Why Do Hedgers Hedge? The Role of Ambiguity *

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Abstract

This study examines how ambiguity affects hedging behaviour in crude oil futures markets. I quantify ambiguity by examining variations in uncertain probabilities and identify the effect of an ambiguity shock on hedging behaviour using an instrument variable approach. The impact of ambiguity contrasts with the impact of risk, while both are equally important in terms of economic and statistical significance. Crucially, the analysis reveals, heterogeneity across different hedger sub-categories: Swap dealers react averse to ambiguity shocks and increase hedging demand whereas the activity of commodity producers is reduced. My research supports classical hedging theories in commodity markets, indicating a rise in hedging activity in uncertain conditions.

JEL classification: G1, G4, Q41

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1 Introduction

In recent years, there has been a growing interest in the economic effects of uncertainty. Major drivers of this development were the global financial crisis in 2007-09, the Covid-19 pandemic and the Russian invasion of Ukraine in February 2022. Each episode was characterized by the fact that, confronted with a shock not experienced for at least a generation, agents struggled to assess economic outlooks and make financial decisions. However, uncertainty is not limited to single outlier events. On the contrary, almost every economic decision is subject to uncertainty which itself has two well-established sources: risk and ambiguity. A situation is perceived as risky, if the outcome of a potential event is a priori unknown, while, at the same time, the decision-maker is perfectly aware of the underlying likelihood of each possible future state. A situation is ambiguous, if the decision-maker is not aware of the underlying likelihood of each possible future state (Knight, 1921).

Numerous experimental studies (e.g., Ellsberg, 1961; Halevy, 2007) have consistently demonstrated that decision-makers tend to avoid ambiguity, as evidenced by their preference for alternatives with clear probabilities (referred to as risk, the known unknowns) over those with vague probabilities (referred to as ambiguity, the unknown unknowns). This ambiguity aversion has proven to be economically significant and has been observed in various experimental market settings, as well as among business owners and managers (e.g., Abdellaoui, Vossmann, & Weber, 2005; Du & Budescu, 2005; Wakker, Timmermans, & Machielse, 2007). Notably, the impact of ambiguity on investment decisions differs significantly from that of risk. An ambiguity-averse decision maker assigns greater weight to the likelihood of unfavorable outcomes while assigning lesser weight to the likelihood of favorable outcomes (Tversky & Kahneman, 1992). This line of thinking aligns with findings from multiple experimental studies, including those conducted by Wu and Gonzalez (1999) and Abdellaoui and Kemel (2014).

But do individuals hedge against ambiguity? So far, the effect of uncertainty on hedging behaviour is not well understood and empirical evidence is limited to experimental settings. However, as ambiguity signifies market incompleteness, Epstein and Ji (2013) stress the need for more empirical evidence to understand the dynamics. This paper contributes to the existing literature by exploring a facet that has been overlooked so far. To offer an empirical viewpoint I examine the link between ambiguity and risk and the strategic hedging decisions made by participants in the futures market.

To answer the research question, I focus on the major energy futures market in the

US namely the crude oil futures market. This US energy futures market serves as a suitable laboratory when studying the effect of uncertainty on hedging behaviour for three main reasons. The first reason is the availability of detailed data on derivative positions. While data on bond and stock holdings are widely available for various investor types, detailed data on derivative positions are typically scarce. The approach employed requires detailed data concerning the positions of diverse trader groups in those markets. Due to regulatory requirements, data on the positioning of different trader groups are publicly available weekly. Here I am interested in positions of commercial traders, commercial traders are typically referred to as hedgers because their business activities expose them to price risks in the underlying commodity. Accordingly, it is assumed that their trading activity is primarily intended to have a risk-reducing effect. Second, US commodity markets are economically important because they generally serve as a benchmark for global crude oil and energy prices.[1] Third, my emphasis lies on crude oil as it holds immense significance as the most important commodity in the contemporary. economy According to the Energy Information Administration (EIA), in 2010, energy expenses, predominantly petroleum-based, comprised 8.3% of the U.S. GDP. Furthermore, energy commodities hold unparalleled significance in financial markets, with crude oil and refined products constituting 61% of the benchmark Goldman Sachs Commodity Index in 2023.

Understanding the drivers of hedging demand in commodity markets is crucial for several reasons. First, it provides insights for policymakers and hedgers into the behaviour of market participants, which can help to understand how these markets function. Second, given that ambiguity provides a market incompleteness, it is essential to conduct empirical analyses to comprehend the underlying dynamics and implications for asset pricing. Third, it helps businesses and investors to better manage risks in ambiguous settings. Finally, it can inform policy decisions that affect these markets, such as regulations around speculation and position limits, by identifying factors that are likely to drive changes in hedging demand. The main objective of this analysis is to comprehend the mechanisms by which factors are incorporated into the decision-making process.

To explore how uncertainty impacts hedging strategies, I analyze the relationship between weekly levels of ambiguity and risk derived from high-frequency price data and position changes as reported by the Commodity Futures Trading Commission (CFTC). My findings indicate that ambiguity possesses both economically and statistically signif-

[1] The Covid-19 pandemic as well as the shortages in energy supply due to the Russian invasion of Ukraine clearly showed how dependent the globalized world economy is on the availability of commodities.

icant predictive capabilities regarding market participation. However, the direction of the effect varies between hedger types. This may be attributable to a different market participant structure and trading motives.

Utilizing a simple Ordinary Least Squares (OLS) methodology, my initial analysis centres on determining how market characteristics such as trading volume respond to these dimensions of uncertainty. In the next step, I focus on commercial traders (i.e. hedgers) relying on the CFTC Commitment of Traders (COT) report data. The identified relationship between hedging activity and ambiguity is consistent with classical hedging theory, i.e. hedgers are more net short in the presence of uncertainty. Regarding risk, a reduction in hedging demand can be observed.

Building on these findings, I examine possible variations between hedgers due to different motivations in their hedging decisions. To investigate this, I draw on the CFTC's Disaggregated Commitment of Traders (DCOT) report, which distinguishes between categories of traders such as producers and swap dealers. Although both fall under the category of hedgers, these groups have distinctly different hedging objectives. In response to increases in uncertainty, producers, the classic hedgers, reduce their positions, which suggests a cautious, wait-and-see attitude. It is assumed that these types of hedgers are pursuing a long-term hedging strategy based on economic fundamentals, which is influenced by their direct involvement in the commodity. Conversely, swap traders increase their hedging demand in response to heightened uncertainty. In the face of uncertainty, they exhibit typical hedging behaviour by exhibiting ambiguity aversion by focusing more on net short positions. In the context of risk, swap traders seem to be attracted to risk in the expectation that they will absorb risk in return for reward. As that approach so far may be attributed to reverse causality, I address potential endogeneity issues and identify the impact of ambiguity and risk shocks on hedging behaviour by, first, using an instrumental variable (IV) approach and, second, estimating impulse response functions using local projections. I use the newspaper article count index of Plante (2019), modelled similarly as Baker, Bloom, and Davis (2016)'s economic policy uncertainty index, instrumenting for ambiguity by focusing on OPEC-related news. It tracks fluctuations in media attention to OPEC, responding to major events and production changes. The second approach, impulse response functions, accounts for endogeneity from a more technical and data-driven perspective and relies on a structural identification imposed by a temporal ordering on the set of variables that is justified by economic theory. Results confirm previous findings.

Studying the concept and the implications of ambiguity has gained prominence among scholars in recent years. A variety of studies examine the implications of ambiguity in various settings. The basic concept is rooted in decision-making theory, suggesting individuals seek to minimize the risk associated with ambiguous situations by hedging their bets.[2] I focus on financial markets, where investors use hedging strategies to protect themselves against uncertain outcomes.

From a theoretical perspective, studies have found a pricing of ambiguity in asset returns (see for example E. Anderson, Hansen, and Sargent (2000); Chen and Epstein (2002); Maenhout (2004)). Testing the relationship between risk, uncertainty, and expected returns empirically, E. W. Anderson, Ghysels, and Juergens (2009) find stronger evidence for an uncertainty-return trade-off than for the risk-return trade-off. They conclude that risk and ambiguity carry a positive premium. Indeed, Erbas and Mirakhor (2007) attribute a large part of the equity premium to aversion to ambiguity. Regarding the implications on investor behaviour, empirical studies mainly show that ambiguity is associated with a reduction in asset holding (Antoniou, Harris, & Zhang, 2015; Ben-Rephael & Izhakian, 2020; Dimmock, Kouwenberg, Mitchell, & Peijnenburg, 2016; Kostopoulos, Meyer, & Uhr, 2022). Dimmock et al. (2016) suggest ambiguity as a missing factor in explaining households' non-participation in the stock market (non-participation puzzle). Accordingly, they propose ambiguity aversion to explain low stock market participation.

Kostopoulos et al. (2022) find that market ambiguity shocks induce traders to increase their trading activity, in particular, investors tend to withdraw their capital from riskier equities. When the aggregated level of ambiguity is high, the authors find, on the one hand, a high number of logins in online broker platforms and, on the other hand, an increased number of trades. Ben-Rephael and Izhakian (2020) obtain similar results for firm-level ambiguity: Their findings reveal that an increase in individual firm-level ambiguity is connected to a subsequent decline in the trading and holding of stocks and options.

However, despite the extensive range of research conducted on the implications of ambiguity in equity markets, there has been a distinct lack of empirical examination dealing with the influence of ambiguity on hedging decisions. Empirical studies in equity markets reveal limited participation in response to ambiguity shocks. At the same time, the response of financial market participants who primarily utilize these markets for hedging purposes remains unclear. Experimental studies give first hints in the direction that

[2] A more philosophical analysis of how individuals deal with ambiguity, can be found in Sunstein (2023).

individuals do not hedge against ambiguity. For example, Oechssler, Rau, and Roomets (2019) show in an experimental study that most participants have no strict preference to hedge against ambiguity. In the experiment that involves making combined forecasts on draws from an ambiguous urn and a risky coin toss, participants are offered a straightforward opportunity to hedge against ambiguity. The researchers could only measure very few hedging attempts, although the hedging option was very easily accessible. Similar results are obtained by Dominiak and Schnedler (2011). These findings seem to go against economic intuition as experimental psychological studies have demonstrated that individuals typically exhibit aversion to ambiguity, [3] as a result one expects individuals to hedge against ambiguity. Theoretical models examining the relation of ambiguity and hedging find that investors' valuation of effective hedging increases with rising ambiguity (Kim, 2021; Wong, 2015). In contrast, modeling markets of uncertain assets and looking at hedging by diversification, Berger and Eeckhoudt (2021) conclude that, contrary to economic intuition, the preference for hedging is not necessarily amplified by ambiguity aversion. The authors posit that, while the level of risk diminishes in the degree of diversification, diversification raises the level of ambiguity, as decision-makers need to take more settings into account. Augustin and Izhakian (2020) investigate the role of risk and ambiguity in pricing credit default swaps (CDS). As an instrument of insurance, CDS guarantee credit protection, and thus their payments are directly associated with the probability of a firm's credit default. Augustin and Izhakian (2020) report that ambiguity offsets the effect of risk and negatively impacts CDS spreads.

So far, empirical research on ambiguity has focused on equity markets. In contrast, ambiguity in the context of hedging has not yet received attention in practical empirical exploration. Results from theory and experiments are mixed and strongly depend on the modulated setting.[4] I aim to identify the implications of ambiguity in the context of hedging decision-making in financial markets, using the commodity futures market as a laboratory.

Given the state of the art, this paper contributes to a better understanding of one of the core functions of futures markets namely the transfer of uncertainty. In particular, I

[3]See Trautmann and Van De Kuilen (2015) for an overview on ambiguity attitudes in a variety of settings.

[4]Ellsberg's conjecture has led to extensive research on ambiguity aversion, which has revealed that individuals' attitudes toward ambiguity are influenced by various factors, such as the likelihood of uncertain events, the domain of outcomes, and the source of uncertainty. For an overview see Trautmann and Van De Kuilen (2015).

attempt to answer the question: What drives hedging decisions in energy markets?

The remainder of this paper is organized as follows. Section 2 introduces the data and derives the quantification method of ambiguity and risk. Section 3 presents the empirical results and discusses the effect of ambiguity on the behaviour of hedgers in commodity markets. Section 4 concludes.

2 Data and Methodology

2.1 Futures Market Data

The measures employed to quantify ambiguity and risk require high-frequency intraday price data for futures contracts. I focus on NYMEX-traded futures for WTI crude oil. Trading in these contracts takes place Sunday through Friday from 5:00 pm to 4:00 pm CT, with a one-hour break starting at 4:00 pm CT daily.

I obtain my data from Barchart cmdtyView (formerly Commodity Research Bureau). The sample starts in May 2008 and ends in December 2022.

In line with established methodologies within the literature, continuous price return series are generated from the nearest-to-maturity contracts available during the sample period. This practice addresses the simultaneity of multiple futures contracts for the same underlying asset with differing maturities. When the trading volume of a subsequent maturity surpasses that of the front-month contract, a rollover to the more actively traded contract is executed on that day. This procedure aligns with the prevailing strategies of commodity futures traders who typically unwind positions as contracts approach the first notice date to avoid the risk of physical delivery obligations. Additionally, the continuous price series is constructed from the most liquid futures contracts that reflect new information more rapidly. The adopted approach to constructing a continuous series also has some implications for return calculation. To avoid computing returns between two different contracts at roll dates, returns are always computed based on two price observations of the same maturity. Following the majority of the literature, futures returns, computed as continuously compounded returns, are calculated as logarithmic price differences, i.e. $r_t = ln(P_t) - ln(P_{t-1})$.

Besides the high-frequency data, I collect data on daily futures contract prices, trading volume and number of contracts outstanding from Barchart cmdtyView to construct the required control variables. Daily continuous price and return series are constructed in accordance with the approach adopted for the intra-day dataset.

2.2 Estimating Hedging Activity

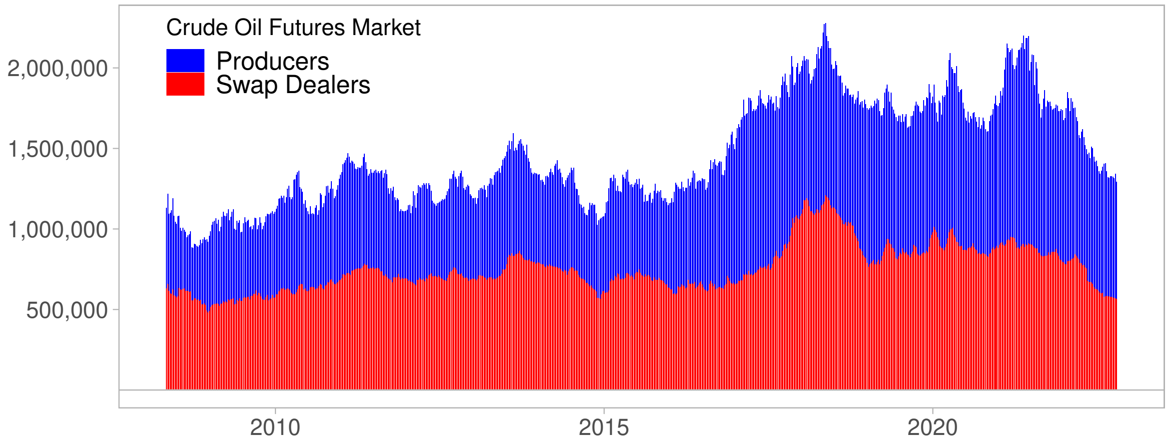
To quantify the activity of hedgers, I utilize data from the CFTC, which publishes various weekly reports on market participants. These reports primarily vary in how broadly they group different types of traders. The most aggregated report is the COT report which contains the aggregated level of long, short and spreading positions and distinguishes three different trader types: commercials, non-commercials, and non-reportables. A trader is classified as commercial if futures contracts are used for hedging purposes (CFTC Regulation 1.3(z), 17 CFR 1.3(z)).[5] In addition to the COT report the CFTC publishes the DCOT report, which provides a more detailed classification of market participants based on their trading motives. In the subsequent analysis, I rely on this disaggregated report: Commercial traders are split into producers, merchants, processors and users (producers hereafter), and swap dealers. Producers refer to hedgers in the classical sense, actively engaged in the underlying physical commodity market hedging against price-changing risk. Swap dealers represent financial traders, aiming to manage the risk exposure in their financial portfolios.[6]

Figure 1 illustrates the number of contracts of hedgers held by specific hedger types. Positions are almost evenly distributed between producers and swap dealers. Note that the sum of positions held by producers and swap dealers represents the positions of commercial traders.

[5]for details on the structure of the COT report I refer to appendix A1.

[6]See Irwin and Sanders (2012) for further details on the CFTC's DCOT report. Detailed definitions of all trader classes in the DCOT report are further provided in the appendix A2.

Figure 1: Contracts of Hedgers Held by Specific Hedger Types



Note: Own illustration based on data from the CFTC's DCOT report. The figure illustrates the contracts held by producers and swap dealers in the commodity futures markets for crude oil during 2008-2022.

Based on the CFTC COT and DCOT reports, I construct several measures to quantify the degree of hedging activity. First, I use hedging pressure (HP) to quantify the net position of hedgers. Hedging pressure is commonly used in the literature as a measure of aggregated hedging demand (Kang, Rouwenhorst, & Tang, 2020; Rouwenhorst & Tang, 2012) and defined as the difference between hedgers' short contracts (HS_t) and hedgers' long contracts (HL_t), scaled by total open interest (OI_t) in week t:

$$HP_t^j = \frac{HS_t^j - HL_t^j}{OI_t} \tag{1}$$

HP indicates the imbalance of short and long positions of hedgers. In the literature, hedging pressure is often described as the requirement for speculators to balance the demand from hedgers. Hence, HP measures the short-term trading pressure of hedgers. Utilizing the COT data on commercial traders and the additional trader type segmentation in the DCOT report, I calculate equation (1) for three different groups $j \in \{\text{Commercials}, \text{Producers}, \text{Swap Dealers}\}$.

Additionally, I examine the impact on the market share of hedgers (MS). Therefore, I calculate this by determining the positions held by the hedging group in relation to the open interest:

$$MS_t^j = \frac{HL_t^j + HS_t^j}{2 \cdot OI_t}. \tag{2}$$

Besides investigating the impact of uncertainty on the aggregate of positions, I look at the impact of long and short positions of the hedger types separately to better understand the underlying mechanism. Hedgers' long and short positions are therefore set in relation to total market open interest.

$$RHL_t^j = \frac{HL_t^j}{OI_t} \tag{3}$$

$$RHS_t^j = \frac{HS_t^j}{OI_t} \tag{4}$$

Table 1 provides descriptive statistics for overall market trading volume and hedging position measures. Panel A shows descriptive statistics for the COT data, and panel B for the DCOT data. The crude oil futures market is identified as very liquid. Trading volume for crude oil is high on average, indicating a highly active market. Average hedging pressure is positive, suggesting that on average, commercials take positions on the short side of the market. However, the presence of negative minimum values indicates that there are instances where net hedging pressure falls on the long side, revealing variability in market sentiment. Producers' average market share is approximately 20%. The average hedging pressure among producers in the crude oil market is positive, aligning with a general defensive strategy against price declines. Swap dealers hold an average market share of 27% in the crude oil market, a significant presence that impacts market dynamics. The average hedging pressure of swap dealers in the crude oil market is also positive, indicating a propensity to hold positions that protect against falling crude oil prices. The provided summary statistics support several empirical conclusions. Firstly, the observed average net short positions held by commercial traders, are in line with Keynes's theory of normal backwardation, which sates that hedgers are net short traders to secure a guaranteed price for their commodity in the future, protecting themselves against the risk of prices decreases. Secondly, I observe significant fluctuations in hedging pressure on a weekly basis, reflecting hedgers' time varying demand for price insurance.

2.3 Constructing Ambiguity and Risk

In decision theory literature, risk relates to situations where the probabilities of outcomes are known or can be estimated and allow a precise assessment of potential losses or gains. In contrast to risk, ambiguity refers to situations where the probabilities of outcomes are unknown or uncertain, making it difficult to assess an investment's potential risk and reward. Ellsberg (1961) defines ambiguity as the lack of information available to render a reliable judgement about the underlying probability distribution. For this reason, he

Table 1: Descriptive statistics for overall market characteristics and hedging variables based on COT data.

Panel A: COT Data

Statistic	Mean	St. Dev.	Min	Max	Median	N
$Trading\ Volume$	4,081,623.000	1,635,897.000	792,969	12,933,948	3,693,028.0	750
$Hedging\ Pressure^{CM}$	0.167	0.074	−0.041	0.303	0.178	750
RHL^{CM}	0.385	0.070	0.273	0.571	0.358	750
RHS^{CM}	0.551	0.034	0.438	0.638	0.554	750

Panel B: DCOT Data

Statistic	Mean	St. Dev.	Min	Max	Median	N
OI^{P}	0.198	0.028	0.135	0.266	0.197	755
$Hedging\ Pressure^{P}$	0.063	0.066	−0.067	0.222	0.045	755
RHL^{P}	0.166	0.044	0.088	0.297	0.164	755
RHS^{P}	0.230	0.042	0.145	0.352	0.221	755
OI^{SD}	0.265	0.056	0.128	0.363	0.266	755
$Hedging\ Pressure^{SD}$	0.103	0.121	−0.185	0.264	0.129	755
RHL^{SD}	0.108	0.051	0.036	0.255	0.084	755
RHS^{SD}	0.211	0.075	0.052	0.329	0.215	755

Note: This table provides descriptive statistics of the defined hedging variables based on the position data of the CFTC (D)COT reports, between May 2008 and December 2022. In Panel A, I provide summary statistics on overall market trading volume and hedging position data based on COT data. . In Panel B, I present summary statistics for hedging position data based on the DCOT data. Hedging pressure for commodity j is defined as commercial traders net short position in relation to total open interest,$HP_t^j = \frac{HS_t^j - HL_t^j}{OI_t}$. Futher I provide descriptive statistics of commercials long, $RHL_t^j = \frac{L_t^j}{OI_t}$, and short positions, $RHS_t^j = \frac{HS_t^j}{OI_t}$, in relation to total open interest.

proposes two broad approaches to empirically measure ambiguity: the first approach relies on directly quantifying the information richness of a setting. This approach is found in studies that quantify ambiguity based on newspaper-based measures or market-based measures like the volatility of volatility (see for example, Augustin and Izhakian (2020); Baker et al. (2016); Brenner and Izhakian (2018); Kostopoulos et al. (2022) and Izhakian, Yermack, and Zender (2022)). In contrast, the second approach indirectly accesses the information density by proxying the disagreement between the available information sets of different actors facing this setting. Empirical investigations that follow the second approach use survey-based estimate forecast disagreement (see for example, E. W. Anderson et al. (2009); David and Veronesi (2013); Drechsler (2013); Ulrich (2013) and Antoniou et al. (2015)). In the Appendix (Section A3), I present a simple model framework that rationalizes why it is reasonable to derive measures of risk and ambiguity from return prices.

I use a recently-developed methodology based on perturbations in uncertain probabilities and follow Augustin and Izhakian (2020); Brenner and Izhakian (2018) and Izhakian et al. (2022). In doing so, I rely on a direct measurement of ambiguity and access the degree of conflicting information based on time series data. The procedure is theoretically based on the expected utility with uncertain probabilities theory (EUUP) (Izhakian, 2017), which assumes investors' preferences for ambiguity are exclusively formed from probabilities. In that way, the degree of ambiguity ($\mho^2$) is measured as the expected value-weighted average of the variances in probabilities:

$$\mho^2 \equiv \int E[\varphi(x)]\, Var[\varphi(x)]dx \qquad (5)$$

where $\varphi(\cdot)$ refers to an unspecified probability density function, $E[\cdot]$ refers to the expected value and $Var[\cdot]$ to the variance. The methodology presupposes that the entirety of the market can be consolidated into a single representative entity that embodies the collective beliefs of all investors within the economic framework. According to the principle of insufficient reason, every distribution is given an equal weighting (Bernoulli, 1713; Laplace, 1814), i.e. the representative agent acts like all his perceived priors are equally likely. In addition, I follow Izhakian and Yermack (2017), assuming returns are normally distributed.[7]

In order to compute ambiguity according to equation (5), one needs to calculate the

[7]Essentially, it seems reasonable for futures prices to follow a log-normal distribution as they are limited to positive values. Consequently, futures returns as logarithmic price differences, follow a normal distribution.

mean and the variance of the return probabilities over the range of probability distributions/priors over a week. To do so I measure ambiguity in two steps: first, I estimate hourly probability distributions based on one-minute return observations and collect them into a set of weekly priors; second, the variability within this set of priors within a week is calculated and aggregated to a weekly measure of ambiguity.

Estimating Hourly Return Distributions: For each hour, I estimate return probability distributions based on one-minute return observations. To do so, I assume normality, thus distributions are fully characterized by mean (μ) and variance (σ^2). To estimate the mean and the variance of distributions I rely on Maximum Likelihood estimation. Assuming normality of returns, formula (5) can be rewritten as:

$$\mho^2 = \int E[\phi(r, \mu, \sigma^2)] \; Var[\phi(r, \mu, \sigma^2)]dr \tag{6}$$

where $\phi(r, \mu, \sigma^2)$ represents the probability density function of the normally distributed returns, r, conditional on the mean, μ, and the variance, σ^2. To estimate the measure of ambiguity according to equation (6), intra-day futures prices are sampled every minute for all liquid hours during the trading hours. For 6 trading days per week, from Sunday to Friday, at most, 138 realized return distributions make up a set of priors in a week. Extreme price changes, particularly returns exceeding 10% in magnitude, are dropped as they are likely caused by incorrect orders, cancelled by the stock exchange (Brenner & Izhakian, 2018). Additionally, trading hours with less than 35 observations are dropped.

Aggregating Priors to the Weekly Level of Ambiguity: To determine the weekly degree of ambiguity, I utilize the variability of probability distributions within a given week. In practical implementation, this involves dividing the range of returns, which spans from -10% to 10%, into 40 bins with $B_l = \left(r_{l-1}, r_l\right]$. In addition, I consider the probability of returns exceeding an absolute value of 10%, resulting in 42 bins in total. For each bin and each hour, I calculate the probability that the return falls in this bin. Visually, the range of bins can be imagined as represented by a histogram. The frequency of intra-day returns observed in each bin determines the height of the corresponding bar in a bin, which in turn represents the probability of returns falling within that bin ($P(B_l) = \Phi(r_l, \mu, \sigma^2) - \Phi(r_{l-1}, \mu, \sigma^2)$, where $\Phi(\cdot)$ represents the cumulative normal probability distribution. Doing so, I end up with a range of hourly return histograms over a week. Using these return histograms, I can calculate the expected probability of a particular bin, $E[P(B_l)]$, and the variance of these probabilities, $Var[P(B_l)]$, over a given week. Thereby, I assume that each histogram is equally likely. In the next step, I assess the volatility across the bins over the course of a week, as an expected probability-weighted average of the variances of probabilities:

$$\mho_t^2[r] \;=\; \frac{1}{w\;ln(\frac{1}{w})}(\sum_{l=1}^{42} E[P(B_l)] \cdot Var[P(B_l)]) \tag{7}$$

To reduce the sensitivity of the results to the chosen bin sizes, $\frac{1}{w\;ln(\frac{1}{w})}$ serves as a scaling factor that functions similarly to Sheppard (1898)'s correction; w accounts for the bin size and is defined as $w = r_{l-1} - r_l$.

Estimating Risk: Besides understanding the impact of ambiguity on hedging, I aim to understand the implications of risk. Following Rothschild and Stiglitz (1970) investors' attitudes towards risk are interpreted as an aversion to mean-preserving spreads in outcomes. Evaluating financial decision problems according to their second-order stochastic dominance, i.e. dominance in volatility, has become a common praxis in economic modelling of risk (Arcand, Hongler, & Rinaldo, 2020). Therefore, I measure risk as the variance of intra-day returns over a week:

$$\sigma_t^2[r] \;=\; \frac{1}{n}\sum_{t=1}^{n}(r_m - \overline{r_t})^2 \tag{8}$$

with n being the number of one-minute return observations within each week, r_m the return of minute m within week t and $\overline{r_t}$ stands for the mean return of week t.

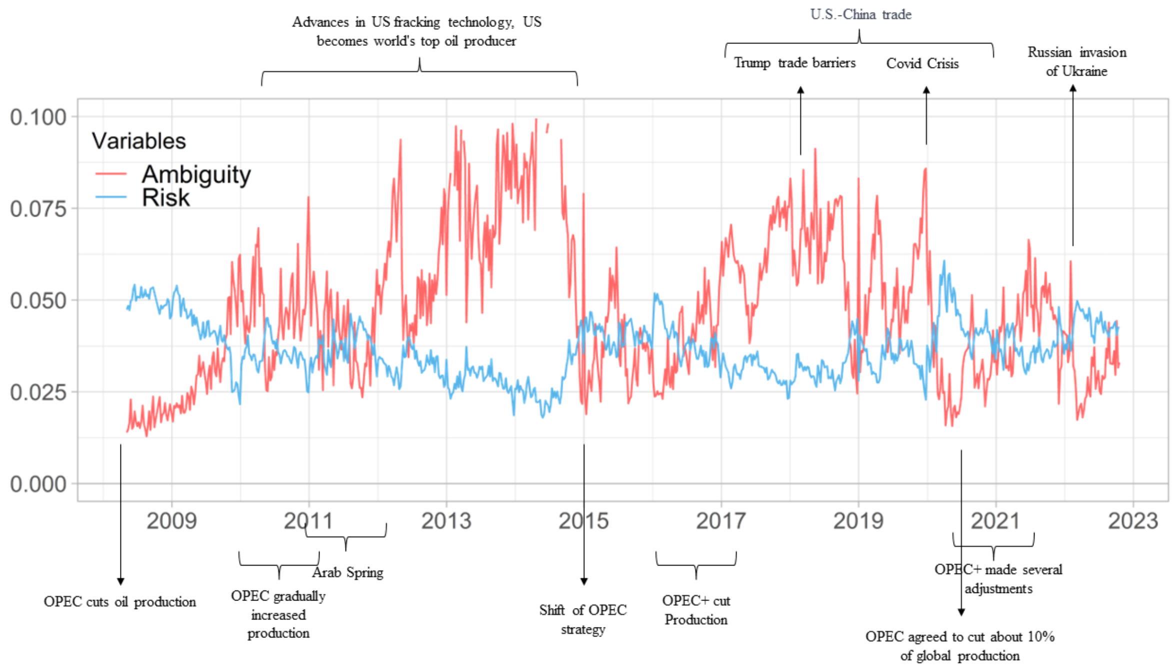
Table 2: Descriptive statistics of uncertainty variables.

Statistic	Mean	St. Dev.	Min	Max	Median	N
Ambiguity	0.003	0.002	0.0002	0.014	0.002	750
Risk	0.036	0.007	0.018	0.061	0.036	750

Note: This table provides descriptive statistics of uncertainty variables based on one minute price observations from Barchart cmdtyView reports between May 2008 and December 2022. The variables are estimated as described in section 2.3. The degree of ambiguity is measured as the expected value weighted average of the variances in probabilities: $\mho^2 = \int E[\phi(r,\mu,\sigma^2)]\; Var[\phi(r,\mu,\sigma^2)]dr$. *Risk is measured as the volatility of intra-day returns:* $\sigma_t^2[r] = 1/n\sum_{t=1}^{n}(r_m - \overline{r})^2$.

Table 2 provides summary statistics for the uncertainty variables.

Figure 2: Ambiguity and Risk in Crude Oil Futures Market 2008-2022.



Note: Own illustration based on data from cmdtyView barchart Database. The figure illustrates ambiguity and risk in crude oil futures market 2008-2022.

Figure 2 illustrates the trajectory of ambiguity and risk in crude oil futures market from 2008 to 2022. This representation captures pivotal events during this period, encompassing both oil-specific incidents, such as OPEC decisions, and broader global occurrences like the 2008 financial crisis. Particularly remarkable is that ambiguity and risk seem to be negatively correlated with each other. Solely using risk as a driving force of hedging decision making may result in omitted variable bias. A salient event is the 2008 financial crisis. In July 2008, crude oil prices peaked over $145 per barrel, driven by heightened demand, especially from China and India. However, the global financial crisis that hit later that year saw oil prices collapse to around $30 per barrel by December, as demand fell sharply. As events were straightforward to interpret, a lower degree of conflicting information drove a lower level of ambiguity, while significant return fluctuations indicated elevated risk. The period between 2010 and 2014 was marked by advancements in fracking technology, spurring a surge in U.S. shale oil production and positioning the U.S. as the foremost oil producer globally. This augmented supply led to a decline in global oil prices. In this span, return volatility was minimal, but ambiguity was heightened due to the rapid and often contradictory influx of information. Ambiguity spikes were consistently observed when specific events led to a sudden surge in information volume and inconsistency. Another example in this regard is the trade war between the U.S. and China which was publicly present from 2018-2020. Initiated by then U.S. President Donald Trump, the trade war involved the two largest economies in the world imposing tariffs on each other's goods, leading to global economic uncertainty and shifts in international trade dynamics, mirrored in a higher level of ambiguity in that time.

3 Hedging Activity under Uncertainty

This chapter empirically investigates the influence of two dimensions of uncertainty - ambiguity and risk - on the trading behaviours of hedgers. To understand the dynamic interplay between these elements and their consequent effects on market properties, my analysis commences with an examination of the broader market reactions in the face of shocks to ambiguity and risk.

3.1 Overall Market Implications

Before investigating the behaviour of hedgers, I aim to get an impression of how uncertainty affects overall position adjustments. To do so, I investigate the impact of ambiguity and risk on trading volume. Therefore, I examine the market size measured by the number of contracts traded in a market during a given period. On one hand, it might be plausible that increased uncertainty leads to higher trading volumes, as traders want to hedge their positions in uncertain times. Traders might have different interpretations of new information and realign their portfolios based on their beliefs. In addition, speculative trading might increase, if traders seek to capitalize on perceived market mispricing due to uncertainty. On the other hand, higher uncertainty might lead to decreased trading volumes as risk-averse investors prefer to stay out of the market, leading to decreased trading activity. They might adopt a wait-and-see approach, holding off on trades until uncertainty is resolved.

$$
\begin{aligned}
TV_{i,t} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\
+\beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} \\
+\sum_{m=1}^{11} \beta_m \cdot M
\end{aligned}
\tag{9}
$$

Consider $TV_{i,t}$ as the trading volume in market i at week t. To address potential endogeneity issues, I use the first lags. The coefficients I focus on are β_1 and β_2, representing the effects of ambiguity and risk, respectively. A positive β_1 implies that an increase in the level of ambiguity is accompanied by an increase in the market's trading volume in the subsequent week. Hence ambiguity is associated with an improved trading activity. A positive β_2 signifies that an increase in risk level aligns with an increase in trading volume in the subsequent week. Thus, risk is linked with improved trading activity. Given my interest in discerning which uncertainty channel (ambiguity versus risk) dominates the channel between uncertainty and market activity, I incorporate both dimensions of uncertainty in the regression. Literature has found previous returns affecting the behaviour of market participants (Barber & Odean, 2008; Gervais, Kaniel, & Mingelgrin, 2001; Grinblatt & Keloharju, 2001). To account for momentum effects and a potential time-varying risk premium I include the basis and past (lagged by one period) return in the regression.[8] In addition, I account for seasonality by relying on monthly dummy variables.

Coefficient estimates are reported in Table 3 column 1 and 2. Trading activity in the crude oil futures market is negatively impacted by ambiguity and by risk. In the manner of economic significance, I find a significant impact of both factors on trading volume in the crude oil market (close to 20% of one standard deviation).

3.2 Implications for Heterogeneous Group of Hedgers

So far, my analysis has revealed that the overall market response to ambiguity and risk is negative. Given that this paper primarily aims to elucidate the behaviours of hedgers, I will now delve deeper into their activities by utilizing COT data from the CFTC.

Following the classical theory of hedging by (Keynes, 1923), hedgers sell futures contracts to secure commodity prices, shielding themselves from unpredictable price changes. This strategy, aimed at maintaining financial stability and controlling operational costs, leads them to typically act as net sellers in the futures market. For example, if a hedger is a producer or holder of a commodity, they are often concerned about the risk of falling prices. By selling futures contracts (taking a short position), they lock in the current price for their product for future delivery.[9] Hedging pressure describes the imbalance of long

[8] To account for the cost of hedging, I include the commodities basis in my regression. The basis measures the risk premium required to incentivize non-commercial traders to absorb excess price risks. In line with Gorton and Rouwenhorst (2006) I built the basis as the difference between the current spot price and the futures price: $B_t = \ln(F(t, T1)) - ln(S_t)$ where $F(t, T1)$ denotes the price of futures contract with maturity in T_1 at time t as the nearest by contract.

[9] In a typical scenario, a hedger who owns or produces a commodity is naturally 'long' in the physical

Table 3: Results for overall market implications and hedgers as heterogeneous group.

	Dependent variable:							
	Trading Volume		Hedging Pressure		Commercials Long		Commercials Short	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ambiguity	-0.181^{***}	-0.220^{***}	0.143^{***}	0.149^{***}	-0.223^{***}	-0.255^{***}	-0.146^{**}	-0.200^{***}
	(0.061)	(0.060)	(0.053)	(0.051)	(0.046)	(0.046)	(0.062)	(0.064)
Risk	-0.143^{*}	-0.173^{**}	-0.330^{***}	-0.329^{***}	0.193^{***}	0.181^{***}	-0.325^{***}	-0.347^{***}
	(0.079)	(0.079)	(0.072)	(0.069)	(0.061)	(0.060)	(0.076)	(0.074)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Monthly fixed effects	NO	YES	NO	YES	NO	YES	NO	YES

*Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% level of significance, respectively. Heteroskedasticity robust standard errors are in parentheses. All variables were standardized and demeaned prior to the regression analysis.*

and short positions held by hedgers in a market. Therefore, it demonstrates the extent to which speculators must compensate by taking on extra positions. Accordingly, one would expect hedging demand should increase in response to a higher degree of uncertainty. To comprehend the ongoing dynamics in response to an increase in uncertainty, I estimate the following equation:

$$\begin{aligned} HP_{i,t} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\ +\beta_3 \cdot Bi,t-1 + \beta_4 \cdot MOMi,t + \beta_5 \cdot LIQU_{i,t} \\ + \sum_{m=1}^{11} \beta_m \cdot M \end{aligned} \tag{10}$$

where $HP_{i,t}$ represents the hedging pressure in market i at week t. To mitigate potential issues with endogeneity, I rely on first lags of uncertainty variables. The coefficients of interest are β_1 and β_2, representing the effects of ambiguity and risk, respectively. A positive β_1 suggests that an increase in ambiguity is followed by a rise in hedging pressure

market since they own the asset whose price is at risk. To counterbalance this long position and protect against price drops, they take a short position in the futures market.

in the subsequent week. This implies that higher ambiguity is associated with increased (decreased) hedging pressure. Similarly, a positive β_2 indicates that an increase in the level of risk leads to an increase in hedging pressure in the following week. Therefore, risk relates to heightened hedging pressure. In line with equation (9) I adjust for momentum effects, a fluctuating risk premium and control for seasonality. In addition, I control for market liquidity to rule out effects on hedging behaviour that are driven by liquidity bottlenecks[10]

Results for regression (10) are shown in Table 3 columns 3 and 4. The coefficient of ambiguity is positive and significant indicating that hedging pressure rises in response to ambiguity. The coefficients for ambiguity are in line with classical hedging theory Keynes (1923), i.e. hedgers are more net short in the presence of uncertainty. Regarding the economic significance of my findings, a one-stand deviation increase in ambiguity leads to a 0.15 standard deviation increase in hedging pressure. The estimated coefficient for risk suggests hedging pressure decreases (significantly). In terms of economic significance, the effect of ambiguity and risk are in a comparable range.

Looking at these results, the question of what drives hedging imbalance arises. Therefore the subsequent analysis focuses on long and short positions of hedgers separately. In line with regression (1) I estimate regressions for commercials' short and long positions separately:

$$\begin{aligned} RHS_{i,t} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\ + \beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} + \beta_5 \cdot LIQU_{i,t} \\ + \sum_{m=1}^{11} \beta_m \cdot M \end{aligned} \tag{11}$$

$$\begin{aligned} RHL_{i,t} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\ + \beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} + \beta_5 \cdot LIQU_{i,t} \\ + \sum_{m=1}^{11} \beta_m \cdot M \end{aligned} \tag{12}$$

where $RHS_{i,t}$ ($RHL_{i,t}$) represents the short (long) positions held by commercials in relation to the overall open interest in market i at week t.

[10] I measure liquidity in market i as $LIQU_{i,t} = \frac{TV_{i,t}}{OI_{i,t}}$, where $TV_{i,t}$ refers to the trading volume and $OI_{i,t}$ denotes the number of contracts outstanding in market i at week t.

The coefficients of interest are β_1 and β_2, representing the effects of ambiguity and risk on short and long positions, respectively. A positive β_1 suggests that an increase in ambiguity is followed by a rise in positions held by commercials in the subsequent week. This implies that higher ambiguity is associated with increased in the corresponding position of hedgers. Similarly, a positive β_2 indicates that an increase in the level of risk leads to an increase in the corresponding position held by commercials in the subsequent week.

Results for regression (11) and (12) can be found in Table 3 columns 5 to 8. Estimated coefficients for ambiguity indicate that an increase in the level of ambiguity leads to a significant reduction of long and short positions in relation to the open interest of hedgers in the subsequent week. Thus, the reduction in hedging pressure can be attributed to the disproportionately stronger impact on long positions, resulting in an overall decrease in net short positions. The estimated coefficients for risk indicate a significant increase in long positions for crude oil and a decrease in short positions for crude oil in the subsequent week.

The regression analysis employs COT data, which distinguishes between hedgers and speculators. However, it does not further subdivide hedgers based on their hedging motivations. Consequently, the group of hedgers analyzed so far is heterogeneous, encompassing entities engaged in the physical spot market as well as financial service providers, who aim to mitigate risks associated with their transactions with customers to diversify their overall risk exposure. As these two groups fundamentally differ concerning their trading motives, the implications of uncertainty shocks on their trading might also differ. Therefore, in the next section, I examine the hedger groups more closely to understand how their responses to uncertainty differ.

3.3 Implications for Producers and Swap Dealers

The DCOT report distinguishes between trader categories such as producers and swap dealers, who, despite both being hedgers, have distinctly different hedging objectives. The group of producers are fundamentally involved in the production, processing, packaging, or handling of physical commodities.[11] They predominantly utilize futures markets as a strategic tool to manage or hedge risks associated with their core business activities. In contrast, swap dealers are entities primarily engaged in dealing with swaps related to

[11] This group also includes merchants, processors, and users.

commodities. They are financial intermediaries and thus institutional investors with no direct engagement in the spot market. Their use of futures markets is principally aimed at managing or mitigating risks linked to their swap transaction activities and mirrors thereby in some way the hedging demand of their customers.

To get an understanding of the implications for the two distinct groups, I modify equation (10), focusing my investigation on the hedging pressure exerted by each hedger group j, where $j \in \{\text{producer}, \text{swap dealer}\}$. This modified approach allows us to more closely examine the dynamics of the reaction of producers and swap dealers in response to uncertainty.

$$\begin{aligned} HP^j_{i,t} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\ +\beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} + \beta_5 \cdot LIQU_{i,t} \\ + \sum_{m=1}^{11} \beta_m \cdot M \end{aligned} \tag{13}$$

The results of the regression analysis, as delineated in Equation (13), are presented in Table 4. For producers, the regression reveals a statistically significant negative coefficient for ambiguity. This finding suggests that increased ambiguity adversely affects hedging behaviour in this market. Additionally, a consistent negative relationship between risk and hedging pressure is observed. In contrast, when examining swap deals, the influence of ambiguity shifts, exhibiting a positive effect. This reversal in the direction of the impact implies that, for swap deals, ambiguity may encourage hedging. However, the influence of risk remains consistently negative, akin to the patterns observed for producers.

In addition to hedging pressure, my analysis extends to examining the market share reactions of hedger subgroups. This aspect is quantified by measuring each hedger's open interest relative to the total open interest in the market. The relationship is modelled as follows in Equation (14):

$$\begin{aligned} MS^j_{i,t} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\ +\beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} + \beta_5 \cdot LIQU_{i,t} \\ + \sum_{m=1}^{11} \beta_m \cdot M \end{aligned} \tag{14}$$

The findings from this regression, as detailed in Table 4, reveal nuanced dynamics between ambiguity and market share across different market participants. For producers in the crude oil futures markets, a negative correlation is observed between ambiguity in one week and their market share in the subsequent week, (4 Panel A). For swap dealers (4 Panel B), the pattern between ambiguity and swap dealers' market share in the subsequent week is positive. Regarding the variable risk, the results indicate a reduction in the market share of both groups.

In line with 3.2 I will further look at the implications for the different positions held by the different trader types. Therefore, I estimate equation (12) and (11) for both hedger subgroups as follows:

$$
\begin{aligned}
RHS_{i,t}^{j} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\
+\beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} + \beta_5 \cdot LIQU_{i,t} \\
+ \sum_{m=1}^{11} \beta_m \cdot M
\end{aligned}
\tag{15}
$$

$$
\begin{aligned}
RHL_{i,t}^{j} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\
+\beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} + \beta_5 \cdot LIQU_{i,t} \\
+ \sum_{m=1}^{11} \beta_m \cdot M
\end{aligned}
\tag{16}
$$

The results pertaining to the impact of ambiguity and risk on producers' long and short positions are presented in Table 4 Panel A. The analysis reveals that ambiguity exerts a negative influence on short positions of producers. Thus, the observed decrease in hedging pressure, previously noted, predominantly stems from an imbalanced effect on long and short positions.

In terms of risk, the impact on long positions of producers appears to be statistically insignificant. However, for short positions, there is a negative relationship with risk in the crude oil market.

Table 4 Panel B details the adjustments in swap dealers' long and short positions in response to varying levels of uncertainty. The findings indicate a tendency among swap dealers to reduce their long positions. In contrast, they increase their short holdings in reaction to heightened ambiguity. This behaviour highlights a strategic shift in their market positions under increased ambiguity, in the way that they go less in long positions and hence their market exposure becomes more net short. In contrast, the data suggests that risk has a converse effect, seemingly attracting swap dealers to augment their long positions in the following week. Swap dealers appear to absorb the observed risk with the aim of earning a risk premium. This observation is robust against controlling for a time-varying risk premium.

In summary, my findings show that the two hedger groups differ in their responses to uncertainty. When the environmental information is highly ambiguous and outcomes are uncertain (this is not limited to negative outcomes), producers tend to retreat by not committing to new positions and instead, adopt a wait-and-see approach. Conversely, swap dealers increase their hedging demand in response to heightened uncertainty. Facing ambiguity, they exhibit typical hedging behaviour, demonstrating ambiguity aversion by leaning more towards net short positions. This effect is mainly driven by their tendency to agree less in long positions. In the context of risk, swap dealers as financial intermediaries are drawn into the market, motivated by the potential to earn a risk premium.

3.4 Short-Run and Long-Run Hedging Pressure

So far we have seen, that producers' hedging demand decreases in response to ambiguity. On the contrary swap dealers show the typical hedging behaviour and increase their ending demand. This raises the question of why those participants behave differently. One potential explanation is, that the hedger groups differ in the time horizon of their hedging strategy. Kang et al. (2020) find, that commercials insurance demand is relatively stable from week to week, evolving gradually in response to producers' and merchants' output adjustments. Higher frequency movements in hedging demand are attributed to liquidity provision. Kang et al. (2020) derive a long-term, slowly evolving component of hedging pressure alongside short-term fluctuations in hedging demand. My subsequent analysis will focus on examining how these two distinct components are influenced by the dimensions of uncertainty. To do so, I calculate the slow-moving part of hedging pressure (Long-Run Hedging Pressure) for both hedgers types (producers and swap dealers) as the 52-week moving average of hedgers net short positions calculated from week t-51 to week t and adjusted by open interest in week t. Based on the long-run hedging pressure I calculate the short-run hedging pressure as the difference between the raw hedging pressure (equation (1)) and the long-run hedging pressure. Based on my identified hedging pressure components I rerun regression (13), respectively for the long-run and short-run hedging pressure of producers and swap dealers.

Results can be found in Table 5. My analysis reveals that for producers, the long-run hedging demand typically shows a significant negative correlation with ambiguity and with risk, as indicated by the average slope coefficient. In contrast, the short-run hedging pressure is positively influenced by both ambiguity and risk.

Regarding swap dealers, the scenario is inverted. Both ambiguity and risk are asso-

Table 4: Results for Producers and Swap Dealers

	Panel A: Producers							
	Market Share		Hedging Pressure		Long		Short	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ambiguity	-0.469^{***}	-0.472^{***}	-0.432^{***}	-0.446^{***}	0.029	0.038	-0.648^{***}	-0.661^{***}
	(0.048)	(0.047)	(0.052)	(0.061)	(0.049)	(0.056)	(0.052)	(0.054)
Risk	-0.308^{***}	-0.369^{***}	-0.198^{***}	-0.267^{***}	-0.045	-0.031	-0.358^{***}	-0.452^{***}
	(0.062)	(0.057)	(0.056)	(0.061)	(0.062)	(0.065)	(0.054)	(0.052)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Monthly fixed effects	NO	YES	NO	YES	NO	YES	NO	YES
	Panel B: Swap Dealers							
	Market Share		Hedging Pressure		Long		Short	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ambiguity	0.296^{***}	0.310^{***}	0.328^{***}	0.356^{***}	-0.307^{***}	-0.341^{***}	0.322^{***}	0.344^{***}
	(0.049)	(0.058)	(0.049)	(0.057)	(0.048)	(0.054)	(0.049)	(0.058)
Risk	-0.159^{**}	-0.103	-0.092	-0.054	0.030	0.011	-0.128^{*}	-0.080
	(0.064)	(0.066)	(0.064)	(0.066)	(0.061)	(0.063)	(0.065)	(0.066)
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Monthly fixed effects	NO	YES	NO	YES	NO	YES	NO	YES

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% level of significance, respectively. Heteroskedasticity robust standard errors are in parentheses. All variables were standardized and demeaned prior to the regression analysis.

ciated with a increase in long-run hedging demand, whereas short-run hedging demand exhibits a decline. Notably, in the short-run context, risk appears to be the primary influencing factor.

In sum, these results support what I found earlier: I find contrasting results for both hedger groups. Producers pursue a long-term hedging strategy driven by economic fundamentals. Ambiguity and risk decrease their long-run hedging demand. On the contrary, their short-run hedging behaviour is positively affected by ambiguity and risk. Conversely, swap dealers increase their long-run hedging demand in response to heightened uncertainty. Their short-run behaviour seems to be mainly driven by risk.

3.5 Identification and Robustness

The main objective of this study is to assess how changes in two different forms of uncertainty affect the hedging decisions of investors. After looking at the basic mechanisms between my hedging variables and the uncertainty dimensions, relying on a simple OLS framework, I now focus on the identification of the effect. Alterations in hedging positions and uncertainty are inherently endogenous, attributable to simultaneity and concurrent variables, including news about fundamental factors that impact both. Increases in price volatility arise from investor purchasing activity or the converse. I intend to tackle this issue in three ways: First, fixing the dependent and independent on the same timeline will likely result in biased estimates. That is why I have used lagged independent variables in section 3.1 to section 3.4 as it is unlikely that uncertainty yesterday can be influenced by hedgers positions today. Second, I apply an instrumental variable approach by using the OPEC newspaper index by Plante (2019) as an instrument for ambiguity. In doing so, I only use the variation in ambiguity that can be explained by newspaper attention to oil and OPEC-related events to identify the effect on hedging behaviour. Third, I implement a recursive identification scheme. In this way, I address potential endogeneity concerns by controlling for past and current effects of all endogenous variables. To do so, I estimate IRF using LP technique of Jordà (2005).

3.5.1 Instrument Variable Approach

The basic idea of an instrumental variable approach is to disentangle the useful exogenous variation in the independent variable from the not useful and endogenous variation it might also carry. The useful part of the variation is used to identify the causal effect (Goldfarb, Tucker, & Wang, 2022).

Table 5: Results for Long-Run and Short-Run Hedging Pressure.

	Panel A			
	Long-Run Hedging Pressure of Producers		Short-Run Hedging Pressure of Producers	
	(1)	(2)	(3)	(4)
Ambiguity	-0.600^{***}	-0.583^{***}	0.158^{**}	0.099
	(0.044)	(0.051)	(0.063)	(0.067)
Risk	-0.414^{***}	-0.461^{***}	0.315^{***}	0.256^{***}
	(0.048)	(0.055)	(0.066)	(0.068)
Controls	NO	YES	NO	YES
Monthly fixed effects	NO	YES	NO	YES

	Panel B			
	Long-Run Hedging Pressure of Swap Dealers		Short-Run Hedging Pressure of Swap Dealers	
	(1)	(2)	(3)	(4)
Ambiguity	0.330^{***}	0.365^{***}	-0.006	-0.023
	(0.045)	(0.053)	(0.056)	(0.058)
Risk	0.105^{*}	0.158^{**}	-0.480^{***}	-0.517^{***}
Controls	NO	YES	NO	YES
Monthly fixed effects	NO	YES	NO	YES

*Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% level of significance, respectively. Heteroskedasticity robust standard errors are in parentheses. All variables were standardized and demeaned prior to the regression analysis.*

I use the newspaper article count index introduced by Plante (2019) as an instrument for ambiguity. The index is constructed similarly to the economic policy uncertainty index by Baker et al. (2016) but focuses on articles related to OPEC events. Doing so, the index measures how attention paid to OPEC varies over time. It shifts in response to significant OPEC gatherings and occurrences related to OPEC production quantities.

For an instrumental variable to be valid and effective in IV regression, it must satisfy three main requirements (Angrist & Pischke, 2009): First, the instrument must be relevant, i.e. it must be correlated with the endogenous explanatory variable. In the case at hand changes in the media attention to OPEC-related events are expected to affect the ambiguity for crude oil from an economic point of view.[12] Further, the instrument must be exogenous and its effect must drive the dependent variable of interest solely through the endogenous explanatory variable. These conditions ensure that the instrument does not directly affect the dependent variable and only affects it through the endogenous explanatory variable. Per definition, ambiguity represents the degree of information that makes it hard to access probabilities to certain outcomes of interest. For example, rumours regarding OPEC decisions that lead to high media attention will also affect the level of ambiguity. A higher level of ambiguity will in turn affect trading behavior. Thus, ambiguity is the channel that transmits the effect.

Results for the IV regression approach can be found in table 6. Results support previous results: The variation in ambiguity that can be explained by the OPEC newspaper index significantly affects trading volume and hedging pressure. Ambiguity seems to be the main driver in the modulated setting.

3.5.2 IRF Framework Validation

LPs provide a flexible and robust way to estimate the IRFs and can therefore help to identify the dynamic effects of shocks in the uncertainty variables ($AMBIGUITY, RISK$) on hedging behaviour. While being more robust to model misspecification, IRFs estimated using LP method are econometrically equivalent to IRFs obtained from a vector autoregression model (Jordà, 2005; Montiel Olea & Plagborg-Møller, 2021; Plagborg-Møller & Wolf, 2021).

[12]The reported F-statistic for the first stage of the IV regression is $\hat{F} = 20.82 > 10$, indicating the OPEC newspaper index as a strong instrument.

Table 6: Results of the Instrument Variable Approach.

	Panel A			
	(1)	(2)	(3)	(4)
	Trading Vollume	Hedging Pressure	Hedging Pressure of Producers	Hedging Pressure of Swap Dealers
Ambiguity	2.852*	3.256**	-1.316	2.889**
	(1.88)	(1.96)	(-1.30)	(2.20)
Risk	2.064	2.070	-0.734	1.795
	(1.63)	(1.47)	(-0.91)	(1.64)
Controls	YES	YES	YES	YES
Monthly fixed effects	YES	YES	YES	YES
Observations	147	147	146	146

*Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% level of significance, respectively. Heteroskedasticity robust standard errors are in parentheses. All variables were standardized and demeaned prior to the regression analysis.*

Therefore, I estimate for each $h = 0, 1, 2, ..., H$ the linear local projections

$$HEDGING_{t+h} = \alpha_h + \beta_h \cdot \mho_t + \gamma_h^{'} \cdot r_t + \sum_{l=1}^{x} \delta_{h,l} \cdot w_{t-l} + \epsilon_{t,h} \tag{17}$$

and

$$HEDGING_{t+h} = \alpha_h + \beta_h \cdot \sigma_t + \gamma_h^{'} \cdot r_t + \sum_{l=1}^{x} \delta_{h,l} \cdot w_{t-l} + \epsilon_{t,h} \tag{18}$$

where $\epsilon_{t,h}$ is the projection residual, and $\alpha_h, \beta_h, \gamma_h, \delta_{h,1}, \delta_{h,2}, ...$ the projection coefficients. $w_t = (r_t^{\prime}, \mho_t, \sigma_t, HEDGING_t, q_t^{\prime})$ represents the total data set. r_t and q_t serve as control variables. Notice that with r_t I control for the contemporaneous values in the projection 18, while q_t accounts for lagged control variables. Notice futher that w_{t-l} is part of the sum and thus includes lagged variables of all variables in the system including the hedging variable itself, such that we control for past observations of all variables in the system (except the controls r_t). For identifying the structure of the model, I impose a temporal ordering on the set of variables. As ambiguity and risk are evaluated weekly, while hedging data from the CFTC, showing the real market positions on Tuesdays, market participants are unable to respond to changes in ambiguity and risk within the same week because such changes *mainly* have not yet occurred. This assumption is, of course, open to criticism but must be assumed for the model to work. Furthermore, I assume that shocks in ambiguity can contemporaneously affect risk but the other way around, as information is first reflected in ambiguity and then dive price volatility.[13]

The IRF of $HEDGING_t$ with respect to $UNCERTAINTY_t$ is given by $\{\beta_h\}_{h \geq 0}$ in equation (18). The LP impulse response estimate at horizon h is effectively defined as

$$\beta_h = E(y_{t+h}|x_t = 1, r_t, \{w_\tau\}_{\tau<t}) \; - \; E(y_{t+h}|x_t = 0, r_t, \{w_\tau\}_{\tau<t})^{14} \tag{19}$$

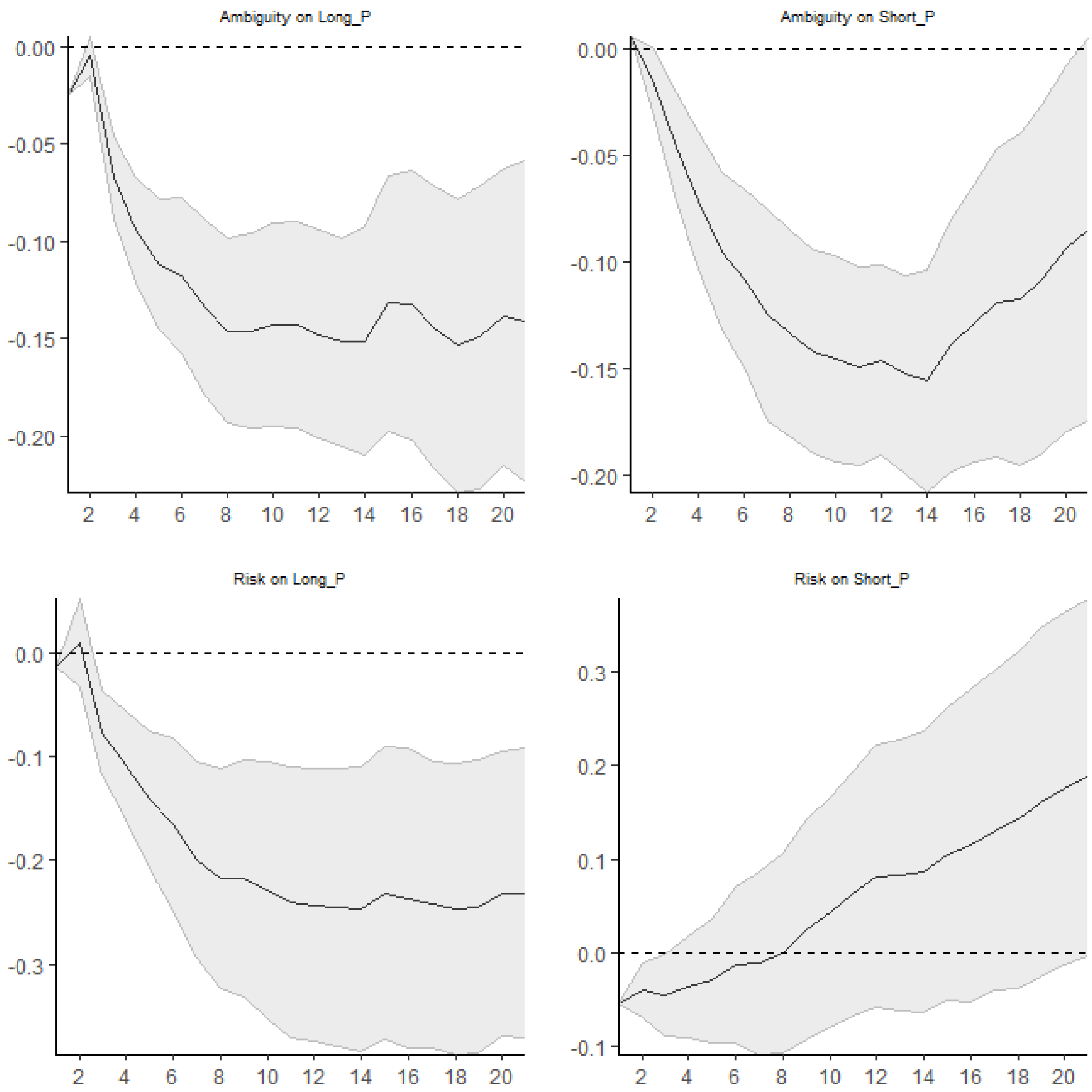
Lags for the endogenous variables (q_t) are selected based on Bayesian information criterion (BIC). To account for heteroscedasticity in variances and autocorrelation in error terms, I rely on Newey and West (1987) standard errors (HAC standard errors).

[13]We're interested in isolating the effect of a particular shock on variables of interest. To achieve identification, a common method is to impose a recursive ordering on the variables and then use the Cholesky decomposition of the variance-covariance matrix of the residuals. This gives a triangular matrix, which can be used to identify the shocks.

[14]For the notation adopted, I posit that the entire data set constitutes a Gaussian vector time series. This Gaussianity assumption is made purely for notational simplicity, allowing for the use of conditional expectations instead of linear projections to give the reader a better understanding.

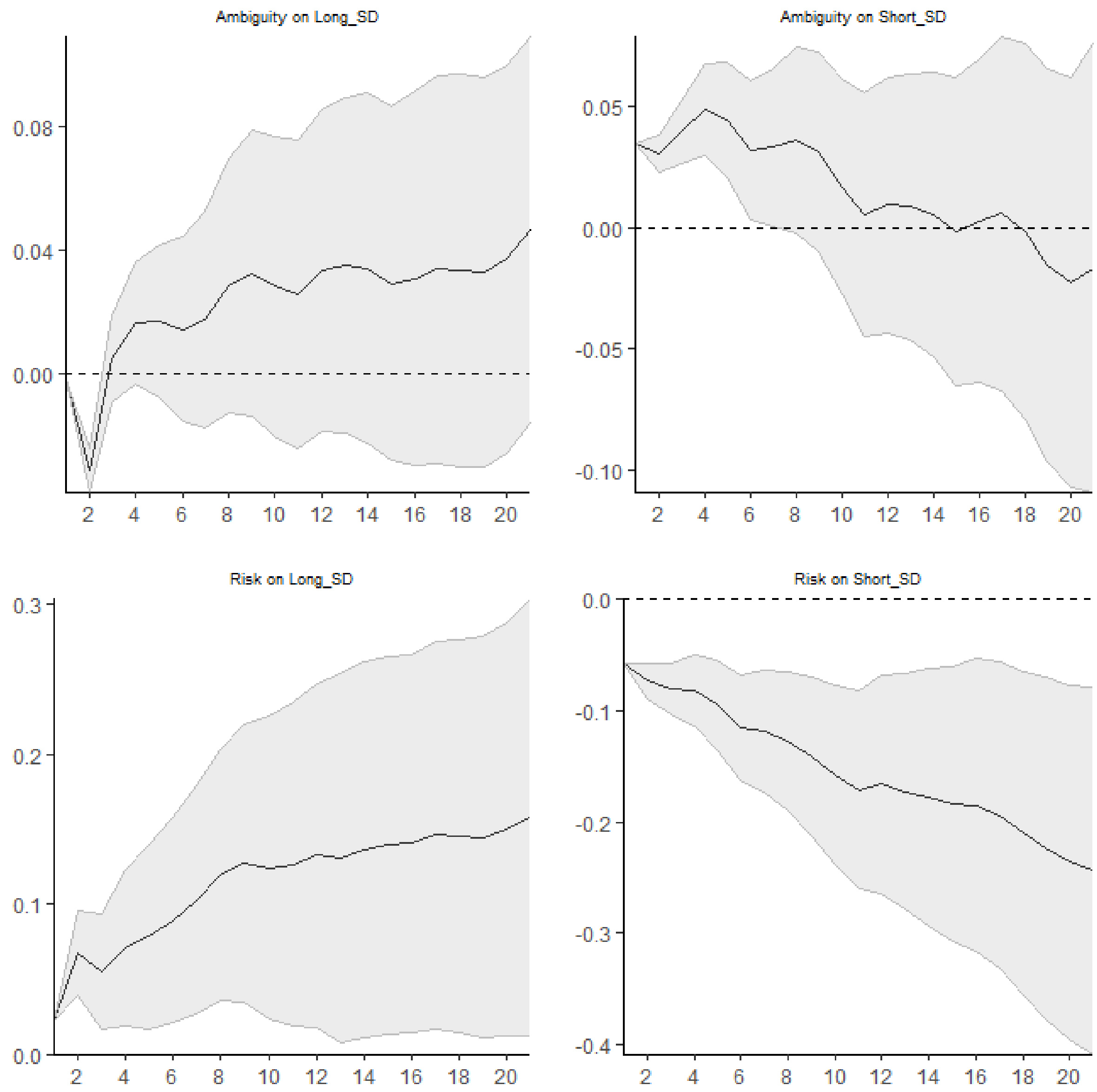
I estimate the relationship as specified in equation 19, where I incorporate the long and short positions of producers and swap dealers as proxies for the $HEDGING_{t+h}$ activity in the variable of interest on the left-hand side of the equation. Results are plotted in Figure 3 and are in line with my results from section 3. I find producers reducing their long and short holdings in response to a shock in ambiguity significantly, resulting in a reduction in hedging demand. In contrast, for swap dealers, my findings support a higher hedging demand in response to ambiguity, which is mainly driven by an increase in short holdings accompanied by a reduction in their long positions. With respect to risk, I find no clear pattern for producers indicating that their hedging strategy is long-term oriented and driven by economic fundamentals. In contrast, swap dealers increased their long positions in the crude oil futures market in response to a risk shock. Here, swap dealers are drawn into the market, attracted by the opportunity to earn a risk premium.

Figure 3: Response of Producers Long and Short Holdings to Uncertainty Shocks in Crude Oil Futures Market.



Note: Estimated impulse response functions of ambiguity and risk on producers long and short position holdings in relation to total open interest. Leg length is optimized using BIC. Grey areas represent 95% confidence intervals. I account for heteroscedasticity and autocorrelation in error terms by using Newey and West (1987) standard errors.

Figure 4: Response of Swap Dealers Long and Short Holdings to Uncertainty Shocks in Crude Oil Futures Market.



Note: Estimated impulse response functions of ambiguity and risk on swap dealers long and short position holdings in relation to total open interest. Leg length is optimized using BIC. Grey areas represent 95% confidence intervals. I account for heteroscedasticity and autocorrelation in error terms by using Newey and West (1987) standard errors.

3.6 Alternative Explanations

A market is called liquid when large volumes of an asset can be bought or sold swiftly without significant price fluctuations. Liquidity can be influenced by various factors, including the number of market participants, the market structure and the availability of information. The latter is strongly related to the degree of uncertainty investors face when making their trading decisions. If the degree of uncertainty is high, market participants may hesitate to trade, fearing they might pay or receive the "wrong" price. This can decrease trading activity and reduce market liquidity. In my main analysis, I control for market liquidity. To ensure that effects on hedger behavior are not driven by liquidity, I will examine this channel by estimatin the following regression:

$$\begin{aligned} LQ_{i,t} = \alpha + \beta_1 \cdot AMBIGUITY_{i,t-1} + \beta_2 \cdot RISK_{i,t-1} \\ + \beta_3 \cdot B_{i,t-1} + \beta_4 \cdot MOM_{i,t} \\ + \sum_{m=1}^{11} \beta_m \cdot M \end{aligned} \tag{20}$$

where $LQ_{i,t}$ represents the market liquidity in market i at week t.[15] As I am interested in how liquidity changes in response to uncertainty, I use ambiguity and risk as dependent variables. To reduce potential problems with endogeneity, I use the first lags.

In Table 7 (column 1-2) I report the estimated coefficients from estimating equation (20). The analysis reveals a statistically significant impact of ambiguity on the liquidity of the crude oil futures market. This finding underscores the importance of controlling for liquidity variations, as it is crucial to distinctly delineate the influence of uncertainty on hedging behaviour from its impact on the provision of liquidity within these markets, which in turn affects hedging decision-making processes.

4 Conclusion

In sum, this paper's contribution is twofold: first, I contribute to the growing research regarding decision-making under uncertainty by investigating the implications of ambiguity and risk for hedging decisions. To do so, I rely on commodity futures markets as a laboratory, as these markets offer a central marketplace to transfer uncertainty between hedgers and speculators. Given that individual hedging decisions are intricately tied to production characteristics and the supply and demand dynamics of specific commodities, I have evaluated ambiguity at the commodity level. Second, my study is the first to quantify ambiguity separately from risk in futures markets, using a seminal approach relying on the uncertainty dimensions' sources (i.e. outcomes vs. probabilities).

[15] I measure liquidity in market i as $LQ_{i,t} = \frac{TV_{i,t}}{OI_{i,t}}$, where $TV_{i,t}$ refers to the trading volume and $OI_{i,t}$ denotes the number of contracts outstanding in market i at week t.

Table 7: Results for overall market implications and hedgers as heterogeneous group.

	Liquidity	
	(1)	(2)
Ambiguity	-0.258^{***}	-0.283^{***}
	(0.048)	(0.049)
Risk	-0.00003	-0.021
	(0.056)	(0.056)
Basis		-0.030
		(0.101)
Momentum		-0.045
		(0.040)
Monthly fixed effects	NO	YES

*Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% level of significance, respectively. Heteroskedasticity robust standard errors are in parentheses. All variables were standardized and demeaned prior to the regression analysis.*

Consistent with traditional hedging theories in commodity markets, I find an increase in hedging pressure under ambiguous conditions, as hedgers seek to mitigate the uncertainty of adverse price movements (Friedman, 1953; Hicks, 1941; Keynes, 1923). Further analysis using a detailed dataset revealed a distinction between hedgers with physical links to the underlying commodity and those with a financial institutional background. In response to ambiguity, I find producers, the classical hedgers, reducing their positions, suggesting a cautious wait-and-see approach. This behaviour aligns with a long-term hedging strategy grounded on economic fundamentals, influenced by their direct involvement with the commodity and the informational advantages it confers. Conversely, swap dealers increase their hedging demand in response to heightened uncertainty. Facing ambiguity, they exhibit typical hedging behaviour, demonstrating ambiguity aversion by leaning more towards net short positions. This effect is mainly driven by their tendency to agree less in long positions. In the context of risk, swap dealers seem to be attracted by risk in anticipation of absorbing risk in exchange for a premium. The behaviour of swap dealers aligns with previous studies on equity markets that show ambiguity is associated with reduced holding of risky assets. To mitigate potential endogeneity concerns, I relied on an IV approach and I employed local projections to estimate impulse response functions, which corroborate my earlier findings.

In this light, understanding the dimensions of uncertainty is a fundamental step for investigating uncertainty transmission between derivatives and the underlying markets, as well as between different actors in these markets. An area of future research interest concerns the pricing of ambiguity in commodity markets: how much do hedgers pay their opposing speculators to capture ambiguity?

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Appendix

A1 The Commitment of Traders Report

The CFTC's COT report publishes the overall contract maturities aggregated long and short positions in the commodity futures markets and thereby classifies the traders according to their trading intent into three categories: commercially motivated traders were referred to as *commercials*, traders not commercially motivated were called *non-commercials*, and exposures not reported on account of their minor trading volume are called *non-reportables*. These position data are collected weekly on Tuesdays, and the open interest, as an aggregate across all contract maturities, is publicly released the following Friday after market close. The allocation of positions is based on the information submitted by clearing members, future commission traders and brokers. Therefore, a trader's trading volume is the first factor that determines whether the position is included in the report as reportable or non-reportable. Based on this, reportable traders are categorized as commercial or non-commercial. Commercials are further split into long and short positions ($Long^{C}$ and $Short^{C}$). The non-commercial positions are composed of long, short and spreading ($Long^{NC}$, $Short^{NC}$ and $Spreading^{NC}$). Non-commercials operate out of financial interest. Due to their small trading volume, minor participants are not subject to reporting requirements. The class of non-reportable traders is categorized as long and short ($Long^{NR}$ and $Short^{NR}$), but nothing is known about their trading incentive, i.e. whether they are commercially driven or not. Generally, between 70%-90% of all positions in a particular futures market are required to be reported.

The following equation shows the composition of the positions of the COT:

$$\begin{aligned}[Long^{NC} + Short^{NC} + 2 \cdot Spreading^{NC}] + [Long^{C} + Short^{C}] + [Long^{NR} + Short^{NR}] \\ = 2 \cdot OI\end{aligned} \tag{21}$$

Where $Long^{NC}$, $Short^{NC}$ and $Spreading^{NC}$ are non-commercial long, short, and spreading positions respectivley, $Long^{C}$ and $Short^{C}$ are the commercial long and short positions and $Long^{NR}$ and $Short^{NR}$ analogously for the non-reporting traders. The open interest (OI) represents the total number of contracts outstanding for crude oil futures. The number of long positions has to equal the number of short contracts, as each contract is recorded twice in the data set, arising from the two perspectives, i.e. the buyer and the seller side. According to CFTC Regulation 1.3(z), 17 CFR 1.3(z), the CFTC classifies traders who use the futures market for hedging purposes as commercials. Consequently, one assumes commercially driven agents have a relation to the underlying physical or cash market they want to hedge against. Alternatively, they may be motivated from a financial perspective by regulating portfolio risks using commodity futures markets. Agents with non-commercial motives, on the other hand, do not have a link to the cash market nor do they intend to hedge. They have speculative interests and intend to generate returns in exchange for bearing risk. Even if the commission emphasizes the primary hedging purpose as motivation for futures market participation of commercials, there is still some room for selected aspects of their trading to be speculative. Even if the distinction is not always totally transparent, the literature mainly views commercially motivated agents as hedgers and their non-commercially counterparts as speculators (Ederington & Lee, 2002; Kang et al., 2020; Manera, Nicolini, & Vignati, 2016; Sanders, Boris, & Manfredo, 2004).

Figure **??** provides details regarding the size expressed as a percentage of total open interest for each trader category. For example in the crude oil market hedgers (commercials) represent the largest trading group with an average market share of around 60%. They are closely followed by the speculators (non-commercials), who hold on average around 40% of the total open interest. Approximately 5% of all positions are not subject to reporting requirements. This rather small share of unreported positions indicates that the crude oil futures market is dominated by large traders holding contracts in large quantities. The percentage of hedgers has barely changed over the sample horizon, as shown in Figure **??** in the appendix. The utilization of the COT report for quantifying hedging behaviour is based on the assumption that it distinguishes precisely between the different categories of traders. However, the report may be prone to errors. Hence, it is subject to criticism in literature. The main issue concerns the fact that not all commercial-driven entities are hedgers and that hedgers do not exclusively hedge. For instance, because of position limits for non-commercial traders, they may have an incentive to prefer to be classified as commercial traders. Thus, actual hedging positions are a subset of the reported commercial positions in the COT. It is likely that traders classified as commercial-driven have a variety of motives. An additional issue are the non-reporting positions because nothing is known about their underlying intent (Ederington & Lee, 2002; Irwin & Sanders, 2012; Sanders et al., 2004).

A2 Definition of Trader Categories of the DCOT

The Disaggregated Commitment of Traders splits traders in the following categories: A "producer/merchant/processor/user" is engaged in the production, processing, packing or handling of a physical commodity and uses futures markets to manage or hedge associated risks. In contrast, a "swap dealer" is an entity that primarily deals in swaps for a commodity and uses futures markets to manage or hedge the risk associated with those transactions. In context of the report a "money manager" refers to a registered commodity trading advisor, registered commodity pool operator, or an unregistered fund identified by CFTC, who manages and conducts organized futures trading on behalf of clients. All other reportable traders who do not fit into any of the above categories are categorized as "other reportables".

A3 Theoretical Motivation of ambiguity and Risk in Futures Returns

I establish the theoretical foundations of ambiguity and risk using the Constant Expected Return Model (CER), as illustrated in model 22. The CER model postulates that an asset's returns are independently and identically distributed as normal over time, characterized by a constant mean and variance. However, I modify this model by treating the mean and variance of returns not as fixed but as state variables that vary over time.

$$R_{t+1} = \mu_t + \sigma_t \cdot \epsilon_{t+1} \tag{22}$$

with

$$\mu_t = \kappa_\mu(\overline{\mu} - \mu_t) + \sigma_\mu \cdot \epsilon_{\mu,t+1} \tag{23}$$

$$\sigma_t^2 = \kappa_\sigma \cdot (\overline{\sigma}^2 - \sigma_t^2) + \sigma_\sigma \cdot \sqrt{\sigma_t^2} \cdot \epsilon_{\sigma,t+1} \tag{24}$$

In Equation 22, $\epsilon_{t,i} \cdot \sigma_i = R_{t,i} - \mu_i$ represents the deviation of the return from it's long-term mean, which can be interpreted as market-impacting news. In this context, the random news shock, $\epsilon_{i,t}$, is conceptualized as an independent and identically distributed (i.i.d.)

standard normal random variable, modulated by the 'news' volatility, σ_i. Consequently, μ and σ are not static but dynamic stochastic processes, varying over time.

To model the time variable mean, μ_t, I rely on an Ornstein-Uhlenbrecht process. In this regard $\overline{\mu}$ is the mean reversion level of the rerun's mean μ. Further κ_μ describes the mean reversion rate. σ_μ indicates how strong the influence of $\epsilon_{\mu,t+1}$, i.e. chance/shocks (unanticipated news). The "news" time variant volatility, σ_t^2, is modelled using a Cox-Ingersoll-Ross Model. In this regard, $\overline{\sigma}^2$ represents the mean reversion level of the "news" volatility. Thus I assume the volatility has an equilibrium value. κ_σ describes the rate the volatility converges to its equilibrium level. σ_σ is the volatilities volatility and describes how strong the process is impacted by $\epsilon_{\sigma,t+1}$, i.e. chance/shocks (unanticipated news). Based on this simple theoretical model, I delineate two distinct forms of uncertainty: Firstly, the risk associated with returns is reflected by the level of returns' volatility. Secondly, ambiguity, characterized as the variability in probabilities, is the driving force behind the parameters of the returns time-invariant mean (μ_t, eq. 23) and variance (σ_t^2, eq. 24).

A4 Aggregating Priors to the Monthly Level of ambiguity

In order to compute ambiguity (equation 5), one needs to calculate the mean and variance of the return probabilities over the range of probability distributions over a week. ambiguity is measured in two steps: first, hourly probability distributions are estimated and build a set of weekly priors. Based on that, the variability of these priors within a week is determined and aggregated to a weekly degree of ambiguity. Plot A1 illustrates the second step. In practical implementation, this involves dividing the range of returns, which spans from -10% to 10%, into 40 bins with $B_l = \left(r_{l-1}, r_l\right]$. In addition, I take into account the probability of returns exceeding an absolute value of 10%, resulting in 42 bins in total. The procedure is schematically illustrated in Figure A1. For each bin, I calculate the probability that the return falls within it during each hour. Visually, the range of bins can be represented by a histogram. The frequency of intra-day returns observed in each bin determines the height of the corresponding bar in a bin, which in turn represents the probability of returns falling within that bin. $P(B_l) = \Phi(r_i, \mu, \sigma^2) - \Phi(r_{i-1}, \mu, \sigma^2)$ where $\Phi(\cdot)$ represents the cumulative normal distribution, which is fully characterized by the returns mean, μ, and variance, σ^2. Using these return histograms, I can calculate the expected probability of a particular bin across the range of return distributions, $E[P(B_l)]$, and also determine the variance of these probabilities, $Var[P(B_l)]$. To achieve this, I assume that each histogram is equally likely. Subsequently, I can assess the volatility across the bins over the course of a week, as an expected probability-weighted average of the variances of probabilities $\mho_m^2[r] = \frac{1}{w\ ln(\frac{1}{w})}(\sum_{i=1}^{42} E[P(B_l)] \cdot Var[P(B_l)])$ (7).

Figure A1: Aggregating Priors to the Monthly Level of Ambiguity