Evaluation of Ambiguity in Commodity Futures Markets: Analysis of Corn and Coffee Futures Prices

by

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Abstract

Ambiguity, defined as the uncertainty in probability distribution of asset prices resulting from misinterpretation of lack of information, is a current feature of financial assets. There are few empirical studies of ambiguity in financial and commodity futures markets. We define an ambiguity measure of corn and coffee futures daily prices, using the VAR framework to evaluate the autoregressive and cross-impact of the ambiguity and log-returns. Results show that the ambiguity in corn futures prices illustrates a higher impact compared with coffee futures prices, with a possible explanation being the action of non-commercial traders. The knowledge of the ambiguity measure in commodity futures markets can be applied to enhance production, storage, trading and hedging decisions.

Key words: ambiguity, coffee and corn futures, autoregressive, cross-impacts.

1. Introduction

The uncertainty in probability distribution of asset prices resulting from misinterpretation or lack of information defines ambiguity. In addition, ambiguity is recognized as Knightian uncertainty (Knight, 1921). The Ellsberg experiment showed that under ambiguous payoffs agents strictly prefer less ambiguity, violating the independence axiom of the subjective expected utility (SEU) model (Ellsberg, 1961). Besides, ambiguity tends to disappear when ambiguous events cannot be compared (Fox and Tversky, 1995).

In particular, ambiguity literature is vast. For example, research in the field has been analyzing the effect of ambiguity in financial markets, in the portfolio choice problem, its impact on liquidity, and its impact on the 2008 financial crisis (Dow and Werlang, 1992; Routledge and Zin, 2009; Boyarchenko, 2012). Also, studies examine ambiguity in commodity futures markets applying a theoretical approach, for example, Lien and Wang (2003), Wong (2015) and Lien and Yu (2017).

As such, mainstream literature on ambiguity in financial and commodity futures markets is predominantly theoretical. The theoretical approach defines the main gap and intellectual tension in the ambiguity literature as a consequence of ambiguity intrinsically abstract conceptual framework: there is a difficulty to empirically formulate a robust degree of ambiguity measure and ambiguity aversion for financial and commodity markets. In particular, commodity futures markets exhibit similar dynamic features with financial markets. These characteristics can extend the knowledge of ambiguity measure and ambiguity aversion in commodity futures market to aid the firm´s effective decisions about production, storage, hedging and trading.

Within this context, the goal of the study is to formulate an empirical ambiguity measure for commodity futures markets, namely the degree of ambiguity, examining the impacts on the market dynamics. As such, we employ Tan, Manahov and Thijssen (2017) approach to compose an empirical framework to explain the corn and coffee futures prices ambiguity of the nearest contracts traded at CME Group and ICE, respectively. First, we regress the maximum and minimum price spread daily average on turnover by volume to remove market noise, defining the residuals as a measure of the degree of ambiguity. Second, we define the interactions between the corn and coffee returns and ambiguity as a system, using a VAR framework to model the relationships between the variables, categorizing the results of the ambiguity impact on the future prices structure dynamics.

In sum, the contributions of this study for commodity futures markets are three-fold. First, the formulation of an empirical approach to measure ambiguity with real data. Second, the investigation of the effect of ambiguity on the corn and coffee futures markets dynamics, and third, the analysis of ambiguity impact on returns and futures prices. To the best of our knowledge, this is the first empirical research to create ambiguity measures and analyze ambiguity impacts in commodity futures market.

2. Literature review

The literature about ambiguity in financial marks is extensive, although mainly theoretical, with few empirical studies. Particularly in commodity futures markets ambiguity literature is scarce and based on theoretical approaches. Concerning financial markets, Epstein and Wang (1994) developed a model of asset price determination with Knightian uncertainty, in which Knightian uncertainty plays a role. Extend the general equilibrium pure exchange economy generalizing the representation of beliefs along the lines of Gilboa and Schmeidler (1989). Results show the proof of existence of equilibrium and the characterization of equilibrium prices by an "Euler inequality". Chen and Epstein (2002) compose a continuous-time intertemporal version of multiple-priors utility, with aversion to ambiguity. Defining, representative agent asset market setting, the model demonstrates restrictions on excess returns defining a risk premium and another premium for ambiguity.

Klibanoff, Marinaci and Mukerji (2005) develop an approach of decision maker preferences, separating ambiguity, defined as a characteristic of the decision maker´s subjective information. Identify that attitudes towards risk are characterized by the shape of a Von Neuman-Morgenstein utility function and an increasing transformation. Maccheroni, Marinacci and Rustichini (2006) illustrate the preferences defined by a utility function on outcomes and an ambiguity index on the set on the states of the world. The utility function describes the decision maker´s attitudes and the index identifies his ambiguity attitudes.

Garlappi, Uppal and Wang (2006) compose a model for an investor with multiple priors and aversion to ambiguity, defining ambiguity aversion in a minimization over the priors. Allowing different degrees of uncertainty about expected returns for various subsets of assets and the return-generating model, estimate closed-form expressions for the optimal portfolio. Comparing with portfolios from classical and Bayesian models, ambiguity-averse portfolios are more stable over time and deliver a higher out-of-sample Sharpe ratio. Epstein and Schneider (2008) analyze the role of uncertain information quality in financial markets, information processing when there is incomplete knowledge about signal quality. Results show that investors demand compensation for low future information quality requiring more compensation for low information quality when fundamentals are more volatile, with asymmetric response to signals skews of the distribution of observed returns.

Illeditsch (2009) examines the effects of aversion to risk and ambiguity, Knightian uncertainty, on the value of a market portfolio when investors receive public information difficult to link to fundamentals and classify as ambiguous. Demonstrate that aversion to risk and ambiguity can express high expected stock market returns and excess volatility and kurtosis of stock market returns. In addition, the skewness of stock returns is negative (positive) if risk aversion of the marginal investor is high (low). Routledge and Zin (2009) model the connection of uncertainty with liquidity, examining a simple market where a monopolist financial intermediary makes a market for a propriety derivative security. As such, a market-maker chooses bid and ask prices for the derivative and, conditional on the market trade, selects an optimal portfolio and consumption.

Miao (2009) analyzes optimal consumption and portfolio choice in a Merton style model with incomplete information when there is a distinction between ambiguity and risk, resultant of the adoption of recursive multiple-priors utility. Shows that is optimal to first use any prior to perform Bayesian estimation and then to maximize expected utility with that prior based on the resulting estimates, with a hedging demand affected by both ambiguity and estimation risk. Klibanoff, Marinaci and Mukerji (2009) illustrate a separation between ambiguity, defined as a characteristic of the decision maker's subjective beliefs, and ambiguity attitude, a characteristic of the decision maker's tastes. In applications these two characteristics may be independent of each other, and the preferences are dynamically consistent showing a recursive representation.

Epstein and Schneider (2010) analyze models of ambiguity aversion. Show that some models, particularly the multiple-priors model of Gilboa and Schmeidler (1989) impact portfolio choice and asset pricing differently from those of subjective expected utility, explaining puzzling data features. Ozsoylev and Werner (2011) analyze information transmission in asset markets when agents' information is ambiguous. Examine a market with risk-averse informed investors, risk-neutral competitive arbitrageurs, and noisy supply of the risky asset. Ambiguous information results in the possibility of illiquid market where arbitrageurs choose not to trade in a rational expectations equilibrium, and for an illiquid market, small informational or supply shocks have relatively large effects on asset prices.

Liu (2011) examines a continuous-time intertemporal consumption and portfolio choice problem under ambiguity, with expected returns of a risky asset following a hidden Markov chain. For the U.S. stock market data, continuous Bayesian revisions under incomplete information generate ambiguity-driven hedging demands that mitigate intertemporal hedging demands, important in the optimal portfolio policies.

Boyarchenko (2012) analyzes the doubts about the quality of information and the quality of modeling techniques ambiguity-averse agents assign to higher probabilities to lower utility states, leading to higher CDS premia and lower equity prices. Using data on financial institutions, found that the sudden increases in credit spreads during the 2008 financial crisis can be explained by changes in the amount of ambiguity faced by market participants and changes in how the total amount of ambiguity was distributed between ambiguity about information quality and ambiguity about model quality. Ju and Miao (2012) propose a novel generalized recursive smooth ambiguity model defining a three-way separation among risk aversion, ambiguity aversion, and intertemporal substitution, with the asset-pricing model explaining a variety of asset-pricing puzzles. Show that ambiguity aversion and learning under ambiguity play a key role in explaining many asset-pricing puzzles.

About ambiguity in commodity futures markets Lien (2000), Lien and Wang (2003), Lien and Yu (2014, 2015 and 2017) developed theoretical studies based on a production and hedging framework. As such, examine the firm´s inertia and the one-to-one hedging, the different effects on price and volume of Knightian traders, and cash flow hedging. In addition, compare the use of the full-hedge and separation theorems in firm´s decision, and the optimism about futures prices uncertainty and hedging.

The particular contribution of this study is the empirical analysis of an ambiguity measure for commodity futures markets. To the best of our knowledge, this specific research problem has not been estimated.

2.1.Ambiguity studies in commodity futures markets

Ambiguity about financial returns derives the features from the Ellsberg paradox. Under the subjective expected utility theory (SEU), a decision maker is indifferent among two indifferent options and a randomized linear combination of them, applying the independence axiom. Mathematically, if for any two options *f, f′* and *f:f′*, then (Tan, Manahov and Thijssen, 2017):

$\alpha.f + (1 - \alpha).f' \sim \alpha.f' + (1 - \alpha).f' \sim \alpha.f + (1 - \alpha).f$ Eq. (1)

Where: $\alpha \in [0, 1]$ and "~" is the indifference operator.

Equation 1 can be rewritten as:

$\alpha.f + (1 - \alpha).f' \sim f' \sim f$ Eq. (2)

However, from the Ellsberg experiment:

$\alpha.f + (1 - \alpha).f' > f' \sim f$, with $\alpha = 0.5$. Eq. (3)

As such, the result from the Ellsberg's experiment violates the independence axiom of the SEU model.

In addition, to analyze ambiguity in financial markets, several studies formulated hypothesis and models. Gilboa and Schmeidler (1989) developed the multiple-prior model with a utility function, the MaxMin expected utility model:

$U(f) = \min_{p \in C} \int u(f)dp$ Eq. (4)

Where: C = set of priors,
f = action,
u = a von Neumann-Morgenstern (VMN) utility function, illustrating the subjective expected utility (SEU) function, and
p = prior probability.

In Equation 4 a decision maker assigns an interval of probabilities to an outcome adopting the minimal probability or the worst-case scenario, expressing ambiguous adversity. Next, the preference on a decision is ranked applying the utility of the worst-case scenario and the decision maker maximizes the utility allocating the wealth using the ranking. The decision process is generated of a minimization and a maximization framework.

This multiple-prior model is extensively used. For example, Dow and Werlang (1992) and Garlappi et al. (2007), Routledge and Zin (2009), Ozsoylev and Werner (2011) and Viale et al. (2014). Specifically for commodity markets, Lien (2000), Lien and Wang (2003), Lien and Yu (2014, 2015 and 2017) estimated the firm´s hedging and production decision using the MaxMin principle. In this study we adopt the multiple-prior model, assuming that investors are ambiguity averse.

3. Methodology and data

Following Tan, Manahov and Thijssen (2017), first we calculate the daily log returns of corn and coffee futures prices as:

$r_t = ln\frac{P_t}{P_{t-1}}$ Eq. 5

Where: r_t calculates the daily log return of corn and coffee futures prices at time *t*, and P_t expresses the corn and coffee futures prices at time *t*.

In addition, to identify the intraday price variability, we modified the degree of ambiguity definition of Tan, Manahov and Thijssen (2017). Specifically, we substituted the bid and ask spread for the high and low daily price spread, which describes valuable information about the temporal dynamic process of a financial asset (Xiong, Li and Bao, 2017; Cheung and Chinn, 2001). As such, Equation 6 defines a proxy of the degree of ambiguity:

$K_t = \frac{lnH_t - lnL_t}{2}$ Eq. 6

Where: K_t = proxy of the degree of ambiguity of prices at time *t*; H_t, *and* L_t = highest and lowest corn and coffee futures prices at time *t*, respectively.

Moreover, we need to assess the impact of market makers on the corn and coffee futures prices dynamics (Tan, Manahov and Thijssen,2017). Therefore we regress the spread calculated using the right hand side of Equation 2 on turnover by volume to remove the part of variation of the spread predicted by the impact of the market makers. Next, we define the residuals as a measure of the degree of ambiguity of the corn and coffee futures prices:

$\frac{lnH_t - lnL_t}{2} = \alpha_0 + \widehat{\alpha_1}V_t + \varepsilon_t$ Eq. 7

Where: $\frac{lnH_t - lnL_t}{2}$ = spread between H_t and L_t at time *t*; α_0 = constant; V_t = daily turnover volume at time *t*; and, ε_t = residuals, a measure of the degree of ambiguity of the corn and coffee futures prices, at time *t*. Since ε_t defines an objective measure of the degree of ambiguity of the corn and coffee futures prices we can apply the Vector Autoregressive – VAR framework to analyze the cross-effects between the degree of ambiguity and the daily log returns. Therefore, we first examine the stationarity of the dependent variables using the Phillips-Perron (PP) and the Augmented Dickey Fuller (ADF) unit root tests for the corn and coffee futures prices ambiguity measure and daily log returns. If both series are stationary, *I*(*0*) we can apply the VAR model without differencing the series.

Next, we formulate the VAR model for the corn and coffee futures ambiguity measure and daily log returns:

$$K_t = C_K + \sum_{i=1}^{n} \hat{\alpha}_{t-i} r_{t-i} + \sum_{i=1}^{n} \hat{\beta}_{t-i} K_{t-i} + \varepsilon_t^K \qquad \text{Eq. 8}$$

$$r_t = C_r + \sum_{i=1}^{n} \hat{\alpha}_{t-i} r_{t-i} + \sum_{i=1}^{n} \hat{\beta}_{t-i} K_{t-i} + \varepsilon_t^r \qquad \text{Eq. 9}$$

Where: r_t = daily log returns of corn and coffee futures prices, at time *t*, defined by Equation 1; K_t = ambiguity measure of the corn and coffee futures prices, at time *t*, defined by the residuals, ε_t, of Equation 3; *n* = number of VAR lags, estimated applying the Ackaike

Infrmation Criteria (AIC); C_K and C_r = constants of the ambiguity measure and daily log returns, respectively; $\hat{\alpha}_{t-i}$ and $\hat{\beta}_{t-i}$ = VAR estimated coefficients for the daily log returns and the ambiguity measure; and, ε_t^K, ε_t^r = ambiguity measure and daily log returns VAR errors, respectively.

After applying Equations 8 and 9 for the corn and coffee ambiguity measure and daily log return series, we analyze the individual coefficients value, signal and statistical significance. Following, we generate the VAR impulse-response functions, illustrating pairwise the autoregressive and cross-effects between the corn and coffee futures prices ambiguity measure and daily log prices. In consequence, each VAR generates four figures describing the impulse-response to a nonfactorized one standard deviation innovation +/- two standard errors, up to ten days ahead of the shock period.

Lastly, we illustrate the pairwise Granger causality test between the corn and coffee ambiguity measure and daily log returns. The Granger test solves bivariate regressions of the form:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_k y_{t-k} + \beta_1 x_{t-1} + \cdots + \beta_k x_{-k} + \epsilon_t \qquad \text{Eq. 10}$$
$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_k x_{t-k} + \beta_1 y_{t-1} + \cdots + \beta_k y_{-k} + u_t \qquad \text{Eq. 11}$$

for all possible pairs of (*x, y*) series in the group. The reported *F*-statistics are the Wald statistics for the joint hypothesis:

$\beta_1 = \beta_2 = \ldots = \beta_k = 0$

For each equation. The null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression. In particular, the Granger causality test models precedence and information content but does not describe causality.

3.1.Data

We analyze high, low prices and daily volume of the March 2019 corn futures nearest contract, and the December 2018 coffee futures nearest contract. Use 481 observations of price and volume data, begin date: Nov. 17th, 2016, end date: Oct. 16th, 2018. Source: www.barchart.com (2018).

4. Results and discussion

We outline the descriptive statistics of corn and coffee futures prices ambiguity measure and daily log returns, Table 1:

Tab. 1. Descriptive statistics. Corn and coffee futures prices ambiguity measure and daily log returns. Period: November 17th, 2016 to October 16th, 2018, 481 observations.

Statistics	Coffee	Corn

	Ambiguity Measure[1]	Log Return[2]	Ambiguity Measure[1]	Log Return[2]
Mean	-2.60E-06	0.9910	8.25E-07	1.00004
Median	-0.0002	0.9997	-0.0005	1.0000
Maximum	0.0235	1.0118	0.0143	1.0078
Minimum	-0.0010	0.9894	-0.0108	0.9930
Std. Dev.	0.0053	0.0031	0.0036	0.0021
Skewness	0.6360	0.2349	0.9563	0.0507
Kurtosis	4.0286	3.9130	4.7780	4.5953
Jarque-Bera	53.5151	21.084	136.3928	51.1038
Probability	0.0000	0.00003	0.0000	0.0000
Sum	-0.0013	479.9407	0.00040	480.0169
Sum Sq. Dev.	0.0136	0.0047	0.0063	0.0022

Source: Research results.

Obs.: 1. Defined by Equation 7; 2. Defined by Equation 6.

The coffee ambiguity measure mean is negative illustrating a low value, -2.60E-06. The median and minimum values are negative, -0.0002 and -0.0097, respectively. The standard deviation is larger than the corn standard deviation, 0.0053 and 0.0036, respectively. In addition, the distribution of coffee ambiguity measure shows skewness and kurtosis, categorized by a large Jarque-Bera test with low *p*-value, rejecting the hypothesis of a normal distribution.

Furthermore, the coffee log return mean, median, maximum and minimum values are close to one. The standard deviation of the corn log return is lower than the coffee standard deviation, 0.0021 and 0.0031, respectively. In addition, coffee futures prices log returns skewness and kurtosis, illustrated by a large Jarque-Bera test with low *p*-value, rejects the hypothesis of a normal distribution. A possible explanation is the higher volatility of coffee prices influencing the ambiguity measure.

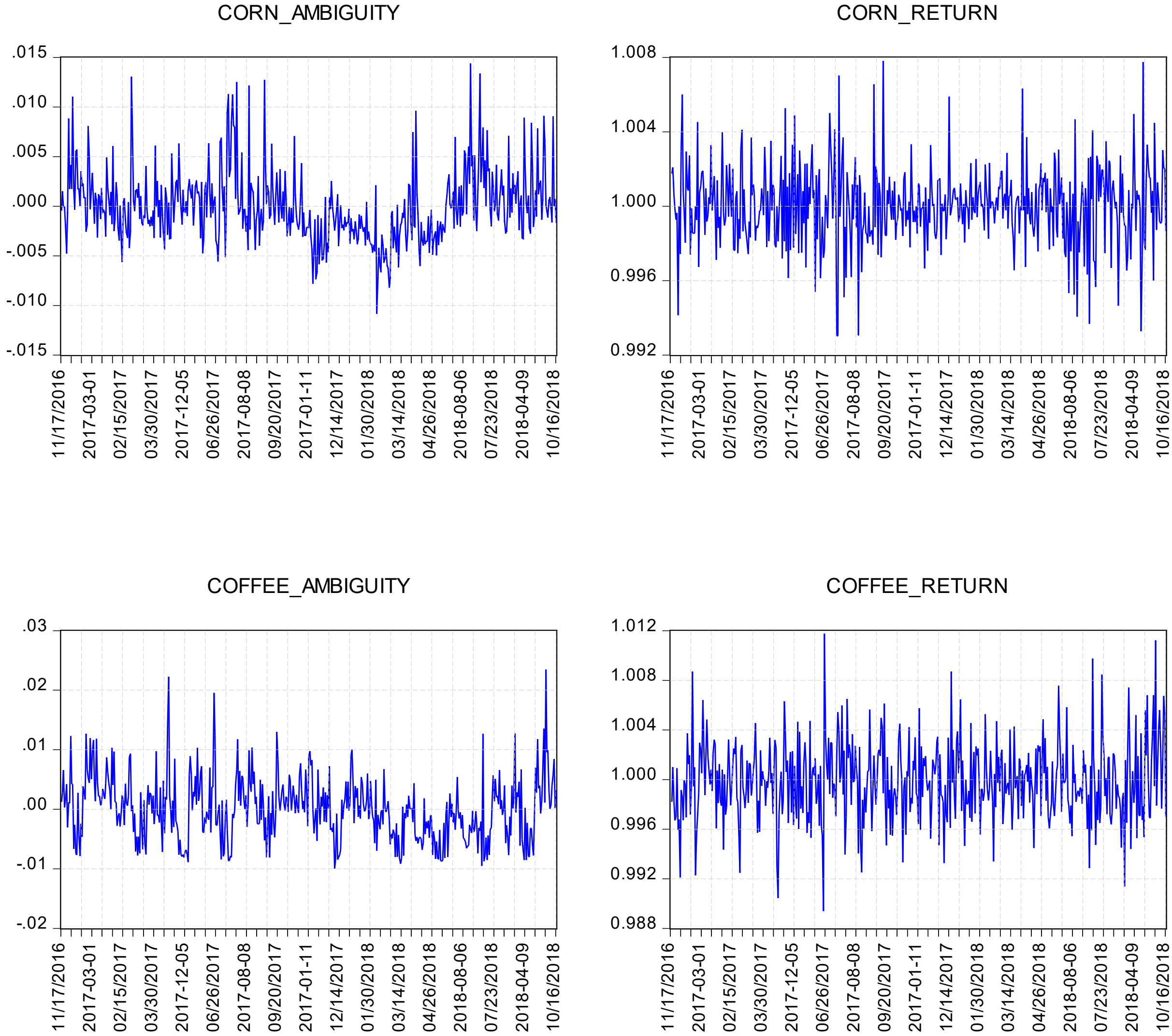
Next, corn ambiguity measure is positive with a low value, 8.25E-07, but median and minimum values are negative, -0.0005 and -0.0108, respectively. In addition, as expressed the corn ambiguity standard deviation is lower than the coffee standard deviation. Moreover, the distribution of corn ambiguity measure shows skewness and kurtosis, described by a large Jarque-Bera test with low *p*-value, rejecting the hypothesis of a normal distribution, analogous with the coffee ambiguity measure.

Equally important, the corn log return mean, median, maximum and minimum values are close to one. As noted, the standard deviation is lower than the coffee log return standard deviation, 0.0021 and 0.0031, respectively. In addition, corn futures prices log returns skewness and kurtosis, categorized by a large Jarque-Bera test with low p-value, rejects the hypothesis of a normal distribution. In sum, coffee and corn futures prices ambiguity measures show distinct patterns. Comparison between the descriptive statistics identifies different signs for coffee and corn ambiguity measure mean values, negative and positive, respectively. In addition, coffee ambiguity measure lists higher maximum and standard deviation values, whereas corn ambiguity measure shows lower median and minimum values. Besides, the corn ambiguity measure identifies higher skewness, kurtosis and Jarque-Bera test values.

Another relevant feature is the difference between the log returns standard deviations.

A possible explanation for the descriptive statistics patters of coffee and corn ambiguity measure and log return is the different specification of the coffee and corn futures contracts, the harvest seasons with different seasonality patterns, storage capabilities, as well as supply and demand and the futures markets commitment of traders actions, particularly the non-commercial traders. Next, Figure 1 expresses the corn and coffee futures prices ambiguity measure and logarithm of daily returns in levels:

Figure 1. Corn and coffee futures prices ambiguity measure and logarithm of daily returns in levels. Period: November 17th, 2016 to October 16th, 2018, 481 observations.



Source: Research results.

Again, the analysis of Figure 1 identifies different patterns of coffee and corn ambiguity measure. Specifically, the corn ambiguity measure shows higher amplitude than the coffee measure and systematic lower values, in line with results of Table 1. Besides, the coffee and corn log returns do not describe marked differences in their dynamics.

As stated, possible explanations are the different market depths and traders classification by hedgers and speculators. For example, aggregate volume for the nearest contracts of March and May 2019 were 7.070 and 2.682, for corn and coffee respectively, on January 28th, 2019 (www.barchart, 2019). In addition, the commitment of non-commercial traders, particularly managed money may illustrate the ambiguity measure and log return dynamics of coffee and corn futures prices, Figure 1. However, the structural change caused by the increased non-commercial traders may have decreased risk premiums, the cost of hedging, price volatility, and integrated commodity markets with financial markets (Irwin and Sanders, 2012; Sánjuan-López and Dawson, 2017).

Next, to use the Vector Autoregressive – VAR framework, we calculate the unit root (UR) tests, Phillips Perron (PP) and Augmented Dickey Fuller (ADF) for the corn and coffee futures prices ambiguity measure and daily log returns in levels, Table 2:

Tab. 2. Unit root (UR) tests. Phillips Perron (PP) and Augmented Dickey Fuller (ADF). Corn and coffee futures prices ambiguity measure and daily log return in levels. Period: November 17th, 2016 to October 16th, 2018, 481 observations. Model with constant.

Unit root (UR) test	Corn Ambiguity Measure	Corn Log Return	Coffee Ambiguity Measure	Coffee Log Return
PP	-18.1573*	-24.1908*	-15.0004*	-20.5875*
ADF	-3.9368*	-23.8002*	-8.6025*	-20.5890*

Source: Research results.

Obs.: (*) Statistically significant at 1%, rejecting the null hypothesis of unit root.

Results of Table 2 show the rejection of the null hypothesis of unit root in both the Phillips Perron (PP) and the Augmented Dickey Fuller (ADF) tests for the corn and coffee futures prices ambiguity measure and daily log return in levels. As such, both series are *I(0)* and we can apply the VAR framework without differencing the series.

Next, we employ the Vector Autoregressive – VAR framework to compose the contemporaneous and lagged endogenous variables relationship structure. Specifically, we construct the equations for the corn futures prices ambiguity measure and daily log return in levels, Table 3:

Tab. 3. VAR model. Corn futures prices ambiguity measure and daily log return.

Lagged variable	Ambiguity measure	Log Return
A_{t-1}^{corn}	0.2189**	0.0649**
A_{t-2}^{corn}	0.0394**	0.0258**
A_{t-3}^{corn}	0.1202**	-0.0027**
A_{t-4}^{corn}	0.1314**	0.0131**
A_{t-5}^{corn}	0.0116**	-0.0231**
A_{t-6}^{corn}	0.0612**	-0.0393**
A_{t-7}^{corn}	0.1735**	-0.0970**
R_{t-1}^{corn}	0.0042***	-0.1146**
R_{t-2}^{corn}	-0.0390***	-0.0682**
R_{t-3}^{corn}	-0.0234***	-0.0658**
R_{t-4}^{corn}	0.0385***	-0.0262**
R_{t-5}^{corn}	-0.0523***	0.0079**
R_{t-6}^{corn}	-0.1130***	-0.0431**
R_{t-7}^{corn}	-0.0003***	-0.0431**
Constant	0.1851	1.3531

Obs.: 1. Number of VAR lags = 7, estimated applying the Ackaike Information Criteria (AIC). 2. Statistical significance: (*) 1%, (**) 5% and (***) 10%, respectively. 3. Symbols: A_i^{corn} = corn futures price daily ambiguity measure, lag *i*; R_i^{corn} = corn futures daily log-return, lag *i*.
Source: Research results.

Results of Table 3 show that the ambiguity measure expresses significant positive and autoregressive pattern affecting the daily log return, with a 5% statistically significance. Moreover, the corn futures price daily log return expresses a lower statistical significance on the impact on the ambiguity measure, 10%. However, the corn futures daily log return translates a statistically significant autoregressive pattern, with a 5% statistical significance.

In addition, the increase of the corn futures prices ambiguity describes mixed net effects on the daily log returns, positive on the first, second and fourth lags, and negative on the third and fifth to seventh lags. In consequence, the degree of ambiguity seems to persist for seven days until the agents update their priors. Equally important, the daily log returns seven lags affect the ambiguity measure with negative impacts, except for the first and fourth lags. Additionally, the coefficients values variation confirms the cross-effect between ambiguity and daily log returns.

As such, the corn futures prices ambiguity measure identifies statistically significant impacts on the autoregressive dynamics of the daily log returns. In consequence, the knowledge of the corn futures prices ambiguity measure dynamics formulates a strategic informational input for hedgers, speculators, traders and producers. For example, the enhanced production and marketing corn strategies may benefit from a lower cost-benefit information identified in the ambiguity measure resulting in economic efficiency.

Furthermore, the ambiguity measure may be used as a metric of the degree of liquidity perceived by the agents of the corn futures market. Consequently, ambiguity-averse traders may identify potential trades. Also, ambiguity is priced in the daily log returns and may impact portfolio selection for non-commercial traders portfolio choices.

Next, we illustrate the Granger causality test between the corn futures price ambiguity measure and the daily log returns, Table 4:

Tab. 4. Pairwise Granger Causality Tests. Corn futures daily log return and ambiguity.

Null Hypothesis	F-Statistic	p-value
CORN_RETURN does not Granger Cause CORN_AMBIGUITY	0.5504	0.7960
CORN_AMBIGUITY does not Granger Cause CORN_RETURN	2.8366	0.0066

Obs.: 1. Sample size: 481. 2. Number of lags: 7.
Source: Research results.

Results of Table 4 express that the corn futures price ambiguity measure Granger-cause the daily log returns, with a 1% statistical significance. However, the daily log returns do not Granger-cause the corn futures price ambiguity. As such, the findings confirm that ambiguity is a strong current pattern in the corn futures prices distribution, and ambiguity-averse investors demand a risk premium illustrated in the lagged price structure. Furthermore, the ambiguity identification may be used in trading, production, marketing and hedging strategies in corn futures markets (Lien and Wang, 2003; Lien and Yu, 2017).

Following, we formulate the VAR model to compose the contemporaneous and lagged endogenous variables relationship structure for the coffee futures prices ambiguity measure and daily log return in levels, Table 5:

Tab. 5. VAR model. Coffee futures prices ambiguity measure and logarithm of daily return.

Lagged variable	Ambiguity measure	Log-Return
A_{t-1}^{coffee}	0.3118**	0.0421**
A_{t-2}^{coffee}	0.2420**	-0.0077**
A_{t-3}^{coffee}	0.0904**	-0.0150**
R_{t-1}^{coffee}	-0.0682***	0.0622**
R_{t-2}^{coffee}	0.0719***	0.0544**
R_{t-3}^{coffee}	0.1254***	-0.0750**
Constant	-0.1292	0.9582

Obs.: 1. Number of VAR lags = 3, estimated applying the Ackaike Information Criteria (AIC). 2. Statistical significance: (*) 1%, (**) 5%, and (***) 10%, respectively. 3. Symbols: A_i^{coffee} = coffee futures price daily ambiguity, lag *i*; R_i^{coffee} = coffee futures daily return, lag *i*; V_i^{coffee} = logarithm of coffee daily volume difference, lag *i*.
Source: Research results.

Results of Table 5, the 3-lagged VAR model of coffee futures prices ambiguity measure and daily log return show that the ambiguity measure expresses significant positive and autoregressive pattern affecting the daily log return, with a 5% statistically significance. The result is similar to the corn futures prices ambiguity measure and log return expressed in Table 3. Likewise, the coffee futures price daily log return expresses lower statistical significance on the impact on the ambiguity measure, 10%. However, the coffee futures daily log return translates a statistically significant autoregressive pattern, with a 5% statistical significance.

In addition, the increase of the coffee futures prices ambiguity describes mixed net effects on the daily log returns, positive on the first, and negative on the second and third lags. In consequence, the degree of ambiguity seems to persist for three days until the agents update their priors. Equivalently relevant, the daily log returns three lags affect the ambiguity measure with mixed net impacts, negative on the first, and positive lags two and three. Additionally, the coefficients values variation confirms the cross-effect between ambiguity and daily log returns.

Besides, similarly with the corn futures prices ambiguity measure, the coffee futures price ambiguity measure identifies statistically significant impacts on the autoregressive dynamics and the daily log returns. As such, the identification of the coffee futures prices ambiguity measure dynamics composes a strategic informational input for hedgers, speculators, traders and producers. As mentioned, the enhanced production and marketing coffee strategies may benefit from a lower cost-benefit information identified in the ambiguity measure, with the additional informational input of the ambiguity knowledge resulting in greater economic efficiency.

Identically with the corn futures price ambiguity measure, the coffee futures price ambiguity measure may be used as a metric of the degree of liquidity assessed by the agents. In consequence, ambiguity-averse traders may identify potential trades. Equally, ambiguity is priced in the daily log returns and may impact portfolio selection for non-commercial traders´ portfolio choices.

Next, we illustrate the Granger causality test between the coffee futures price ambiguity measure and the daily log returns, Table 6:

Tab. 6. Pairwise Granger Causality Tests. Corn futures daily log return and ambiguity.

Null Hypothesis	F-Statistic	p-value
COFFEE_RETURN does not Granger Cause COFFEE_AMBIGUITY	1.8705	0.1337
COFFEE_AMBIGUITY does not Granger Cause COFFEE_RETURN	0.6023	0.6137

Obs.: 1. Sample size: 481. 2. Number of lags: 3.
Source: Research results.

Results of Table 6 express that the coffee futures price ambiguity measure does not Granger-cause the daily log returns. Furthermore, the daily log returns do not Granger-cause the coffee futures price ambiguity. As such, ambiguity is a weak pattern of the coffee futures prices, and comparing with corn futures ambiguity-averse investors demand a lower risk premium illustrated in the lagged price structure expressed in Table 5.

In conclusion, the analysis of the corn and coffee futures prices ambiguity measure show that ambiguity is a current pattern of futures prices. In addition, results illustrate that compared with coffee, the corn futures price ambiguity expresses a stronger impact on the underlying price distribution. Consequently, agents demand a higher risk premium in the corn futures prices. A possible explanation can be the continuous active trades of non-commercial agents in the corn futures market. Moreover, ambiguity can be assessed with objective metrics applying for the corn and coffee futures markets as an additional liquidity measure defining a strategic informational input.

5. Summary and conclusions

The goal of the study is to formulate an empirical ambiguity measure for commodity futures markets, namely the degree of ambiguity, examining the impacts on the market dynamics. First, we formulate an empirical approach to measure ambiguity with real data, corn and coffee futures daily prices. Next, we apply the VAR framework to estimate the autoregressive and cross-impacts of the ambiguity measure and the log-return of corn and coffee futures prices on daily periods, the markets dynamics, analyzing ambiguity impact on returns and futures prices.

As such, results show that the ambiguity measure is an existing feature of corn and coffee futures prices. The ambiguity measure illustrates positive and negative values for corn and coffee futures prices, respectively, with a higher standard deviation for the coffee futures prices. One reason can be the intensity of non-commercial traders in the corn futures market.

In addition, ambiguity for the corn futures prices expresses a longer impact, measured by the number of lags of the VAR, compared with the coffee futures prices, seven and three lags, respectively. The result distinguishes a stronger impact of ambiguity on the corn futures market, indicating different trading and position patterns, which can be illustrated by the activity of non-commercial traders. The feature is a consequence of the financialization of commodity futures market, which attract more trading volumes for storable commodities instead of softs.

Moreover, as outlined in the literature, the comprehension of the ambiguity measure in commodity futures price can be used to enhance production, storage, trading and hedging strategies. Since ambiguity is a current feature of the commodity future price dynamics, it describes an added and positive informational input for decision makers.

The limitation of this study is the analysis of only two commodity futures prices, corn and coffee, instead of a commodity bundle, e. g., oil, gas, storable and softs. In addition, future research can analyze the cross-impact between ambiguity and log-return of different commodities, for example corn and coffee futures prices. Other lines of study is the examen of the cross-impact of ambiguity measure and log-return between commodities and financial assets, and the evaluation of the ambiguity measure and hedging strategies.

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