) t+1	(4) t+1 to t+5	(5) t+1 to t+5	(6) t+1 to t+5	(7) t+1 to t+10	(8) t+1 to t+10	(9) t+1 to t+10
AMBG(Z)	0.003	0.003	0.003	0.016***	0.015***	0.015***	0.021**	0.020**	0.020**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.001	0.000	0.002	0.004	0.004	0.005	-0.000	-0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IVS(Z)	0.062***	0.059***	0.053***	0.075***	0.068***	0.059***	0.083***	0.073***	0.061***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IVS(Z)$\times AMBG(Z)$		-0.007***	0.000		-0.017***	-0.007		-0.027***	-0.014*
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
IVS(Z)$\times RISK(Z)$			0.012***			0.017***			0.023***
			(0.00)			(0.00)			(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	NO	NO	NO	NO	NO	NO	NO
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,614,965	5,614,965	5,614,965	5,613,858	5,613,858	5,613,858	5,612,232	5,612,232	5,612,232
AdjR^2	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003

Table 6: Call and put options' cumulative delta-hedged returns

This table reports the findings from daily panel regressions, in which stock option cumulative delta-hedged returns on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), risk ($RISK$), and other firm characteristics. We calculate the options' end of day prices based on the midpoint between the end of day best bid and best ask quotes (OptionPRC t). Based in the prices, the option's daily delta-hedged return is calculated as $[(OptionPRC_t - OptionPRC_{t-1}) - \Delta_{t-1}(StockPRC_t - StockPRC_{t-1})]/OptionPRC_{t-1}$. To aggregate the call or put options at the firm level, we form value-weighted portfolios using day t-1 open interest dollar value as the weight. We fix day t-1 open interest dollar value to allow for a natural buy and hold interpretation. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG(AvgAMBG)$ and $RISK(AvgRISK)$. This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	CCUMRET(Z)					*PCUMRET(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.138***	-0.174***	-0.182***	-0.184***	-0.185***	-0.194***	-0.251***	-0.292***	-0.321***	-0.360***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
RISK(Z)	0.305***	0.403***	0.492***	0.542***	0.652***	0.313***	0.433***	0.513***	0.577***	0.680***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,099,959	6,005,322	5,935,581	5,877,097	5,776,690	6,020,006	5,927,494	5,859,923	5,804,013	5,708,099
AdjR^2	0.162	0.156	0.163	0.169	0.177	0.106	0.124	0.141	0.156	0.175

Table 7: Call and put options' bid-ask spread

This table reports the findings from daily panel regressions, in which call and put options bid-ask spreads on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), risk ($RISK$), and other firm characteristics. Call and put measures are reported in Columns 1-5 and Columns 6-10, respectively. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG(AvgAMBG)$ and $RISK(AvgRISK)$. This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	CBAS(Z)					*PBAS(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	0.001	0.006***	0.007***	0.006***	0.007***	-0.000	0.006***	0.008***	0.007***	0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.064***	0.035***	0.033***	0.032***	0.028***	0.032***	0.005***	0.001	0.001	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,693,356	4,580,004	4,542,915	4,511,320	4,456,246	4,040,028	3,935,647	3,899,788	3,868,782	3,814,211
AdjR^2	0.574	0.562	0.556	0.552	0.545	0.541	0.531	0.527	0.523	0.516

Table 8: Call and put options around News Event Days

The table extends the analysis conducted in Table 3 based on ... The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG$($AvgAMBG$) and $RISK$($AvgRISK$). This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open Interest

	COI				*POI*			
	EDAY		*8-K*		*EDAY*		*8-K*	
	(1) t	(2) t+5	(3) t	(4) t+5	(5) t	(6) t+5	(7) t	(8) t+5
AMBG(Z)	-0.007**	-0.005	-0.017***	-0.017***	-0.026**	-0.024**	-0.016***	-0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
RISK(Z)	0.014***	0.020***	-0.009	0.008	0.015***	0.022***	0.015**	0.025***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES
Observations	92,165	92,171	87,818	87,822	90,887	90,897	86,514	86,539
AdjR^2	0.805	0.818	0.811	0.807	0.784	0.793	0.846	0.844

Panel B: Trading volume

	CVOL				*PVOL*			
	EDAY		*8-K*		*EDAY*		*8-K*	
	(1) t	(2) t+1	(3) t	(4) t+1	(5) t	(6) t+1	(7) t	(8) t+1
AMBG(Z)	-0.037***	-0.019***	-0.050***	-0.030***	-0.026***	-0.017***	-0.060***	-0.030***
	(-5.00)	(-3.71)	(-6.14)	(-4.98)	(-3.28)	(-3.22)	(-7.83)	(-6.17)
RISK(Z)	0.318***	0.083***	0.378***	0.167***	0.299***	0.077***	0.372***	0.165***
	(21.81)	(9.39)	(17.01)	(11.29)	(19.91)	(8.12)	(16.27)	(10.15)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES
Observations	94,331	93,104	89,994	88,946	92,824	91,738	88,617	87,606
AdjR^2	0.533	0.470	0.373	0.397	0.496	0.442	0.343	0.362

A Appendix - Estimating equity ambiguity

The measure of ambiguity, denoted by $\mho^2$ and defined by Equation (1), represents an expected probability-weighted average of the variances of probabilities. We follow the recent literature (e.g., Brenner and Izhakian, 2018; Augustin and Izhakian, 2020; Izhakian et al., 2021) and estimate the monthly degree of ambiguity for each firm's equity using intraday stock return data from TAQ. To estimate ambiguity as implemented in Equation (7) below, the expectation of and the variation in return probabilities across the set of possible prior probability distributions, $\mathcal{P}$, must be measured.

We assume that the intraday equity return distribution for each time interval during the day in a given day represents a single prior distribution, P, in the set of possible distributions, $\mathcal{P}$, and the number of priors in the set is assumed to depend on the number of time intrevals in the month. Each prior (distribution) in the set is represented by the thirty-second observed intraday returns on the firm's equity, in a time interval of 1170 seconds during the trading hours.[21] Thus, the set of priors consists of 20 realized distributions, at most, over a day. For practical implementation reasons, we discretize return distributions into n bins $B_\ell = (r_{\ell-1}, r_\ell]$ of equal size, such that each distribution is represented by a histogram, as demonstrated in Figure B.1. The height of the bar for each bin is the frequency of intraday returns observed in that bin and, thus, represents the probability of the returns in that bin. Equipped with these 20 return histograms, we compute the expected probability in a particular bin across the return distributions, $\mathrm{E}\left[\mathrm{P}\left(B_\ell\right)\right]$, as well as the variance of these probabilities, $\mathrm{Var}\left[\mathrm{P}\left(B_\ell\right)\right]$. To this end, an equal likelihood is assigned to each histogram.[22] We use these equally likely histograms to compute the daily degree of ambiguity of stock j as follows

$$\mho^2\left[r_j\right] \equiv \frac{1}{\sqrt{w\left(1-w\right)}} \sum_{\ell=1}^{n} \mathrm{E}\left[\mathrm{P}_j\left(B_\ell\right)\right] \mathrm{Var}\left[\mathrm{P}_j\left(B_\ell\right)\right]. \tag{7}$$

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

[21]Our findings are robust to the use of different time intervals, implying a different number of distributions per day.

[22]Equal weighting is consistent with the principle of insufficient reason, which states that given n possibilities that are indistinguishable except for their names, each possibility should be assigned a probability equal to $\frac{1}{n}$ (Bernoulli, 1713; Laplace, 1814); with the idea of the simplest non-informative prior in Bayesian probability (Bayes et al., 1763), which assigns equal probabilities to all possibilities; and with the principle of maximum entropy (Jaynes, 1957), which states that the probability distribution which best describes the current state of knowledge is the one with the largest entropy.

[Figure B.1]

In our implementation, we sample thirty-second stock returns from 9:30 to 16:00. Thus, we obtain intradaily histograms of up to 39 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 within 15 seconds distance from that time point. If there is no trade price within this distance, we drop this 30 second observation. We ignore returns between closing and next-day opening prices to eliminate the impact of overnight price changes and dividend distributions. We drop all time intervals with fewer than 10 thirty-second returns, and then we drop days with fewer than 10 intraday return distributions.[23] In addition, we drop extreme returns ($\pm 5\%$ log returns over thirty seconds), as many such returns are due to improper orders that are often later canceled by the stock exchange. We normalize the intraday thirty-second rates of return to daily returns.[24]

For the bin formation, we divide the range of normalized returns into 1,002 intervals. We form a grid of 1,000 bins, from -100% to $+100\%$, each of width 0.2%, in addition to the left and right tails, defined as $(-\infty, -100\%]$ and $[+100\%, +\infty)$, respectively. We compute the mean and the variance of probabilities for each bin, assigning an equal likelihood to each distribution (i.e., all histograms are equally likely).[25] Some bins may not be populated with return realizations. Therefore, we assume a normal return distribution and use its moments to extrapolate return probabilities. That is, $\mathrm{P}_j(B_\ell) = \Phi(r_\ell; \mu_j, \sigma_j) - \Phi(r_{\ell-1}; \mu_j, \sigma_j)$, where $\Phi(\cdot)$ denotes the cumulative normal probability distribution, characterized by its mean μ_j and variance σ_j^2 of returns.[26]

An important characteristic of the measure of ambiguity implied by EUUP is that it is outcome independent (up to a state space partition), which allows for a risk-independent examination of the impacts of ambiguity on financial decisions. Specifically, the measure of ambiguity $\mho^2$ captures the

[23] For robustness, we run all the regression tests excluding all time intervals with fewer than 15 thirty-second returns and all days with fewer than 15 intraday return distributions. The findings are essentially the same.

[24] Our findings are robust to the inclusion of extreme price changes, as well as to a cutoff at a level of 1% in terms of log returns.

[25] The assignment of equal likelihoods is equivalent to assuming that the daily ratios $\frac{\mu}{\sigma}$ are Student-t distributed. When $\frac{\mu}{\sigma}$ is Student-t distributed, cumulative probabilities are uniformly distributed (Kendall and Stuart, 2010, Proposition 1.27, p. 21).

[26] As in French et al. (1987), Brenner and Izhakian (2018) and Augustin and Izhakian (2020) apply the Scholes and Williams (1977) adjustment for non-synchronous trading to estimate the variance of returns. Scholes and Williams (1977) suggest adjusting the volatility of returns for non-synchronous trading as $\sigma_t^2 = \frac{1}{N_t}\sum_{\ell=1}^{N_t}\left(r_{t,\ell} - \mathrm{E}\left[r_{t,\ell}\right]\right)^2 + 2\frac{1}{N_t - 1}\sum_{\ell=2}^{N_t}\left(r_{t,\ell} - \mathrm{E}\left[r_{t,\ell}\right]\right)\left(r_{t,\ell-1} - \mathrm{E}\left[r_{t,\ell-1}\right]\right)$. This adjustment mitigates microstructure effects caused by bid-ask bounce. For robustness, we run all regression tests in which ambiguity is computed using this adjusted volatility of returns. The findings are essentially the same.

variation in the frequencies (probabilities) of the outcomes, without incorporating the magnitudes of the outcomes. In contrast, the measure of risk captures the variation in the magnitudes of the outcomes without incorporating the variation in the frequencies with which the outcomes are observed. Thus, the measure of ambiguity is risk independent, just as standard measures of risk are ambiguity independent, implying that these two measures capture distinct aspects of uncertainty.

Other proxies for ambiguity in the literature include the volatility of mean returns (Franzoni, 2017), the volatility of volatility of returns (Faria and Correia-da Silva, 2014), or the disagreement of analysts' forecasts (Anderson et al., 2009). These measures are sensitive to changes in the set of outcomes (i.e., are outcome dependent), so they are risk dependent and, therefore, less useful for this study. For similar reasons, skewness and kurtosis (as well as other higher moments of the return distribution) are also different from $\mho^2$, as the former are outcome dependent and the latter is outcome independent. Time-varying mean, time-varying volatility, and jumps (return shocks) are outcome dependent as well.

Figure B.1 also demonstrates that ambiguity is independent of outcomes and, therefore, independent of risk. Consider, for example, an extreme return (i.e., a stock price jump or a shock). If the partition of the state space remains unchanged, one of the bins will be associated with a higher return, but the probability of that particular bin, or any other bin, remains unchanged. Therefore, ambiguity remains unchanged.[27] If, on the other hand, the partition of the state space changes, then one additional bin may be added to the histogram, thereby characterizing a new event. This new bin may also affect the population of other bins, and therefore, affect ambiguity. 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, since 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 the aggregate market ambiguity and suggest that, in their sample, $\mho^2$ does not capture other well-known uncertainty factors including skewness, kurtosis, the volatility-of-mean, the volatility-of-volatility, volatility jumps, unexpected volatility, downside risk, mixed data sampling measure of volatility forecasts (MIDAS), investor sentiment, and several others. Augustin and Izhakian (2020) study the implications of firm am-

[27]To illustrate, consider a rate of return on an investment that is determined by a coin toss with unknown probabilities, where heads yields a 2% return and tails a 1% return. Even if after 10 coin tosses the rate of return for heads changes to 10% (i.e., a jump), ambiguity remains unchanged, since no new information about probabilities has been obtained.

biguity for the spread of credit default swaps and suggest that, in their sample, $\mho^2$ also does not capture these factors at the firm level.[28] To further mitigate the concerns that $\mho^2$ captures other well-known uncertainty factors or market-microstructure effects, in Section 5.4, we examine the explanatory power of $\mho^2$ relative to these uncertainty factors at the daily firm level.

[28] In a battery of robustness tests, Augustin and Izhakian (2020) also mitigate concerns that the measure of ambiguity $\mho^2$ is sensitive to the selection of the time interval of intraday rate of returns, the bin size, and the type of parametric probability distribution used to extrapolate bins' probabilities.

B Appendix - Variable definitions and additional tests

Figure B.1: Ambiguity measurement

This figure illustrates the way we compute the ambiguity measure for each firm-day, based on intraday stock returns, sampled at thirty-second intervals from 9:30 to 16:00. For each firm-day, these samples create 20 intraday histograms of up to 39 intraday returns. For each intraday histogram, we discretize the time-period return distribution into n bins of equal size $B_\ell = (r_{\ell-1}, r_\ell]$. The height of each intraday histogram bin is the fraction of intraday returns observed in that bin, representing the probability of that bin's outcome. For simplicity, this figure shows three histograms with six bins. Across the intraday return distributions, we compute the expected probability of returns in a bin as $\mathrm{E}\left[\mathrm{P}_j\left(B_\ell\right)\right]$ and the variance of probabilities as $\mathrm{Var}\left[\mathrm{P}_j\left(B_\ell\right)\right]$. Finally, we compute firm-day ambiguity as $\mho^2\left[r_j\right] \equiv 1/\sqrt{w\left(1-w\right)}\sum_{\ell=1}^{n} \mathrm{E}\left[\mathrm{P}_j\left(B_\ell\right)\right] \mathrm{Var}\left[\mathrm{P}_j\left(B_\ell\right)\right]$, where we scale the weighted-average variance of probabilities by the bin size $w = r_\ell - r_{\ell-1}$.

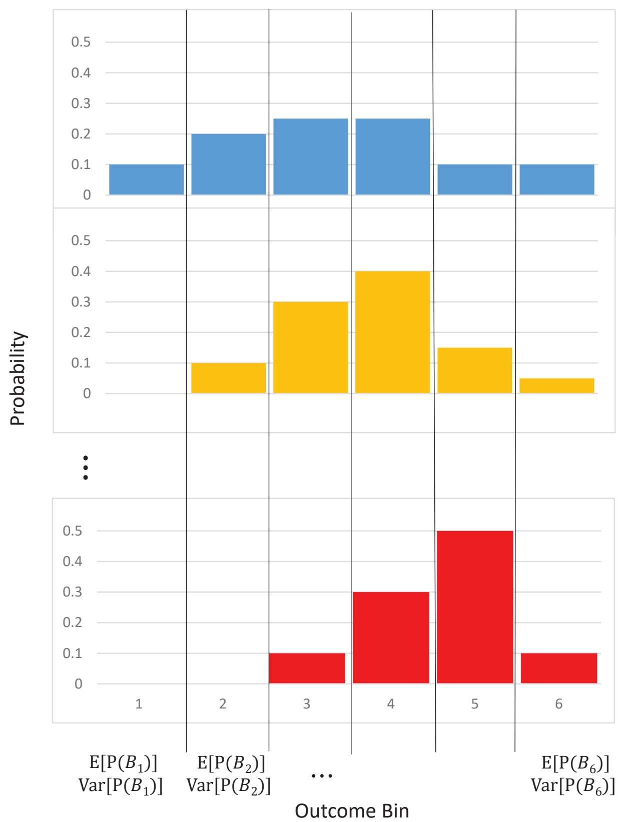


Figure B.2: Impulse Response Functions excluding day-0 effect

This figure plots the impulse responses of the trading and liquidity measures to a one-standard-deviation shock to *AMBG* and *RISK*. For each dependent variable (*DEP*), it estimates a daily vector autoregression (VAR) system of *DEP*, *AMBG*, and *RISK*, with five lags of each of the variables. All variables are defined in Table B.1, where *AMBG*, *RISK*, and *DEP* are trimmed at the top and bottom 0.1% of their sample distribution. All regression tests include the full set of firm control variables together with firm fixed effects and date fixed effects. The VAR system takes the following form

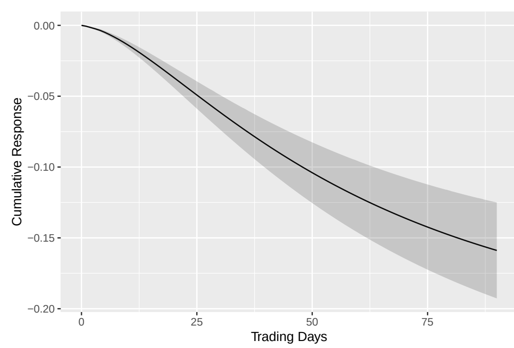
$$DEP_{j,t} = \alpha_1 + \sum_{i=1}^{5} \beta_{1,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{1,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{1,i} \cdot DEP_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{1,j,t};$$

$$AMBG_{j,t} = \alpha_2 + \sum_{i=1}^{5} \beta_{2,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{2,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{2,i} \cdot DEP_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{2,j,t};$$

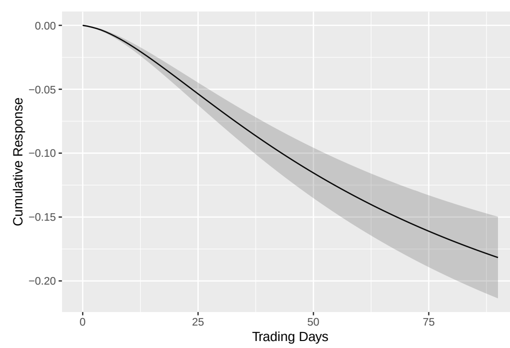
$$RISK_{j,t} = \alpha_3 + \sum_{i=1}^{5} \beta_{3,i} \cdot AMBG_{j,t-i} + \sum_{i=1}^{5} \gamma_{3,i} \cdot RISK_{j,t-i} + \sum_{i=1}^{5} \delta_{3,i} \cdot DEP_{j,t-i} + \Gamma \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{3,j,t}.$$

The estimated coefficients of this system are reported in Table B.2. This figure includes three groups of graphs: open interest (Graphs A-D), trading volume (Graphs E-H) and delta-hedged returns (Graphs I-L). Each group plots the cumulative response of *DEP* to a one-standard-deviation shock to *AMBG* or *RISK*. To estimate the effect of *AMBG* (*RISK*) on *DEP*, the Cholesky order is set zero. That is, day t effect is not allowed to enter the system updating process. Each graph depicts the response in the subsequent $0, \ldots, 90$ trading days, listed on the x-axis. The solid line depicts the variable response and the dashed gray lines depict the 95% confidence intervals.

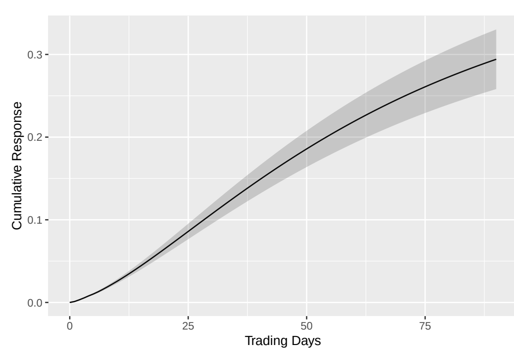
Panel A: Response of call option open interest to firm ambiguity



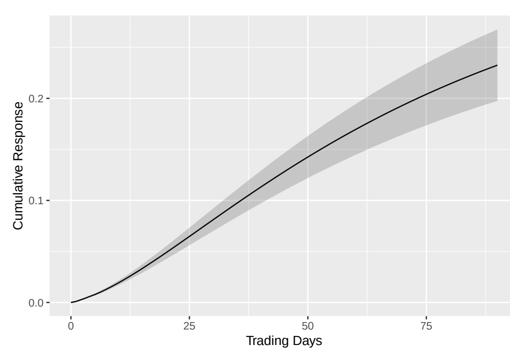
Panel B: Response of put option open interest to firm ambiguity



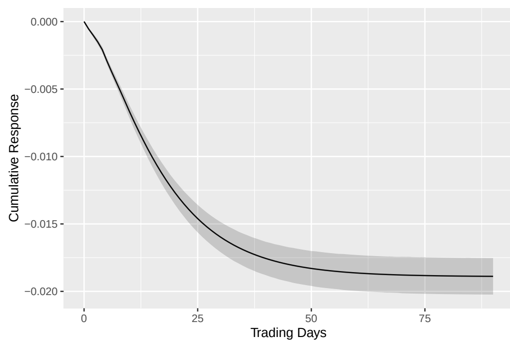
Panel C: Response of call option open interest to firm risk



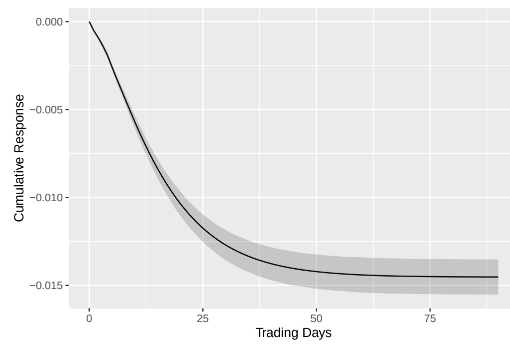
Panel D: Response of put option open interest to firm risk



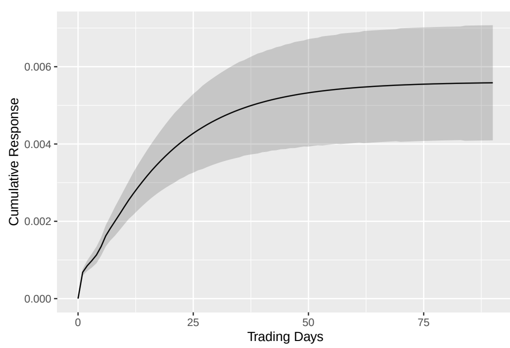
Panel E: Response of call option volume to firm ambiguity



Panel F: Response of put option volume to firm ambiguity



Panel G: Response of call option volume to firm risk



Panel H: Response of put option volume to firm risk

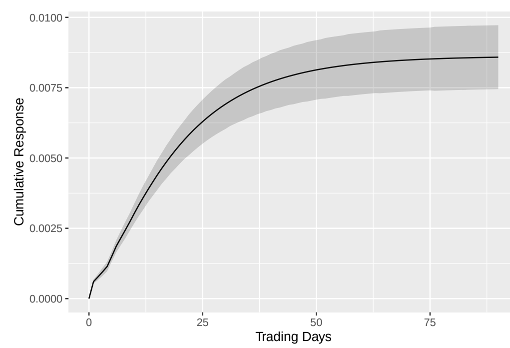


Table B.1: Variable definitions

Variable	Definition
Ambiguity and Other Moments	
$AMBG$	The daily ambiguity, measured as detailed in Section 2.1. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
$MktAMBG$	$AMBG$ of the S&P500 index (SPY ticker).
$\Delta MktAMBG$	Daily changes in $MktAMBG$, calculated as $MktAMBG_t - MktAMBG_{t-1}$.
$RISK$	The daily risk, measured as detailed in Section 2.2. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
VIX	The CBOE volatility index, calculated based on the implied volatility of the S&P500 options.
ΔVIX	Daily changes in VIX, calculated as $VIX_t - VIX_{t-1}$.
VOM	Daily volatility-of-mean, calculated as the variance of the averages' return over 20 intraday time intervals, where each interval's average is computed using 30-second returns. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
VOV	Daily volatility-of-volatility, calculated as the variance of the variances of return over 20 intraday time intervals, where each interval's variance is computed using 30-second returns. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
$SKEW$	Daily realized skewness, computed using 30-second intraday returns. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
$KURT$	Daily realized kurtosis, calculated using 30-second intraday returns. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
$AvgAMBG$	The 21 trading day trailing average of $AMBG$ over trading days $t-27,\ldots,t-6$.
$AvgRISK$	The 21 trading day trailing average of $RISK$ over trading days $t-27,\ldots,t-6$.
$AvgVOM$	The 21 trading day trailing average of VOM over trading days $t-27,\ldots,t-6$.
$AvgVOV$	The 21 trading day trailing average of VOV over trading days $t-27,\ldots,t-6$.
$AvgSKEW$	The 21 trading day trailing average of $SKEW$ over trading days $t-27,\ldots,t-6$.
$AvgKURT$	The 21 trading day trailing average of $KURT$ over trading days $t-27,\ldots,t-6$.
Option Variables	
Filters	The options data is obtained from OptionMetrics. To reduce noise due to contract expiration or unusual maturities, only call and put options with maturities of 7 to 365 days are considered. In addition, we follow Muravyev(2016), Christoffersen et al. (2018) and Muravyev and Ni (2020) and apply the following additional filters: we keep option contrasts with absolute deltas between 0.1 to 0.9, keep contracts with positive open interest, keep contracts with valid bid-ask spread information, drop contracts where the spread to midpoint ratio is greater than 70%, drop contracts with bid-ask spread above \$3, and drop contracts with midpoints below \$0.10 cents.
COI	The daily sum of the open interest of call options written on the stock, divided by the stock outstanding shares. We account for the fact that open interest is lagged by one day after November 28$^{\text{th}}$, 2000. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
POI	The daily sum of the open interest of put options written on the stock, divided by the stock outstanding shares. We account for the fact that open interest is lagged by one day after November 28$^{\text{th}}$, 2000. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.

Variable	Definition
Option Variables (Cont.)	
CVOL	The daily sum of trading volume of call options written on the stock, divided by the stock's number of shares outstanding. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
PVOL	The daily sum of trading volume of put options written on the stock, divided by the stock's number of shares outstanding. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
CCUMRET	the delta-hedged cumulative return of call options written on the stock. Call options' end of day prices based on the midpoint between the end of day best bid and best ask quotes (PRC t). Based in the prices, the option's daily delta-hedged return is calculated as $[(PRC_t - PRC_{t-1}) - \delta_{t-1}(PRC_t - PRC_{t-1})]/PRC_{t-1}$. To aggregate the call or put options at the firm level, we form value-weighted portfolios using day t-1 open interest dollar value as the weight. We fix day t-1 open interest dollar value to allow for a natural buy and hold interpretation. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
PCUMRET	the cumulative delta-hedged return of put options written on the stock. The calculation is similar to *CCUMRET* calculation.
CBAS	The daily average bid-ask spread of call options written on the stock, calculated as the difference between the best offer and the best ask divided by their midpoint. We take the value-weighted average across all options for a given stock, using the daily options' dollar volume as the weight. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
PBAS	The daily average bid-ask spread of put options written on the stock, calculated as the difference between the best offer and the best ask divided by their midpoint. We take the value-weighted average across all options for a given stock, using the daily options' dollar volume as the weight. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
AvgCOI	The 21 trading day trailing average of *COI* over trading days $t-27, \ldots, t-6$.
AvgPOI	The 21 trading day trailing average of *POI* over trading days $t-27, \ldots, t-6$.
AvgCVOL	The 21 trading day trailing average of *CVOL* over trading days $t-27, \ldots, t-6$.
AvgPVOL	*PVOL* The 21 trading day trailing average of *PVOL* over trading days $t-27, \ldots, t-6$.
AvgCBAS	The 21 trading day trailing average of *CBAS* over trading days $t-27, \ldots, t-6$.
AvgPBAS	The 21 trading day trailing average of *PBAS* over trading days $t-27, \ldots, t-6$.
Other Stock Variables	
SVOL	Daily stock volume, calculated as the number of daily traded shares divided by the number of shares outstanding. To reduce the effect of outliers, the top and bottom 0.1% of the sample distribution are trimmed.
LnSize	The natural logarithm of the firm's size in million dollars, following Fama and French (1992).
LnBM	The natural logarithm of the firm's book-to-market ratio, rebalanced every June, following Fama and French (1992).
InstHold	The firm's fraction of institutional holdings taken from Thomson Reuters Institutional (13F) Holdings database.
RET	The daily stock return, as reported by CRSP.
CumRet	The stock's cumulative return over the 21 trading days $t-27, \ldots, t-6$.
LnNumEst	The natural logarithm of one plus *NumEst*, where *NumEst* is the number of analysts covering the firm according to the most recent information from I/B/E/S.
$\ln \frac{1}{AvePrc}$	The natural logarithm of one over the average stock price (*AvePrc*), adjusted for splits, where *AvePrc* is calculated over trading days $t-27, \ldots, t-6$.

Table B.2: Call and put options' variables in a VAR setting

This table reports the findings from daily panel regressions, which serve as the base of our VAR analysis. In particular, our options' and stock measures are regressed on five lags of ambiguity ($AMBG$), risk ($RISK$), and the dependent variable (DEP). All variables are defined in Table B.1. All variables are trimmed at the top and bottom 0.1% of their sample distribution. All regression tests include the full set of firm control variables together with firm fixed effects and date fixed effects. (Z) stands for a Z-Score adjustment. The regression specifications take the following form

$$\begin{aligned} DEP(Z)_{j,t} \quad = \quad & \alpha + \sum_{i=1}^{5} \beta_i \cdot AMBG(Z)_{j,t-i} + \sum_{i=1}^{5} \gamma_i \cdot RISK(Z)_{j,t-i} + \sum_{i=1}^{5} \delta_i \cdot DEP(Z)_{j,t-i} + \\ & \delta \cdot CONTROLS_{j,t} + \eta_j + \theta_t + \epsilon_{1,j,t}. \end{aligned} \tag{8}$$

The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1) $COI(Z)$	(2) $POI(Z)$	(3) $CVOL(Z)$	(4) $PVOL(Z)$	(5) $CRET(Z)$	(6) $PRET(Z)$	(7) $CBAS(Z)$	(8) $PBAS(Z)$
$AMBG(Z)\ t-1$	-0.001***	-0.001***	-0.006***	-0.008***	-0.011***	0.001	0.003***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z)\ t-2$	-0.000**	-0.000*	-0.002***	-0.002***	0.002**	-0.002*	0.002***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z)\ t-3$	0.000	-0.000	-0.001**	-0.002***	0.005***	-0.002*	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z)\ t-4$	-0.000	-0.000	-0.001**	-0.002***	0.004***	-0.000	-0.000	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z)\ t-5$	-0.000	-0.000	-0.003***	-0.002***	0.004***	-0.001	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z)\ t-1$	0.002***	0.002***	0.013***	0.015***	0.018***	-0.003*	0.011***	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z)\ t-2$	0.001***	0.001***	-0.004***	-0.004***	0.004***	-0.000	0.001	-0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z)\ t-3$	0.000	-0.000	-0.002*	-0.001	-0.001	0.002	-0.000	-0.003*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z)\ t-4$	0.000	-0.000	-0.001	-0.001	-0.004**	0.004**	-0.004***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z)\ t-5$	-0.001***	-0.001***	0.000	0.003***	-0.002	0.003*	0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

	(1) *COI(Z)*	(2) *POI(Z)*	(3) *CVOL(Z)*	(4) *PVOL(Z)*	(5) *CRET(Z)*	(6) *PRET(Z)*	(7) *CBAS(Z)*	(8) *PBAS(Z)*
$DEP(Z)\ t-1$	0.866***	0.871***	0.292***	0.274***	-0.202***	0.143***	0.217***	0.212***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$DEP(Z)\ t-2$	-0.035***	-0.044***	0.121***	0.119***	-0.043***	0.044***	0.157***	0.154***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$DEP(Z)\ t-3$	0.095***	0.104***	0.086***	0.084***	-0.006***	0.016***	0.131***	0.131***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$DEP(Z)\ t-4$	0.013***	0.008**	0.074***	0.074***	0.004***	0.009***	0.115***	0.115***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$DEP(Z)\ t-5$	0.038***	0.041***	0.085***	0.085***	0.004***	0.004***	0.113***	0.113***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,778,604	5,704,053	5,864,429	5,777,571	5,823,013	5,725,106	3,439,335	2,694,917
AdjR^2	0.968	0.971	0.428	0.393	0.208	0.127	0.602	0.577

Table B.3: Call and put options' open interest and trading volume based on moneyness

The table extends the analysis conducted in Table 3 and Table 4, where firm's options open interest and trading volume are aggregated on each day based on contract moneyness. The moneyness groups $DR1$, $DR2$ and $DR3$ are defined as $0.1 <= |\Delta| <= 0.40$, $0.40 < |\Delta| < 0.60$, and $0.60 < |\Delta| <= 0.90$, respectively. To estimate the coefficients we stack each firm daily measures in the same regression and interact *AMBG* and *RISK* with dummy variables based on the three defined moneyness groups (*AMBG_DR1*- *AMBG_DR3* and *RISK_DR1*- *RISK_DR3*). The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable (*AvgDEP*), *AMBG*(*AvgAMBG*) and *RISK*(*AvgRISK*). This allows to account for the persistence in the dependent variables, and explore the effect of changes in *AMBG* and *RISK* relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and *t*-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open interest

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG_DR1(Z)	-0.012***	-0.013***	-0.014***	-0.014***	-0.014***	-0.012***	-0.013***	-0.015***	-0.016***	-0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_DR2(Z)	-0.009***	-0.010***	-0.010***	-0.011***	-0.012***	-0.010***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_DR3(Z)	-0.001	-0.001	-0.000	-0.000	-0.000	-0.008***	-0.008***	-0.007***	-0.007***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_DR1(Z)	0.002	0.003	0.004*	0.004*	0.003	-0.006***	-0.004*	-0.002	-0.002	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_DR2(Z)	-0.004***	-0.002	-0.001	-0.000	0.000	0.017***	0.017***	0.016***	0.016***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_DR3(Z)	-0.009***	-0.007***	-0.006***	-0.005***	-0.003*	0.033***	0.033***	0.035***	0.036***	0.036***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
p-Val Diff	<0.001	<0.001	<0.001	<0.001	<0.001	0.061	0.005	<0.001	<0.001	<0.001
Observations	14,287,737	14,287,583	14,287,788	14,287,842	14,287,902	14,105,298	14,105,262	14,105,442	14,105,576	14,105,683
AdjR^2	0.644	0.646	0.651	0.652	0.654	0.671	0.672	0.678	0.678	0.679

Panel B: Trading volume

	CVOL(Z)					*PVOL(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG_DR1(Z)	-0.039***	-0.019***	-0.013***	-0.011***	-0.009***	-0.042***	-0.027***	-0.022***	-0.020***	-0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_DR2(Z)	-0.043***	-0.026***	-0.020***	-0.017***	-0.014***	-0.036***	-0.021***	-0.015***	-0.012***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_DR3(Z)	-0.025***	-0.012***	-0.009***	-0.009***	-0.009***	-0.020***	-0.007***	-0.003*	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_DR1(Z)	0.129***	0.047***	0.022***	0.016***	0.008***	0.119***	0.047***	0.024***	0.016***	0.012***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_DR2(Z)	0.131***	0.053***	0.028***	0.022***	0.016***	0.117***	0.049***	0.029***	0.023***	0.019***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_DR3(Z)	0.135***	0.063***	0.040***	0.033***	0.026***	0.129***	0.064***	0.044***	0.037***	0.031***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
p-Val Diff	<0.001	<0.001	0.029	0.338	0.900	<0.001	<0.001	<0.001	<0.001	<0.001
Observations	14,873,117	14,572,341	14,458,208	14,355,486	14,164,250	14,595,725	14,346,982	14,262,558	14,184,373	14,029,350
AdjR^2	0.288	0.284	0.273	0.262	0.243	0.270	0.266	0.256	0.247	0.233

Table B.4: Call and put options' open interest and trading volume based on maturity

The table extends the analysis conducted in Table 3 and Table 4, where firm's options open interest and trading volume are aggregated on each day based on contract maturity. The maturity groups $MR1$, $MR2$ and $MR3$ are defined as *Maturity <= 3 months*, *3 < Maturity <= 6 months*, and *6 < Maturity <= 12 months*, respectively. To estimate the coefficients we stack each firm daily measures in the same regression and interact *AMBG* and *RISK* with dummy variables based on the three defined maturity groups (*AMBG_MR1*- *AMBG_MR3* and *RISK_MR1*-*RISK_MR3*). The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable (*AvgDEP*), *AMBG*(*AvgAMBG*) and *RISK*(*AvgRISK*). This allows to account for the persistence in the dependent variables, and explore the effect of changes in *AMBG* and *RISK* relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open interest

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG_MR1(Z)	-0.019***	-0.020***	-0.022***	-0.023***	-0.025***	-0.025***	-0.026***	-0.027***	-0.028***	-0.029***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_MR2(Z)	-0.005***	-0.005***	-0.004***	-0.004***	-0.004***	-0.007***	-0.007***	-0.007***	-0.007***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_MR3(Z)	-0.001	-0.001	-0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_MR1(Z)	-0.010***	-0.009***	-0.008***	-0.008***	-0.008***	0.021***	0.020***	0.020***	0.020***	0.018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_MR2(Z)	0.000	0.001	0.002	0.002	0.003*	0.013***	0.014***	0.015***	0.015***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_MR3(Z)	-0.005**	-0.003	-0.001	0.000	0.002	0.006**	0.008***	0.010***	0.011***	0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
p-Val Diff	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Observations	13,954,191	13,953,941	13,953,829	13,953,749	13,953,506	13,525,611	13,525,497	13,525,543	13,525,476	13,525,283
AdjR^2	0.629	0.632	0.636	0.638	0.640	0.633	0.635	0.640	0.642	0.642

Panel B: Trading volume

	CVOL(Z)					*PVOL(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG_MR1(Z)	-0.052***	-0.035***	-0.029***	-0.027***	-0.026***	-0.055***	-0.036***	-0.031***	-0.027***	-0.025***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_MR2(Z)	-0.021***	-0.010***	-0.007***	-0.006***	-0.006***	-0.019***	-0.009***	-0.006***	-0.005***	-0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG_MR3(Z)	-0.015***	-0.004*	-0.000	0.001	0.001	-0.012***	-0.002	0.002	0.003	0.004*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_MR1(Z)	0.108***	0.035***	0.011***	0.005**	-0.001	0.102***	0.035***	0.013***	0.006**	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_MR2(Z)	0.113***	0.054***	0.035***	0.029***	0.024***	0.109***	0.057***	0.040***	0.034***	0.029***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK_MR3(Z)	0.115***	0.059***	0.042***	0.037***	0.032***	0.111***	0.061***	0.044***	0.038***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
p-Val Diff	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Observations	14,477,438	14,198,711	14,106,537	14,019,723	13,846,917	14,010,078	13,749,932	13,664,803	13,584,760	13,423,421
AdjR^2	0.333	0.334	0.331	0.325	0.314	0.298	0.297	0.293	0.288	0.279

Table B.5: Call and put options' open interest - reporting the full set of controls

This table reports the full set of results from Table 3. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.012***	-0.012***	-0.013***	-0.013***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	-0.004***	-0.003**	-0.001	-0.001	-0.000	0.015***	0.016***	0.017***	0.017***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnSize	0.003	0.003	0.003	0.003	0.003	-0.016***	-0.017***	-0.018***	-0.019***	-0.021***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnBM	-0.016***	-0.017***	-0.018***	-0.018***	-0.020***	-0.005*	-0.005**	-0.005**	-0.006**	-0.007**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CumRet	0.004***	0.004***	0.004***	0.003***	0.003***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LnNumEst	0.013***	0.014***	0.015***	0.015***	0.016***	0.022***	0.022***	0.023***	0.023***	0.023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
InstHold	0.019**	0.020**	0.021**	0.021**	0.022**	0.002	0.003	0.004	0.004	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\ln \frac{1}{AvePrc}$	-0.027***	-0.031***	-0.035***	-0.039***	-0.046***	-0.076***	-0.082***	-0.087***	-0.092***	-0.101***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
RET	0.015***	0.014***	0.014***	0.014***	0.013***	-0.009***	-0.009***	-0.008***	-0.008***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AvgDEP	0.653***	0.650***	0.649***	0.645***	0.639***	0.722***	0.718***	0.716***	0.713***	0.705***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
AvgAMBG	0.136	0.059	-0.016	-0.098	-0.229	-0.210	-0.240	-0.318	-0.362	-0.498*
	(0.22)	(0.21)	(0.22)	(0.22)	(0.22)	(0.27)	(0.27)	(0.27)	(0.28)	(0.27)
AvgRISK	23.001***	23.097***	23.872***	24.950***	26.565***	4.632	4.130	4.446	4.726	5.610
	(2.67)	(2.71)	(2.75)	(2.80)	(2.89)	(3.59)	(3.59)	(3.62)	(3.62)	(3.60)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,871,968	5,872,005	5,872,150	5,872,179	5,872,223	5,791,506	5,791,552	5,791,681	5,791,760	5,791,788
AdjR^2	0.837	0.837	0.840	0.839	0.839	0.846	0.846	0.848	0.847	0.845

Table B.6: Call and put options' trading volume - reporting the full set of controls

This table reports the full set of results from Table 4. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	CVOL(Z)					*PVOL(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.040***	-0.023***	-0.018***	-0.017***	-0.016***	-0.039***	-0.023***	-0.018***	-0.015***	-0.013***
	(-16.88)	(-15.68)	(-14.93)	(-14.14)	(-13.39)	(-15.32)	(-13.82)	(-13.55)	(-13.27)	(-12.03)
RISK(Z)	0.137***	0.058***	0.033***	0.026***	0.020***	0.132***	0.059***	0.037***	0.029***	0.024***
	(24.92)	(17.96)	(13.30)	(11.65)	(9.61)	(23.94)	(17.49)	(14.03)	(12.16)	(10.59)
LnSize	-0.006	-0.009	-0.011	-0.011	-0.011	-0.000	-0.003	-0.004	-0.005	-0.005
	(-0.87)	(-1.29)	(-1.52)	(-1.59)	(-1.45)	(-0.06)	(-0.42)	(-0.53)	(-0.68)	(-0.65)
LnBM	-0.021***	-0.022***	-0.022***	-0.022***	-0.023***	-0.016***	-0.016***	-0.017***	-0.017***	-0.017***
	(-4.82)	(-4.72)	(-4.61)	(-4.58)	(-4.59)	(-3.48)	(-3.40)	(-3.34)	(-3.31)	(-3.40)
CumRet	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(8.29)	(6.29)	(5.06)	(4.15)	(3.66)	(11.59)	(9.67)	(8.60)	(8.85)	(7.99)
LnNumEst	0.018***	0.014*	0.013*	0.013	0.010	0.032***	0.032***	0.032***	0.032***	0.032***
	(2.58)	(1.95)	(1.75)	(1.62)	(1.27)	(4.21)	(3.93)	(3.89)	(3.81)	(3.63)
InstHold	0.017	0.018	0.015	0.015	0.017	0.015	0.013	0.013	0.014	0.016
	(1.47)	(1.42)	(1.17)	(1.19)	(1.25)	(1.21)	(1.04)	(1.02)	(1.07)	(1.17)
$\ln \frac{1}{AvePrc}$	-0.134***	-0.151***	-0.157***	-0.163***	-0.169***	-0.143***	-0.149***	-0.150***	-0.152***	-0.154***
	(-13.43)	(-13.99)	(-14.19)	(-14.32)	(-14.33)	(-13.44)	(-13.40)	(-13.22)	(-13.19)	(-13.05)
RET	0.029***	0.012***	0.008***	0.006***	0.005***	-0.014***	-0.004***	-0.002***	-0.001***	-0.000*
	(35.05)	(24.99)	(22.10)	(19.13)	(16.97)	(-24.06)	(-10.83)	(-7.93)	(-4.01)	(-1.86)
AvgDEP	3.450***	3.463***	3.436***	3.379***	3.271***	4.082***	4.055***	4.013***	3.944***	3.810***
	(24.98)	(23.11)	(22.85)	(21.92)	(20.16)	(25.66)	(24.52)	(23.52)	(22.67)	(21.27)
AvgAMBG	1.068***	-0.733**	-1.293***	-1.566***	-1.735***	0.384	-1.432***	-1.971***	-2.275***	-2.519***
	(2.98)	(-2.27)	(-4.01)	(-4.82)	(-4.88)	(0.95)	(-3.86)	(-5.36)	(-6.07)	(-6.44)
AvgRISK	-100.412***	-25.524***	-2.941	3.766	10.294**	-94.148***	-26.064***	-5.856	1.609	6.391
	(-17.70)	(-5.61)	(-0.68)	(0.87)	(2.36)	(-16.98)	(-5.80)	(-1.33)	(0.36)	(1.44)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,008,137	5,940,699	5,924,982	5,910,826	5,884,918	5,922,273	5,857,357	5,841,742	5,828,234	5,802,097
AdjR^2	0.400	0.409	0.408	0.404	0.395	0.369	0.373	0.371	0.367	0.359

Table B.7: Trading volume based Put-call ratio and stock return predictability

This table reports the findings from daily panel regressions, in which DGTW adjusted cumulative stock returns from trading day $t+1,\ldots,t+10$ are regressed on trading day t's put-call volume ratio (*PCVOL_RATIO*), ambiguity (*AMBG*), risk (*RISK*), the interaction of *PCVOL_RATIO* with *AMBG* and *RISK* controlling for other firm characteristics. In particular, *PCVOL_RATIO* is calculated as day t's aggregate put option trading volume divided by the aggregate trading volume of both call and put options (P/(C+P)). Columns 1-3, 4-6 and 7-9 report results for cumulative returns based on one, five and ten trading days, respectively. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable (*AvgDEP*), *AMBG*(*AvgAMBG*) and *RISK*(*AvgRISK*). This allows to account for the persistence in the dependent variables, and explore the effect of changes in *AMBG* and *RISK* relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	$DGTW_t1$			$DGTW_t5$			$DGTW_t10$		
	(1) t+1	(2) t+1	(3) t+1	(4) t+1_t+5	(5) t+1_t+5	(6) t+1_t+5	(7) t+1_t+10	(8) t+1_t+10	(9) t+1_t+10
AMBG(Z)	0.004	0.004	0.004	0.020***	0.020***	0.020***	0.028***	0.028***	0.028***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.009	0.009	0.009	0.042**	0.042**	0.042**	0.061***	0.061***	0.061***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PCVOL_RATIO(Z)	-0.011***	-0.011***	-0.011***	-0.014***	-0.014***	-0.014***	-0.018***	-0.018***	-0.018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$PCVOL\_RATIO(Z)\times AMBG(Z)$		0.002**	0.002		0.003	0.005		0.003	0.004
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
$PCVOL\_RATIO(Z)\times RISK(Z)$			-0.000			0.003			0.002
			(0.00)			(0.00)			(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	NO	NO	NO	NO	NO	NO	NO
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,002,463	5,002,463	5,002,463	5,001,520	5,001,520	5,001,520	4,999,809	4,999,809	4,999,809
AdjR^2	0.004	0.004	0.004	0.010	0.010	0.010	0.016	0.016	0.016

Table B.8: Option based measures and stock return predictability - firm fixed effects

This table repeats the analysis reported in Table 5 including firm fixed effects. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG$($AvgAMBG$) and $RISK$($AvgRISK$). This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: The put-call open Interest ratio

	$DGTW_t1$			$DGTW_t5$			$DGTW_t10$		
	(1) t+1	(2) t+1	(3) t+1	(4) t+1_t+5	(5) t+1_t+5	(6) t+1_t+5	(7) t+1_t+10	(8) t+1_t+10	(9) t+1_t+10
AMBG(Z)	0.005**	0.005**	0.005**	0.018***	0.018***	0.018***	0.027***	0.027***	0.027***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.006	0.006	0.006	0.023	0.023	0.023	0.043**	0.043**	0.043**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta PC\_RATIO(Z)$	-0.310***	-0.305***	-0.304***	-0.351***	-0.345***	-0.344***	-0.362***	-0.356***	-0.355***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta PC\_RATIO(Z) \times AMBG(Z)$		0.034***	0.031***		0.044***	0.037***		0.046***	0.039***
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
$\Delta PC\_RATIO(Z) \times RISK(Z)$			-0.005			-0.012***			-0.013**
			(0.00)			(0.00)			(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,822,491	5,822,491	5,822,491	5,820,016	5,820,016	5,820,016	5,817,886	5,817,886	5,817,886
AdjR^2	0.027	0.027	0.027	0.014	0.014	0.014	0.018	0.018	0.018

Panel B: The implied volatility spread measure

	$DGTW_t1$			$DGTW_t5$			$DGTW_t10$		
	(1) t+1	(2) t+1	(3) t+1	(4) t+1_t+5	(5) t+1_t+5	(6) t+1_t+5	(7) t+1_t+10	(8) t+1_t+10	(9) t+1_t+10
AMBG(Z)	0.004	0.004	0.004	0.018***	0.017***	0.017***	0.025***	0.024***	0.024***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.004	0.004	0.006	0.025	0.024	0.026*	0.044**	0.043**	0.045**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IVS(Z)	0.063***	0.060***	0.054***	0.075***	0.070***	0.063***	0.083***	0.076***	0.068***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IVS(Z)$\times AMBG(Z)$		-0.006***	-0.000		-0.014***	-0.008		-0.021***	-0.013*
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
IVS(Z)$\times RISK(Z)$			0.012***			0.012**			0.014*
			(0.00)			(0.00)			(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,614,952	5,614,952	5,614,952	5,613,843	5,613,843	5,613,843	5,612,216	5,612,216	5,612,216
AdjR^2	0.004	0.004	0.004	0.009	0.009	0.009	0.016	0.016	0.016

Table B.9: Call and put options' cumulative delta-hedged returns - firm fixed effects

This table repeat the analysis conducted in Table 6 including firm fixed effects. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable (*AvgDEP*), *AMBG*(*AvgAMBG*) and *RISK*(*AvgRISK*). This allows to account for the persistence in the dependent variables, and explore the effect of changes in *AMBG* and *RISK* relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and *t*-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	CCUMRET					*PCUMRET*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.139***	-0.175***	-0.183***	-0.183***	-0.181***	-0.193***	-0.246***	-0.284***	-0.309***	-0.341***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
RISK(Z)	0.311***	0.409***	0.500***	0.551***	0.662***	0.314***	0.435***	0.514***	0.578***	0.680***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,099,948	6,005,311	5,935,571	5,877,084	5,776,677	6,019,993	5,927,483	5,859,912	5,803,999	5,708,088
AdjR^2	0.162	0.157	0.164	0.171	0.182	0.106	0.124	0.143	0.158	0.179

Table B.10: Call and put options' cumulative delta-hedged returns - Monthly *RISK* and *AMBG*

To link our option return findings reported in Table 6 with Cao and Han (2013), in this table we also reports the coefficient estimates of the monthly *RISK* and *AMBG* measures (*AvgRISK* and *AvgAMBG*) included in the regressions reported in Table 6. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable (*AvgDEP*), *AMBG*(*AvgAMBG*) and *RISK*(*AvgRISK*). This allows to account for the persistence in the dependent variables, and explore the effect of changes in *AMBG* and *RISK* relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	CCUMRET(Z)					*PCUMRET(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.138***	-0.174***	-0.182***	-0.184***	-0.185***	-0.194***	-0.251***	-0.292***	-0.321***	-0.360***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
RISK(Z)	0.305***	0.403***	0.492***	0.542***	0.652***	0.313***	0.433***	0.513***	0.577***	0.680***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
AvgAMBG	0.002***	0.002***	0.003***	0.003***	0.003***	0.002***	0.003***	0.003***	0.003***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AvgRISK	-0.030***	-0.039***	-0.049***	-0.055***	-0.069***	-0.028***	-0.036***	-0.042***	-0.047***	-0.055***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,099,959	6,005,322	5,935,581	5,877,097	5,776,690	6,020,006	5,927,494	5,859,923	5,804,013	5,708,099
AdjR^2	0.162	0.156	0.163	0.169	0.177	0.106	0.124	0.141	0.156	0.175

Table B.11: Call and put options' open interest and volume based on firm size subsamples

This table reports the findings from daily panel regressions, in which call and put stock option open interest (Panel A) and volume (Panel B) on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), risk ($RISK$), and other firm characteristics conditioning on firm size. In particular, the dummy variables Size1-Size3 are equal to one if the firm is assigned to size terciles 1-3, respectively, and zero otherwise. $AMBG \times Size1$ — $AMBG \times Size3$ ($RISK \times Size1$ — $RISK \times Size3$) are the interaction of $AMBG$ ($RISK$) with $Size1$-$Size3$ dummy variables. Call and Put measures are reported in Columns 1-5 and Columns 6-10, respectively. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG$($AvgAMBG$) and $RISK$($AvgRISK$). This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open Interest

	COI(Z)					POI(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
$AMBG(Z) \times Size1$	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.006***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Size2$	-0.012***	-0.013***	-0.013***	-0.013***	-0.013***	-0.010***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Size3$	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Size1$	-0.007***	-0.006***	-0.006***	-0.006***	-0.006***	0.009***	0.010***	0.010***	0.010***	0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Size2$	0.001	0.003	0.005**	0.006**	0.007***	0.021***	0.022***	0.024***	0.024***	0.024***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Size3$	0.019***	0.025***	0.031***	0.034***	0.039***	0.060***	0.062***	0.066***	0.067***	0.069***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,887,441	5,887,438	5,887,517	5,887,539	5,887,564	5,806,847	5,806,844	5,806,942	5,806,963	5,807,012
AdjR^2	0.843	0.843	0.844	0.844	0.842	0.856	0.855	0.857	0.857	0.854

Panel B: Volume

	CVOL(Z)					*PVOL(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
$AMBG(Z) \times Size1$	-0.014***	-0.011***	-0.011***	-0.011***	-0.011***	-0.005***	-0.006***	-0.005***	-0.006***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Size2$	-0.028***	-0.019***	-0.017***	-0.016***	-0.016***	-0.022***	-0.014***	-0.012***	-0.011***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Size3$	-0.043***	-0.022***	-0.016***	-0.014***	-0.013***	-0.042***	-0.022***	-0.016***	-0.013***	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Size1$	0.112***	0.044***	0.024***	0.018***	0.013***	0.104***	0.044***	0.026***	0.020***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Size2$	0.175***	0.073***	0.041***	0.031***	0.023***	0.172***	0.075***	0.047***	0.035***	0.030***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Size3$	0.288***	0.150***	0.102***	0.087***	0.072***	0.312***	0.171***	0.122***	0.103***	0.089***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,008,137	5,940,699	5,924,982	5,910,826	5,884,918	5,922,273	5,857,357	5,841,742	5,828,234	5,802,097
AdjR^2	0.402	0.409	0.408	0.404	0.395	0.371	0.374	0.372	0.367	0.359

Table B.12: Call and put options' open interest and volume - sub periods

This table reports the findings from daily panel regressions, in which call and put stock option open interest (Panel A) and volume (Panel B) on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), risk ($RISK$), and other firm characteristics conditioning on three subperiods. In particular, the dummy variables Sub1-Sub3 are equal to one if the sample period is 2002-2006, 2007-2012, and 2013-2018, respectively, and zero otherwise. $AMBG \times Sub1$–$AMBG \times Sub3$ ($RISK \times Sub1$ — $RISK \times Sub3$) are the interaction of $AMBG(RISK)$ with $Sub1$-$Sub3$ dummy variables. Call and Put measures are reported in Columns 1-5 and Columns 6-10, respectively. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG(AvgAMBG)$ and $RISK(AvgRISK)$. This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open Interest

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
$AMBG(Z) \times Sub1$	-0.011***	-0.012***	-0.012***	-0.013***	-0.014***	-0.011***	-0.012***	-0.012***	-0.012***	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Sub2$	-0.014***	-0.014***	-0.014***	-0.015***	-0.015***	-0.015***	-0.016***	-0.016***	-0.016***	-0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Sub3$	-0.009***	-0.010***	-0.010***	-0.010***	-0.010***	-0.011***	-0.011***	-0.012***	-0.012***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Sub1$	0.004*	0.006***	0.007***	0.008***	0.009***	0.020***	0.021***	0.021***	0.022***	0.022***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Sub2$	-0.005**	-0.003	-0.001	-0.000	0.001	0.015***	0.016***	0.018***	0.018***	0.018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Sub3$	-0.006***	-0.006***	-0.005***	-0.005***	-0.006***	0.011***	0.012***	0.013***	0.013***	0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,887,441	5,887,438	5,887,517	5,887,539	5,887,564	5,806,847	5,806,844	5,806,942	5,806,963	5,807,012
AdjR^2	0.843	0.843	0.844	0.844	0.842	0.856	0.855	0.857	0.856	0.854

Panel B: Volume

	$CVOL(Z)$					$PVOL(Z)$				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
$AMBG(Z) \times Sub1$	-0.031***	-0.021***	-0.020***	-0.019***	-0.018***	-0.031***	-0.021***	-0.017***	-0.017***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Sub2$	-0.044***	-0.027***	-0.022***	-0.020***	-0.020***	-0.043***	-0.026***	-0.021***	-0.018***	-0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$AMBG(Z) \times Sub3$	-0.044***	-0.022***	-0.015***	-0.013***	-0.011***	-0.043***	-0.022***	-0.015***	-0.012***	-0.009***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Sub1$	0.147***	0.069***	0.043***	0.037***	0.030***	0.136***	0.066***	0.044***	0.036***	0.032***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Sub2$	0.145***	0.060***	0.033***	0.024***	0.016***	0.139***	0.060***	0.036***	0.025***	0.018***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$RISK(Z) \times Sub3$	0.123***	0.047***	0.024***	0.018***	0.014***	0.122***	0.052***	0.032***	0.025***	0.021***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Date Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,008,137	5,940,699	5,924,982	5,910,826	5,884,918	5,922,273	5,857,357	5,841,742	5,828,234	5,802,097
AdjR^2	0.400	0.409	0.408	0.404	0.395	0.369	0.373	0.371	0.367	0.359

Table B.13: *AMBG* and other uncertainty proxies

This table reports the findings from daily panel regressions, in which call and put stock option open interest (Panel A), trading volume (Panel B), and cumulative delta-hedged returns (Panel C) on trading day $t, \dots, t+5$ are regressed on trading day t's ambiguity (*AMBG*), risk (*RISK*), and other firm characteristics. In each panel, "Base" refers to the main specification reported in the paper. "No uncertainty controls" is a specification that excludes *RISK* and *AvgRISK*. "Full uncertainty controls" is a specification that includes *RISK* together with *VOV*, *VOM*, *SKEW*, and *KURT* together with their rolling averages. For brevity, the table only reports the *AMBG* coefficients. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open Interest

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
Base										
AMBG(Z)	-0.012***	-0.012***	-0.013***	-0.013***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No uncertainty controls										
AMBG(Z)	-0.012***	-0.012***	-0.013***	-0.013***	-0.014***	-0.015***	-0.016***	-0.016***	-0.016***	-0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Full uncertainty controls										
AMBG(Z)	-0.012***	-0.012***	-0.013***	-0.013***	-0.013***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Trading Volume

	CVOL(Z)					PVOL(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
Base										
AMBG(Z)	-0.040***	-0.023***	-0.017***	-0.016***	-0.015***	-0.039***	-0.024***	-0.018***	-0.016***	-0.013***
	(-16.88)	(-16.03)	(-15.07)	(-14.06)	(-13.78)	(-15.32)	(-14.28)	(-14.36)	(-13.88)	(-11.92)
No uncertainty controls										
AMBG(Z)	-0.051***	-0.028***	-0.021***	-0.019***	-0.018***	-0.049***	-0.028***	-0.021***	-0.018***	-0.015***
	(-19.73)	(-17.48)	(-16.02)	(-15.08)	(-14.27)	(-18.09)	(-15.67)	(-14.94)	(-14.44)	(-13.24)
Full uncertainty controls										
AMBG(Z)	-0.041***	-0.023***	-0.018***	-0.017***	-0.016***	-0.041***	-0.023***	-0.018***	-0.015***	-0.014***
	(-17.08)	(-15.56)	(-14.91)	(-14.12)	(-13.45)	(-15.78)	(-13.89)	(-13.64)	(-13.39)	(-12.20)

Panel C: Cumulative delta-hedged returns

	CCUMRET(Z)					PCUMRET(Z)			
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3
Base									
AMBG(Z)	-0.139***	-0.175***	-0.183***	-0.183***	-0.181***	-0.193***	-0.246***	-0.284***	-0.309***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
No uncertainty controls									
AMBG(Z)	-0.163***	-0.206***	-0.221***	-0.224***	-0.231***	-0.216***	-0.279***	-0.323***	-0.354***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Full uncertainty controls									
AMBG(Z)	-0.142***	-0.179***	-0.188***	-0.188***	-0.188***	-0.199***	-0.253***	-0.292***	-0.318***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)

Table B.14: *AMBG*, *VOM* and *VOV*

This table reports the findings from daily panel regressions, in which call and put stock option open interest (Panel A), trading volume (Panel B), and cumulative delta-hedged returns (Panel C) on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), volatility-of-mean (VOM), volatility-of-volatility (VOV) and other firm characteristics. There are two separate specifications in each panel based on VOM("$AMBG$ and VOM") and VOV("$AMBG$ and VOV"), controlling for their trailing averages. For brevity, the table only reports the $AMBG$, VOM, and VOV coefficients. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open Interest

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG and VOM										
AMBG(Z)	-0.012***	-0.012***	-0.012***	-0.013***	-0.013***	-0.015***	-0.015***	-0.015***	-0.016***	-0.016***
	(-12.43)	(-12.77)	(-13.12)	(-13.35)	(-13.83)	(-13.91)	(-14.18)	(-14.63)	(-14.80)	(-15.29)
VOM(Z)	0.003***	0.004***	0.004***	0.005***	0.005***	0.010***	0.010***	0.011***	0.011***	0.011***
	(3.87)	(5.11)	(5.97)	(6.39)	(6.80)	(12.62)	(13.08)	(13.76)	(13.88)	(13.79)
AMBG and VOV										
AMBG(Z)	-0.012***	-0.012***	-0.013***	-0.013***	-0.014***	-0.015***	-0.015***	-0.016***	-0.016***	-0.016***
	(-12.59)	(-12.94)	(-13.30)	(-13.54)	(-14.03)	(-14.06)	(-14.33)	(-14.79)	(-14.96)	(-15.45)
VOV(Z)	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.001**	-0.001**	-0.001**	-0.001***	-0.002***
	(-9.08)	(-9.01)	(-9.22)	(-9.49)	(-9.75)	(-2.50)	(-2.44)	(-2.52)	(-2.65)	(-3.17)

Panel B: Trading volume

	CVOL(Z)					*PVOL(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG and *VOM*										
AMBG(Z)	-0.049***	-0.027***	-0.021***	-0.018***	-0.017***	-0.048***	-0.027***	-0.020***	-0.017***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VOM(Z)	0.100***	0.038***	0.023***	0.019***	0.014***	0.095***	0.038***	0.024***	0.018***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AMBG and *VOV*										
AMBG(Z)	-0.050***	-0.027***	-0.021***	-0.019***	-0.017***	-0.049***	-0.027***	-0.020***	-0.017***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VOV(Z)	0.020***	0.005***	0.001	0.000	-0.000	0.022***	0.007***	0.003***	0.002**	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel C: Cumulative delta-hedged returns

	CCUMRET(Z)					*PCUMRET(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG and *VOM*										
AMBG(Z)	-0.160***	-0.202***	-0.216***	-0.220***	-0.225***	-0.215***	-0.277***	-0.320***	-0.350***	-0.389***
	(-22.95)	(-22.15)	(-20.03)	(-17.53)	(-15.00)	(-25.95)	(-25.02)	(-24.38)	(-23.76)	(-21.44)
VOM(Z)	0.289***	0.374***	0.439***	0.477***	0.546***	0.296***	0.380***	0.439***	0.477***	0.541***
	(36.46)	(39.15)	(41.07)	(40.67)	(39.49)	(41.89)	(47.15)	(47.56)	(45.93)	(44.82)
AMBG and *VOV*										
AMBG(Z)	-0.162***	-0.205***	-0.220***	-0.224***	-0.231***	-0.216***	-0.278***	-0.322***	-0.352***	-0.391***
	(-23.33)	(-22.43)	(-20.22)	(-17.64)	(-15.10)	(-26.09)	(-25.17)	(-24.46)	(-23.81)	(-21.45)
VOV(Z)	0.026***	0.031***	0.050***	0.059***	0.076***	0.033***	0.053***	0.070***	0.086***	0.107***
	(5.50)	(5.31)	(7.77)	(8.01)	(8.78)	(7.90)	(10.34)	(11.98)	(13.00)	(13.41)

Table B.15: $AMBG$ and dispersion of analyst forecast (DAF)

This table reports the findings from daily panel regressions, in which call and put stock option open interest (Panel A), trading volume (Panel B), and cumulative delta-hedged returns (Panel C) on trading day $t, \dots, t+5$ are regressed on trading day t's ambiguity ($AMBG$), risk ($RISK$) the dispersion of analyst forecasts (DAF) and other firm characteristics. For brevity, the table only reports the $AMBG$, $RISK$, and DAF coefficients. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. All specifications include the trailing avergaes of the dependent variable ($AvgDEP$), $AMBG$($AvgAMBG$) and $RISK$($AvgRISK$). This allows to account for the persistence in the dependent variables, and explore the effect of changes in $AMBG$ and $RISK$ relative to their trailing benchmarks. (Z) stands for a Z-Score adjustment. Firm and date fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open Interest

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.012***	-0.012***	-0.013***	-0.013***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	-0.004***	-0.003**	-0.001	-0.001	-0.000	0.015***	0.016***	0.017***	0.017***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DAF(Z)	0.005***	0.006***	0.006***	0.006***	0.006***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Trading volume

	CVOL(Z)					PVOL(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.040***	-0.023***	-0.018***	-0.017***	-0.016***	-0.039***	-0.023***	-0.018***	-0.015***	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.137***	0.058***	0.033***	0.026***	0.020***	0.131***	0.059***	0.037***	0.029***	0.024***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
DAF(Z)	0.008***	0.008***	0.007***	0.008***	0.007***	0.010***	0.011***	0.011***	0.011***	0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel C: Cumulative delta-hedged returns

	CCUMRET(Z)					PCUMRET(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.139***	-0.175***	-0.183***	-0.183***	-0.181***	-0.193***	-0.246***	-0.284***	-0.309***	-0.341***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
RISK(Z)	0.311***	0.409***	0.500***	0.551***	0.662***	0.314***	0.435***	0.514***	0.578***	0.680***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
DAF(Z)	-0.000	0.005	0.015**	0.020**	0.038***	0.004*	0.004	0.005	0.008	0.013
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)

Table B.16: *AMBG* controlling for market *AMBG* and *VIX*

This table reports the findings from daily panel regressions, in which call and put stock option open interest (Panel A), trading volume (Panel B), and cumulative delta-hedged returns (Panel C) on trading day $t, \ldots, t+5$ are regressed on trading day t's ambiguity (*AMBG*), risk (*RISK*) and other firm characteristics controlling for changes in market ambiguity (Δ*MktAMBG*) and changes in *VIX* (Δ*VIX*). For brevity, the table only reports the *AMBG*, *RISK*, *MktAMBG* and *VIX* coefficients. The sample period is from January 2002 to December 2018. The options trading data is taken from OptionMetrics. All variables are defined in Table B.1. (Z) stands for a Z-Score adjustment. Firm and day-of-the-week fixed effects are included in each specification. Standard errors are double clustered by firm and date, and t-statistics are reported in parentheses below the coefficient estimates. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Open Interest

	COI(Z)					*POI(Z)*				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.009***	-0.010***	-0.010***	-0.011***	-0.011***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	-0.020***	-0.019***	-0.017***	-0.016***	-0.015***	0.032***	0.033***	0.034***	0.035***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ*MktAMBG (Z)*	-0.001	-0.001	-0.001	-0.001	-0.001	0.001*	0.001*	0.001*	0.001*	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ*VIX (Z)*	0.008***	0.008***	0.008***	0.008***	0.008***	-0.007***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel B: Trading volume

	CVOL(Z)					PVOL(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.036***	-0.023***	-0.018***	-0.016***	-0.015***	-0.042***	-0.028***	-0.022***	-0.020***	-0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RISK(Z)	0.110***	0.047***	0.025***	0.019***	0.013***	0.125***	0.062***	0.041***	0.032***	0.027***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Δ*MktAMBG (Z)*	-0.000	-0.001	-0.001	-0.000	0.000	0.000	0.001	-0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Δ*VIX (Z)*	0.018***	0.008***	0.006***	0.005***	0.004**	-0.004**	0.001	-0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Panel C: Cumulative delta-hedged returns

	CCUMRET(Z)					PCUMRET(Z)				
	(1) t	(2) t+1	(3) t+2	(4) t+3	(5) t+5	(6) t	(7) t+1	(8) t+2	(9) t+3	(10) t+5
AMBG(Z)	-0.159***	-0.227***	-0.274***	-0.303***	-0.347***	-0.325***	-0.464***	-0.562***	-0.642***	-0.748***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)
RISK(Z)	0.431***	0.647***	0.736***	0.857***	1.057***	0.709***	0.942***	1.147***	1.290***	1.514***
	(0.03)	(0.08)	(0.08)	(0.09)	(0.10)	(0.04)	(0.05)	(0.07)	(0.07)	(0.08)
Δ*MktAMBG (Z)*	0.008	0.040*	-0.029	0.002	-0.038	0.005	-0.056***	-0.053**	-0.076**	-0.078**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Δ*VIX (Z)*	1.111***	0.975***	1.006***	1.077***	1.052***	0.311***	0.696***	0.682***	0.729***	0.785***
	(0.05)	(0.07)	(0.08)	(0.08)	(0.11)	(0.05)	(0.05)	(0.07)	(0.08)	(0.09)