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Analysis of Financial Speculators' Herd Behaviour Impact on the Instability of Commodity Prices. Evidence from Weekly WTI Crude Oil Market Data Using Uncertainty Theory (2018–2024)

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Abstract

Aim: The purpose of this paper is to model the herd behavior of financial speculators in order to demonstrate its effect on the instability of commodity prices, particularly WTI crude oil prices, following recent events: the COVID-19 pandemic, the war in Ukraine and the war in the Middle East.

Methodology: The authors approach relies on introducing uncertainty theory and VNM[1] expected utility, rather than relying on ARDL modelling and dummy variables over the period 2018–2024, using weakly data provided by the CFTC.

Results: Our findings indicate the significant effect of variables, buying and selling positions of financial speculators and the war in Ukraine, namely increasing mimetic behavior of traders' and financial speculators' impact on prices. This result is valuable for a short-term relationship; however, there is

[1] Abbreviation of Von Newmann and Morgenstern.

no long-term relationship, which means no co-integration which can be interpreted by the efficiency of WTI crude oil market in long term.

Implications and recommendations: The prices of certain commodities have become unpredictable over the recent years, and the effect of fundamentals is becoming increasingly negligible in the face of speculators' decisions on the financial markets. Hence the importance of taking stock of the impact of the mimetic behavior of financial speculators, and of regulating their activity.

Originality/value: In contrast to earlier research, introducing the behaviour or psychological impact of recent events on speculative behaviour on the financial markets and, in turn, on the physical markets makes this study unique. Therefore, rather than focusing on the direct impact of financial speculation on oil prices, this study aims to capture the indirect influence. The statistical tool used was ARDL modelling combined with the theory of uncertainty and VNM expected utility theory in order to capture this indirect effect, originally linked to the risk aversion of the various market players. This feature is very important because it allows to predict more precisely future market behavior and trends.

Keywords: financial speculators, herd behavior, WTI crude oil prices, uncertainty theory, ARDL modelling

1. Introduction

Deregulation and financial liberalisation have promoted the entry of new players into commodity futures markets, resulting in various forms of speculation. Financial institutions such as hedge funds and commodity index funds have assumed an ever greater role in commodity futures markets in the past decade (Büyükşahin & Robe, 2014). In general, physical market speculation is limited to commodity professionals, such as producers, traders, and users. Financial investors, whether individuals or organized into various types of investment funds, were scarce on the physical market, particularly in the oil market (US Governmental Affairs, 2007). These various players are divided into two categories: commercials and speculators (Levine & Coburn, 2009). This distinction was institutionalised in American markets with the establishment of the Commodity Exchange Authority (CEA) in 1936. Another entity, the CFTC[2], was established in 1974 to supervise and regulate the futures markets, and releases weekly reports to increase transparency. The distinction criterion used by the CFTC is based on the purpose of the intervention. However, another category of participant remains difficult to classify, as it is made up of participants whose purpose is to hedge an existing position, but which does not concern a commercial, but a financial transaction (UNCTAD, 2011).

Since 2008 the CFTC has revised the classification of these players by reclassifying them in the non--commercial category. Generally speaking, the CFTC, in its published DCOT reports, distinguishes between five types of participants as follows: commercials (producers, users, merchant, processor), swap dealers, money managers, other reportables, non-reportables.

In recent years, following Kilian (2009) and Jovanovic (2007)and then Zhang et al. (2017), hedge funds have been accused of contributing to the fragility of the equilibrium and accentuating the uncertainty that increasingly characterises the commodities market. This causal relationship is due to their increased intervention in the futures market following the collapse of the fixed exchange rate regime, and to the liberalisation and financial globalisation that have gradually taken hold (Aulerich et al., 2012).

The latest events are the lockdown caused by the Covid-19 pandemic which has shaken the world economy, and the political crises in Eastern Europe in 2022 and in the Middle East in 2023, and have made oil prices highly volatile. This is why it is becoming essential to identify the real determinants of oil prices by reviving the hypothesis of the major impact of financial speculation.

In fact, this question must currently be asked not only for oil prices but also for all other commodities, since they are largely influenced by other factors linked to increasing financialisation, which has led to

[2] Commission of Financial Trade and Commodities.

greater uncertainty about future price trends (Djamal, 2022). Since the 2000s, producers have discovered effective hedging solutions on the futures market to reduce uncertainty about their trading position. Financial investors, looking for new markets to diversify their investment portfolios and reduce the impact of inflation, have found these long-term markets a favorable environment in which to maximize their profits. New forms of speculation have therefore gradually emerged to contribute on a large scale to the financialisation of commodity markets. However, in the economic literature, opinions are mixed and forever divided on the growing effect of financial speculation on prices. Between supporters and opponents of regulating or even limiting the role of financial speculation, empirical studies are inconclusive. To this end, this paper attempts to introduce the behavior of professionals and non-professionals into the analysis in order to conclude on the effect of financial speculation on oil prices volatility. Thus, the authors used the theory of uncertainty and expected utility VNM in the theoretical part in order to justify, firstly, the mathematical modelling of the mimetic behavior of financial speculators, and secondly, proceeded to the empirical analysis by testing the effect of this behavior on oil prices. Hence, it appeared essential to design an econometric model based on CFTC data in order to provide an objective answer to this problem.

2. Literature Review

Between the opponents and supporters of the effect of speculation on commodity price volatility, the debate never ceases to generate a great deal of interest. In a 2009 press release, the European Commission expressed its views on the subject, stating that there was no concrete evidence of a causal link between speculation on derivatives markets and excessive volatility and price rises on the underlying physical markets (Lagi et al., 2011). The European Commission believes that speculation plays an important role in these markets by providing them with the necessary liquidity; however, UNCTAD does not share the same opinion. In a report published in 2011, it condemned the action of speculators on the commodities markets as harmful, requiring urgent financial regulation to limit speculative positions on these markets, which they believe are the cause of disruption and price volatility (UNCTAD, 2011). The Dodd-Frank Act passed in 2010, and the implementation and reform, once again, of the Common Agricultural Policy in 2013, aiming to regulate financial speculation, are just some of the measures that justify the significant impact of speculation on price volatility (Aulerich et al., 2014). Masters stated that the growth in the market capitalisation of specialised commodity funds, and/or funds whose financial assets are indexed to commodity prices, can create a wave of fictitious forward demand, causing a sharp rise in spot prices. This can destroy the signals sent by the physical market and may lead to excessive price volatility (Sornette et al., 2009).

Masters was not the only one to comment on the significant impact of speculation, as numerous reports (US Governmental affairs, 2007; Juvenil & Petrella, 2015; Masters, 2008; Masters & White, 2008; Hamilton, 2009a; Hamilton, 2009b) have highlighted the speculative factor to explain the exacerbated variations in oil prices over this period. A number of other recent studies revived this phenomenon (Cifarelli & Paladino, 2010) used a modified CAPM and GARCH-M model to test the hypothesis of the impact of speculating strategies on price departures from their fundamentals, and came to the conclusion that there is substantial evidence linking changes in the price of oil to a decline in the price of stocks. Ludwig (2019) claimed that the rise in financial investment and derivatives has made commodities prices more susceptible to changes in the world economy, which then led to a rise in volatility. Similarly, Venegas et al. (2024), using a Dynamic Conditional Correlation (DCC) GARCH model, indicated that financial speculation, especially via passive investments, such as ETFs, has intensified price volatility in commodity futures.

Note that oil price volatility has been measured and shown, but these studies have only weakly statistically and empirically shown a causal relationship between increased financialisation and oil price instability. Buyuksahin & Harris (2011) concluded on a scant evidence of this impact using Granger causality test. Irwin et al. (2009) attested that the available statistical evidence did not indicate that positions for any group in commodity futures markets, including long-only index funds, consistently lead changes in futures prices. This could be due to a lack of understanding of the short, medium, and long-term temporal dynamics involved in price formation, or to incomplete information on oil financial markets. Irwin & Sanders (2012) criticised the weekly data from the CFTC, that the impact could be obvious if the data were daily. Many other studies have been carried out to justify the importance of the positive effect of speculation and its marginal role in the volatility of cereal prices, (cf. Rolli, 2012; Cordier & Gohin, 2011; Hamilton & Wu, 2015; Hernandez & Torrero, 2010; Krugman, 2009; European Commission, 2011), and consequently that financial speculation is justified by the liquidity it provides to futures markets. According to another study (Irwin et al., 2009), there is a historical pattern of attacks upon speculation during periods of extreme market volatility.

In general, the studies carried out focused on the absolute and direct impact on prices. The psychologic and mimetic behaviour of financial speculators and the real causes that motivate them to make buying and/or selling decisions were not taken into account in the various estimated models. A study by (Li, 2018) indicated the effect of financial speculators' risk aversion on their behaviour in the commodities markets, however it did not highlight the mimetic behaviour that this phenomenon can generate.

The authors' approach differs from those previous by taking the logic a step further and focusing on the indirect effect and the real causes that motivate speculators to make buying or selling decisions on financial markets. The research was inspired by the study of (Djamal & Said Chawki, 2018) in 2018, focused on the wheat market, relying on the theory of uncertainty and measuring the results by the expected utility of Von Newman and Morgenstern and VAR modelling, which showed that the impact was significant during the period 2012–2018. Thus, it seems clear that the psychological impact (risk aversion) materialised by the mimetic behavior of financial speculators must be introduced into the modelling analysis as a determining phenomenon.

2.1. Oil Price Instability

The instability of oil prices has been a recurring phenomenon since the first wells were discovered, particularly during periods of crisis (1973, 1979, 2008, 2019, 2022, 2023). However, starting from 2014 the international crude oil price has experienced the most significant volatility since the 2008 financial crisis (Lu et al., 2021). The price of oil is as much a geopolitical factor as an economic one, which explains why it is so unstable in response to political events and changes (Chevallier, 2010). The earliest instabilities recorded, commonly known as 'oil shocks', were those of 1971, 1973 and 1979. The first of these came just after the collapse of the Bretton Woods system, and the situation worsened over the following two years with the Yom Kippur war in the Middle East, followed by the Iran-Iraq conflict, which caused the price of oil to soar, as shown in Figure 1.

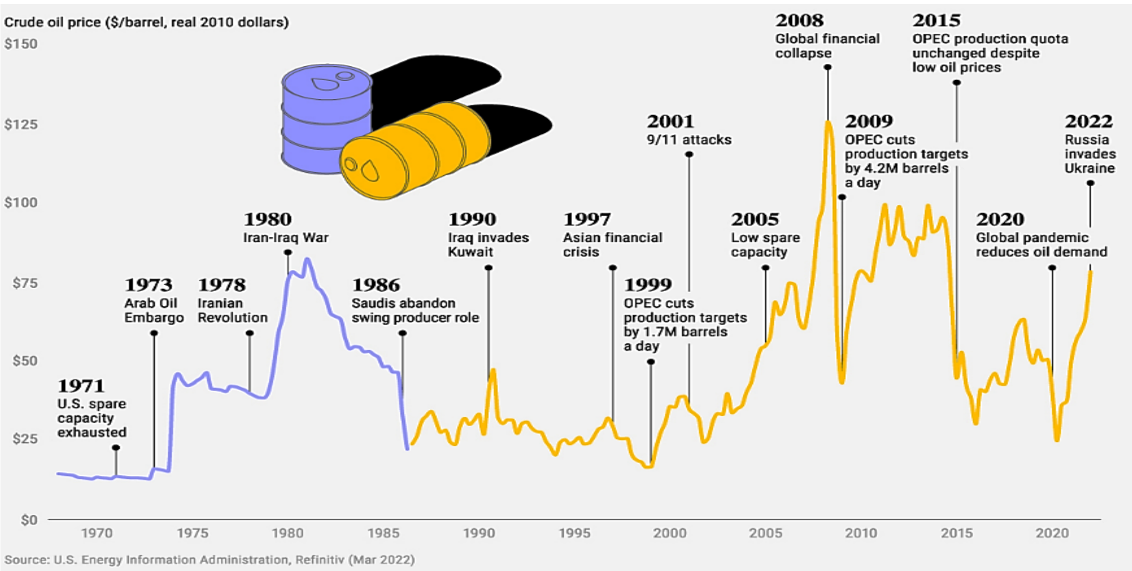

Fig. 1. Oil price trends (1970–2023)

Source: US Energy information administration Refinitiv.

After a period of calm and stability from the late 1980s to the early 2000s, the growing demand for energy from China, India and Brazil accelerated the rise in oil prices while maintaining a relatively stable level, however the situation deteriorated during the global financial crisis of 2007–2008. Between January and July, the price of a barrel of oil rose from \$96 to \$144, a staggering increase that had never been seen before. Since the crisis, oil price volatility has become a recurring phenomenon, as shown in Figure 1, with prices fluctuating between \$80 and \$130 a barrel. Just after July 2008, there was a steep fall in prices to \$40, before prices picked up again during the Arab revolution in 2011, rising sharply to \$128/barrel before stabilising at \$100/barrel thereafter. The stability did not last long as prices collapsed in 2015 to below \$50/barrel, and \$30/barrel in 2016. This steep fall prompted the biggest producers (Saudi Arabia, Russia, Venezuela and Qatar) to freeze production in order to stem the fall in prices. Despite these measures to limit supply, uncertainty reigned over the following years, with prices hovering around \$50/barrel until early 2020. The global economic recession caused by the Covid-19 pandemic dragged prices down to below \$20/barrel. This sharp fall did not last long with the post-crisis global economic recovery of 2019, and prices jumped considerably with the beginnings of the Russo-Ukrainian conflict in January 2022, when the price of a barrel reached a threshold of \$86/barrel. This rise was fueled by the war in February of the same year, pushing prices over the \$100/barrel mark to reach \$117/barrel in March. This period once again demonstrated the instability of the oil market, seemingly becoming a tradition (see Figure 2).

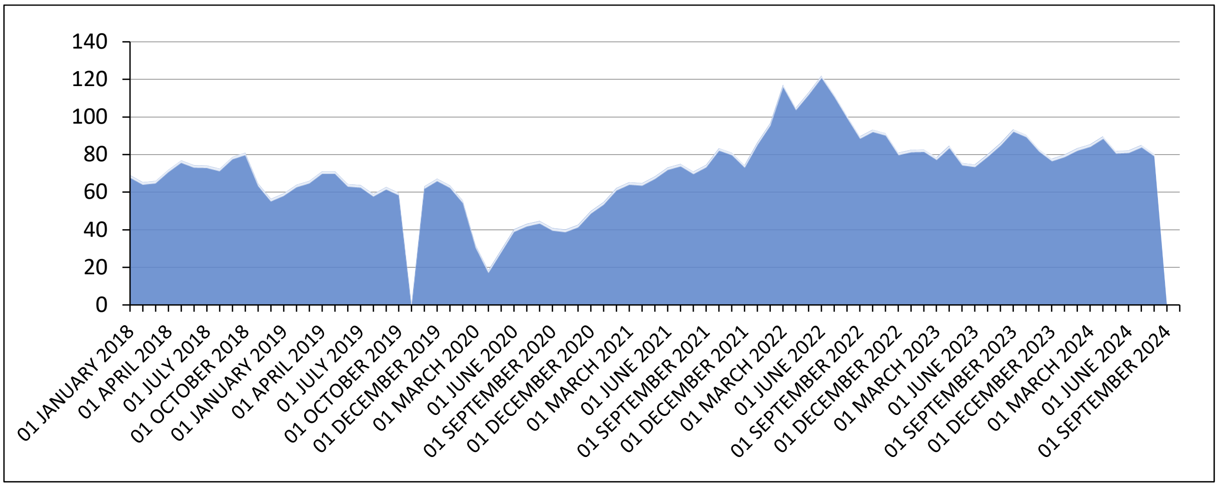

Fig. 2. Monthly price trend for a barrel of oil dollars/barrel (2018–2024)

Source: authors' elaboration based on CFTC's Stat.

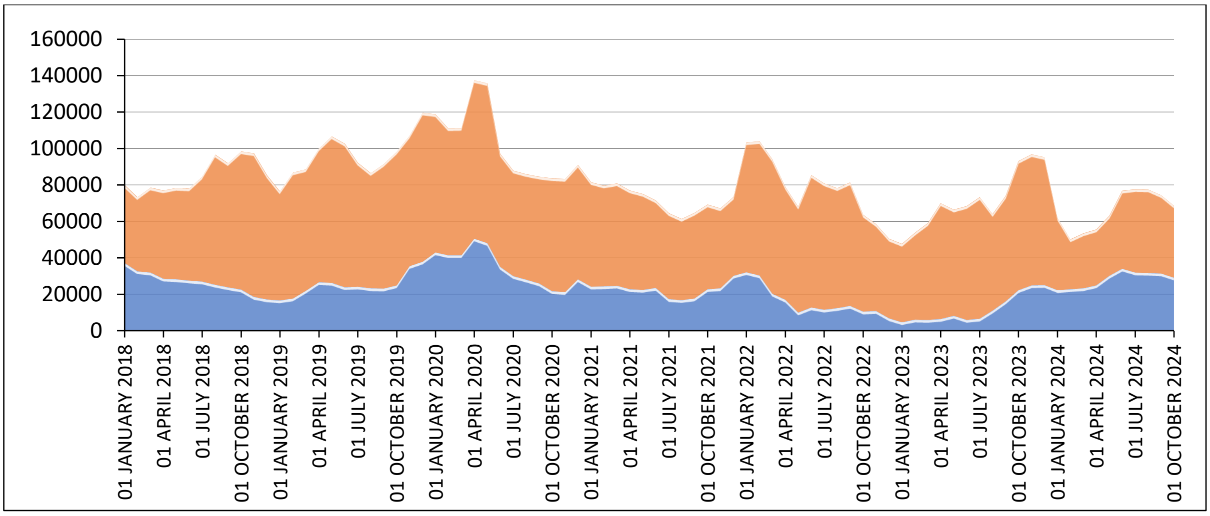

Fig. 3. Trend in the number of buying and selling positions held by financial speculators on oil prices (2018–2024)

Source: authors' elaboration based on CFTC's Stat.

The year of 2023 was marked by another political crisis in the Middle East, with Iran's involvement in the Israeli-Palestinian war fueling further uncertainty about the trend in oil prices, which continue to fluctuate between rising and falling prices, combined with relative stability in the first half of 2024.

From the above one can see that the last two decades have been marked by significant instability in oil prices, linked both to uncertainty and to the expectations of the main players (see Figure 2). There is also a strong link between oil price volatility and the various political, economic, financial and health crises, which suggests that factors other than fundamentals are having a dominant effect. The figure clearly shows that there is a correlation between speculative positions on futures markets and oil prices.

2.2. The Mimicry of Financial Speculators

When investors decide to ignore their own information and signals in order to follow the decisions observed by other analysts and investors, market efficiency will be difficult to verify, and variations in fundamentals alone cannot explain price movements (Stiglitz, 1975). Information is an important element in price determination, and (Fama, 1970) traditionally recognised the importance of its role in the efficient market hypothesis.

Market participants continuously update their expectations by referring to public or individual information, which means that prices change either when information is provided by market entrants, or individually (Chevallier, 2010). This information will generate a transaction, which in turn will affect prices.

The efficient market hypothesis stipulates that market participants value their assets based on fundamentals, a behavior deemed rational because any action is the result of solemnly disclosed information, or individual information. However, in certain circumstances, the behavior of individuals deviates from its rational path by following an action taken by the majority of market participants, which is known as 'herd behavior' and considered the result of uncertainty (Eeckhoudt et al., 2011).

Mimetic behavior involves a group making decisions that are both systematic and erroneous on the part of a group (Machina, 1987). Citing the case of an investor who intuitively acts by mimicry when prepared to make a given investment, ignoring the decisions of other investors, but changes his/her mind when he/she realizes that the other investors have abandoned the investment. Mimicry can take a number of forms which be described as irrational, but are not rational. Recent models describe mimicry as a deviation from rationality, known as noise trading, which means acting on the market at random. Pseudo signals can affect investors' decisions, a phenomenon known as issuing a buy or sell order with the aim of deceiving other, less informed investors, in order to profit from this wave of being followed by taking the opposite position before the others even realise it. Changes in beliefs and feelings can be translated into actions, or even strategies, particularly for investors. This hypothesis states that the formation or evolution of prices in the past provides information for predicting future prices, hence the decision to buy after prices have risen, and sell after prices have fallen, regardless of changes in fundamentals. To this end, investors use algorithms and computer software to help them anticipate future prices.

If the majority of market participants use the same rules and methods, a collective movement in the market will cause signals to be emitted that will affect prices, creating a phenomenon of mimicry outside of the variations in fundamentals. Mimicry can be completely rational, and in this context, spurious herding should be distinguished from intentional herding. As described by (Bikhchandani & Sharma, 2001), this behavior involves making the same decision independently of others when faced with the same situation. This is not mimicry in the true sense of the word, but an action resulting from information disclosed to the public, and does not really contradict the efficient market hypothesis. Taking the example of the banking panic, the war in Ukraine, or the lifting of the US embargo on Iran, this information can have an effect on the demand for oil, which will fall, in the knowledge that the market should be flooded by an increase in Iranian supply in the near future, causing prices to fall. In contrast to the former, intentional mimicry involves imitating the actions of other investors for much more psychological reasons, and is based on four motives:

1. Claiming an intrinsic preference for compliance on the part of individuals, due to a weakness in their ability to analyse and process data.
2. When one is confident in one's skills, in this case not making decisions that contradict those decisions of other market participants in order to maintain a good reputation with the public.
3. Following terms of employment imposed by the efficiency of the manager. In the case of an investor acting on behalf of others, the latter chooses his/her portfolio after having seen that the benchmark decision has been made; this behavior can only be explained by a single objective, which is remuneration, which increases with the manager's performance.
4. Information-based mimicry is the most important reason for this intentional behavior. It is an imitation resulting from behavior that consists of gleaning information by observing that of others.
5. In behavioral finance, if mimetic behavior affects prices, the first investors to react to this situation will make the biggest profits, and the situation becomes less profitable for those following, And this is how the wave of mimicry tends to diminish until it dies out completely. During the period from the onset of this mimetic behavior until its disappearance, it is difficult to analyse market data properly, and worse still, impossible to distinguish the best-informed investors from those who are less well-informed. This situation is characterised by total uncertainty and vagueness, and market participants may believe that the majority of investors have the right information, leading to dramatic price movements, speculative bubbles and excessive volatility.

According to this analysis, financial investors can act for a number of reasons, whether rational or irrational, and their behavior can lead to prices deviating from fundamentals over a longer period, creating a situation of total uncertainty by affecting the decision-making process of risk-averse economic agents, in particular producers, consumers and certain investors. This effect is most visible in the commodities markets, particularly cereals and oil.

It is very difficult to predict and analyse the behavior of market participants, hence empirical studies have been inconclusive. Statistical methods and field surveys provided little evidence of the presence of mimetic behavior in the markets, being even contradictory, while some concluded that the phenomenon is present, and others that it is absent. The most significant studies seem to concern the mimicry of financial analysts, where individual behavior is clearly identifiable, which is not the case for portfolio managers.

Clearly, one can say that price movements are linked mainly to changes in fundamentals, and at the same time to the games played by investors on the various stock markets. Buying and selling decisions are entrusted to microcomputers and algorithms that make millisecond decisions. As a result, various strategies have emerged, such as spoofing and layering, which are harmful and create dangerous mimicry. On 6 May 2010 the main US stock market index fell by almost 10% in five minutes, generating a loss of 800 billion dollars. No stock market is excluded from this observation: false signals are emitted with the aim of creating a following that is profitable for few investors and destructive for the real economy as a whole. In circumstances like these, uncertainty is heightened for risk-averse producers, and decision-making in this context has become an arduous task. In fact, if the market is efficient in the sense of Fama (1970), the futures price formed is assumed to be the expectation of the future spot price of the commodity. However, due to the hedging pressure of risk-averse producers, the futures price would be biased downwards relative to the expected future spot price, i.e.

$$F_0(t_1) < E_0[S_{(t1)}] \tag{1}$$

with $F_0(t_1)$ the forward price formed at $t_0$for maturity t_1, $E_0\left[S_{t_1}\right]$ the expectation at t_0 of the spot price at maturity t_1

or

$$E_0\left[S_{t_1}\right]= F_0(t_1) + \textit{risk premium}.$$

The systematic difference between the forward price and the expected future spot price would be the remuneration of the ‘long only’ speculator who buys at the forward price and sells a few weeks later at the spot price, thus systematically gaining the value of the bias. According to the theory of ‘normal backwardation’, the speculative gain would be the remuneration for the transfer of risk from the producer to the speculator. The producer, for their part, would cede the risk of falling prices in return for a risk premium paid to the speculator.

Ultimately, the speculator systematically earns the risk premium and obtains an additional positive or negative return depending on price movements (loss if the price falls and gain if the price rises while holding the long position). However, if prices behave randomly, due to random supply and/or demand shocks, the ‘long only’ speculator (systematic buyer) has a zero expected return on randomness, and therefore systematically earns only the risk premium. Taking into account the participation of financial speculators in the formation of futures prices, the question needs to be asked: what impact can herd or mimetic behavior have on price movements on the physical market?

A study of the behavior of market participants in a situation of uncertainty, with reference to a microeconomic approach based on the theory of uncertainty and utility seems obvious, and may provide a clear and detailed answer to this phenomenon in order to conclude on the impact of financial speculation.

3. Methodology

From the above, the study took the logic a step further by consolidating the authors’ ideas and hypotheses. The purpose was to describe the behavior of a risk-averse producer in the face of uncertainty, linked both to variations in market fundamentals and to false signals sent out by the market following speculative waves. One should take in account the recent circumstances that could have affected the financial speculator’s behavior, namely the Covid-19 pandemic, the Russian-Ukrainian crisis, and the war in the Middle East, all characterised by dummy variables. As the utility function was a logarithmic function according to Bernoulli’s new theory of risk, the variable necessary to be introduced into this model takes the following form: ‘*ln(w)*’(von Neumann et al., 1944).

The body responsible in the United States for regulating, monitoring and collecting data on the commodities futures markets, in particular the OTC* market, and for disseminating information to the public, is the CFTC –a commission which periodically publishes the Commitments of Traders reports which disclose the net long and short positions taken by the various market players (speculators and traders), thus each week it provides the total open positions of the players on the futures contract in question. There are two types of data: the first table shows pure positions in futures contracts, while the second shows the sum of pure positions in futures contracts and equivalent positions in options on the underlying futures contract. The total positions of the players, i.e. pure futures contract and equivalent option, were used in the causality analysis.

As explained earlier, it is clear that a distinction must be made in these reports between commercial and non-commercial traders, with long positions meaning buy positions and short positions meaning sell positions. Open interest is the total number of contracts opened (purchases and sales) by all categories of traders. The collected statistics were taken from the CBOT market, the Chicago Board of Trade. As far as traders’ positions are concerned, all the data came from the CFTC’s weekly reports. For monthly WTI Brent prices, the database was sourced from the UNCTAD website, and the prices expressed in US dollars per barrel.

The considered time series contained 348 observations and ran from January 2018 to October 2024, and was estimated using Eviews version 9 software.

Model specification

The econometric estimation consisted in regressing the value of historical prices on the value of current prices, and on the other variables which could have a positive effect on the determination of the forward price, namely the variation in speculators' positions (buy positions, sell positions).

From the above one can identify, firstly the variables chosen as follows:

〖UTF〗 _((*t*)) : the utility function of the professional at time *t* such that, *UTF*((*t*)) = *U*(*x*), *x* represents the wealth of the professional which is the unit price of a barrel of oil.

(Lopint)*t* – the number of open positions on the futures market.
(Lopo)*t* – the variation in the position of long speculators (swap dealers, money managers), for period *t*.
(Shopo)*t* – the variation in the position of short speculators (swap dealers, money managers), for period *t*.
(Spr)*t* –the spread, the difference between sell decisions and buy decisions.

If one considers a risk-averse trader (this was the authors' hypothesis), his/her utility function can take the following form:

$$f(t) = ln\,x \Rightarrow \Delta f(t) = \frac{d\,ln\,x}{dx} = \frac{1}{x}, \quad (2)$$

where *w* represents the wealth of a trader, being the unit price of a barrel of oil expressed in US dollars. Therefore one can introduce the logarithm into the previous relationship to obtain the utility function that characterises the mimetic behavior of financial speculators.

In order to take account of recent facts and events that should have affected the behavior of financial investors on futures markets, the authors introduced the following dummy variables:

Dum1:the dummy variable describing the effect of the Covid-19 pandemic,
Dum2: the dummy variable describing the effect of the Russian-Ukrainian political crisis,
Dum3: the dummy variable describing the effect of the conflict in the Middle East.

Before the estimation stage, first the various stationarity tests for all the variables that make up the model had to be carried out to see if there were any seasonal effects. Moreover, as usual, before estimating any econometric model it was essential to determine the degree of correlation between the variables selected. Thus the authors obtained the correlation matrix from the Eviews software as follows:

Table 1. Matrix correlation

	UTF	LOPINT	LOPO	LSHOPO	LSPR	DUM1	DUM2	DUM3
UTF	1	0.315945	0.416591	-0.543159	-0.277274	-0.678590	0.609681	0.234842
LOPINT	-0.315945	1	0.538955	0.654043	0.317408	0.012566	-0.5314446	0.003736
LOPO	-0.416591	0.538955	1	0.789504	0.031124	-0.042609	-0.6156249	-0.259584
LSHOPO	-0.543159	0.654043	0.789504	1	0.558398	0.212217	-0.8566104	-0.418021
LSPR	-0.277274	0.317408	0.031124	0.558398	1	0.352247	-0.5271841	-0.292869
DUM1	-0.678590	0.012566	-0.042609	0.212217	0.352247	1	-0.3793936	-0.192952
DUM2	0.609681	-0.531444	-0.615624	-0.856610	-0.527184	-0.379393	1	0.508580
DUM3	0.234842	0.003736	-0.259584	-0.418021	-0.292869	-0.192952	0.5085807	1

Source: authors' elaboration using Eviews software.

The matrix indicated a negative correlation between the UTF variable and the short positions, as well as the spread and DUM1, yet positively correlated with LOPINT, LOPO and DUM2, DUM3. As for the degree of correlation, there was a high degree of correlation between UTF and the variables LSHOPO, DUM1 and DUM2, with coefficients of 54.31%, 0.67% and 0.60%, with a less significant correlation between the variables LOPINT, LOPO, LSPR and DUM3.

Stationary tests To select the right model, the first step was to run the stationary tests, utilising Eviews software, and the obtained results are shown in Table 2

Table 2. Stationary tests

Variables	Levels	ADF		PP		KPSS	
		t_{stat}	t_{tab}	t_{stat}	t_{tab}	t_{stat}	t_{tab}
D(UTF)	1% level	-13.82194	-3.449053	-13.73828	-3.449053	0.045985	0.739000
(first difference)	5% level		-2.869677		-2.869677		0.463000
	10% level		-2.571174		-2.571174		0.347000
D(LOPINT)	1% level	-5.284780	-3.449738	-18.57299	-3.449053	0.039873	0.739000
(first difference)	5% level		-2.869978		-2.869677		0.463000
	10% level		-2.571335		-2.571174		0.347000
D(LOPO)	1% level	-20.29658	-3.449053	-20.29090	-3.449053	0.032493	0.739000
(first difference)	5% level		-2.869677		-2.869677		0.463000
	10% level		-2.571174		-2.571174		0.347000
D(LSHOPO)	1% level	-16.02384	-3.449108	-19.95783	-3.449053	0.071877	0.739000
(first difference)	5% level		-2.869701		-2.869677		0.463000
	10% level		-2.571187		-2.571174		0.347000
LSPR (at level)	1% level	-3.248798	-3.448998	-3.219607	-3.448998	0.686045	0.739000
	5% level		-2.869653		-2.869653		0.463000
	10% level		-2.571161		-2.571161		0.347000

Source: authors' elaboration using Eviews software.

As shown in Table 2, the various stationarity tests revealed the stationarity of the chosen variables at first difference, with the exception of the SPR variable, which is stationary at level, therefore the appropriate model was the ARDL model.

ARDL (AutoRegressive Distributed Lag) modelling is an econometric method used to analyse long-term and short-term relationships between variables. It can be used to estimate models with integrated variables of different orders, which makes it flexible (Pesaran & Shin, 1999). One of the main advantages of ARDL is that it does not require all variables to be stationary, moreover it can be used to perform co-integration tests. Finally, this approach is particularly useful for time series as it takes into account the lags of the explanatory variables.

ARDL models are linear time series models in which both the dependent and independent variables are related not only contemporaneously, but across historical (lagged) values as well. In particular, if Y_t is the dependent variable and $, x_1, x_2 \dots \dots x_k$ are *k* explanatory variables, a general ARDL(p, $q_1, q_2 \dots \dots q_k$) model is given by (Kripfganz & Schneider, 2023):

$$y_t = \mu + \sum_{k=1}^{p} p_k y_{t-k} + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon. \tag{3}$$

The static model is where *p* = 0 and *q* = 0.

Standard statistical methods such as OLS may identify an erroneous link between the variables when data series move together over time, as is typical of economic variables e.g. demand, income, etc. An ECM finds a long-term relationship between the variables while permitting short-term departures from this relationship in order to combat it. A unit root is frequently present in time-series data. This is made possible by an ECM, which finds a long-term relationship – often based on economic theory – between factors like short and long positions of financial speculators while permitting short-term variations from this relationship.

Hence one can also present the ARDL model, specifying the long run and short run, as follows:

$$\Delta y_t = \mu + \underbrace{\sum_{k=1}^{p} p_k \Delta y_{t-k} + \sum_{j=0}^{q} \beta_j \Delta x_{t-j}}_{\text{Short Run}} + \underbrace{\lambda y_{t-1+\theta} x_{t-1+}}_{\text{Long Run}} \varepsilon\,. \tag{4}$$

In the equation below there is a long-run relationship between variables *y* and *w*, which both contain a unit root (by assumption), but the short-run relationship is affected by *w* and another variable, *x*, which does not contain a unit root:

$$\Delta y_t = \sum_{k=1}^{p} p_k \Delta y_{t-k} + \sum_{j=0}^{q} \beta_j \Delta x_{t-j} + \sum_{l=0}^{r} \gamma_r W_{t-1} + \lambda(y_{t-1} - \theta W_{t-1}) + \varepsilon_t , \quad (5)$$

where λ, *P*, β , and *y* are parameters to be estimated and is a random error term.

Before estimating the model, one should first determinate the lag structure order.

Table 3. Selection of lag order

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-254.3663	NA	1.10e-08	1.537449	1.616280	1.568860
1	3038.273	6430.33*	5.68e-17	-17.54278	-16.91213*	-17.29149*
2	3091.957	102.6313	5.52e-17*	-17.57033*	-16.38787	-17.09917
3	3116.406	45.73482	6.39e-17	-17.42592	-15.69163	-16.73488
4	3133.021	30.39518	7.74e-17	-17.23542	-14.94931	-16.32450
5	3168.045	62.63093	8.42e-17	-17.15320	-14.31528	-16.02241
6	3201.177	57.88479	9.29e-17	-17.05987	-13.67012	-15.70920
7	3224.001	38.93352	1.09e-16	-16.90589	-12.96432	-15.33534
8	3250.058	43.37798	1.26e-16	-16.77093	-12.27755	-14.98051
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						

Source : authors' Elaboration using Eviews Software.

One can see from Table 3 that lag 1 is chosen as a lag order.

Next use the AIC (Akaike information criterion) to first select the ARDL model that offers statistically significant results with optimum parameters.

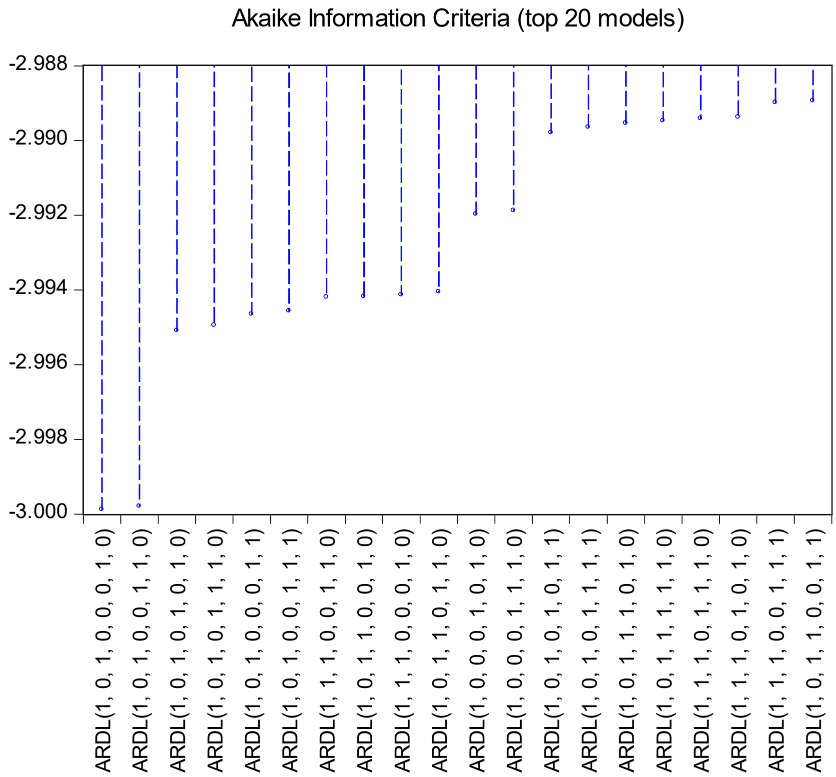

Fig. 4. Optimal ARDL selection

Source: authors' elaboration using Eviews software

The information criterion values for the top twenty models are provided by the AKAIKE criterion, as shown in Figure 4;since it provides the lowest AIC value, the optimal ARDL(1, 0, 1, 0, 0, 0, 1, 0) is the best model.

On the basis of the information obtained from Table 3 and Figure 4, the authors estimate an ARDL(1, 0, 1, 0, 0, 0, 1, 0). This model was selected to study the relationship between the independent variable (UTF) and a set of exogenous variables, considered as determinants of the herd behavior of financial speculators.

After running the ARDL model using Eviews software, the following results were achieved.

Table 4. ARDL model

Dependent Variable: UTF
Method: ARDL
Date: 01/17/25 Time: 20:21
Sample (adjusted): 1/09/2018 8/27/2024
Included observations: 347 after adjustments
Maximum dependent lags: 1 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (1 lag, automatic): LOPINT LOPO LSHOPO LSPR
DUM1 DUM2 DUM3
Fixed regressors: C
Number of models evalulated: 128
Selected Model: ARDL(1, 0, 1, 0, 0, 0, 1, 0)

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.*
UTF(-1)	0.964958	0.016438	58.70305	0.0000
LOPINT	0.028858	0.025872	1.115405	0.2655
LOPO	0.037138	0.018637	-1.992756	0.0471
LOPO(-1)	0.042694	0.016602	2.571693	0.0105
LSHOPO	-0.066556	0.027838	-2.390809	0.0174
LSPR	0.009948	0.012129	0.820198	0.4127
DUM1	-0.015065	0.012048	-1.250383	0.2120
DUM2	0.171907	0.054040	3.181102	0.0016
DUM2(-1)	0.200037	0.053759	-3.721018	0.0002
DUM3	-0.005569	0.010752	-0.517988	0.6048
C	0.383122	0.335738	1.141134	0.2546
R-squared	0.972109	Mean dependent var		4.178157
Adjusted *R*-squared	0.971279	S.D. dependent var		0.313673
S.E. of regression	0.053159	Akaike info criterion		-2.999881
Sum squared resid	0.949486	Schwarz criterion		-2.877857
Log likelihood	531.4794	Hannan-Quinn criter.		-2.951296
F-statistic	1171.106	Durbin-Watson stat		1.454168
Prob(*F*-statistic)	0.000000			

*Note: *p*-values and any subsequent tests do not account for model selection.

Source: authors' elaboration using Eviews software.

However, the interpretation of the results in Table 4 did not allow to identify the relationship between the variables in the model, either in the short or in the long term, hence the need to carry out the bounds test performed by Pesaran & Shin (1999) and (Pesaran et al., 2001). Moreover, the model stability was just as important as the bounds test, and the CUSUM test proposed inBrown et al. (1975) was applied, based on the sum of residuals. It represents the curve of the cumulative sum of the residuals together with 5% critical lines, thus the model parameters are unstable if the curve lies outside the critical zone between the two critical lines and stable if the curve lies between the two critical lines.

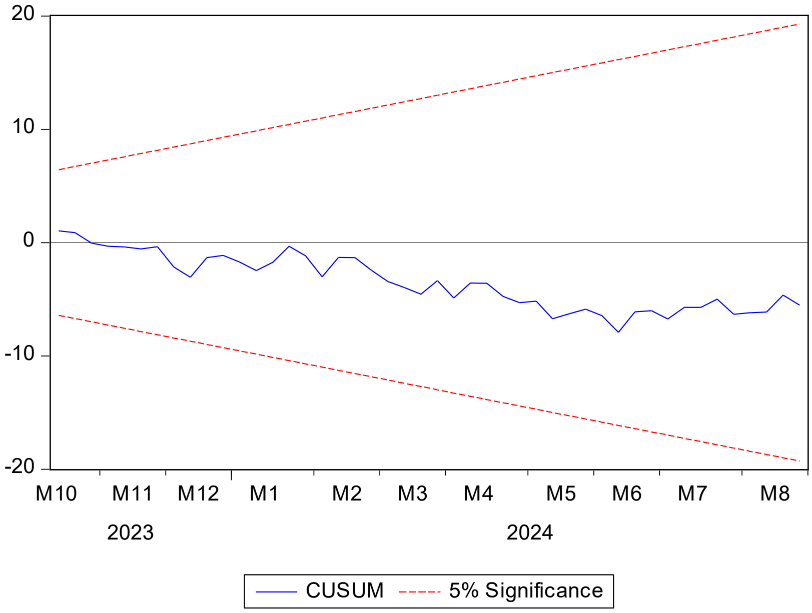

Fig. 5. CUSUM test

Source: authors' elaboration using Eviews software.

The results show that the plot remains within the critical bounds, indicating no evidence of any significant structural instability for the model.

The following step, also decisive in the study's modelling approach, was the bounds test.

Table 5. Bounds test

ARDL Bounds Test Date: 01/14/25 Time: 10:16 Sample: 1/09/2018 8/27/2024 Included observations: 347 Null Hypothesis: No long-run relationships exist				
Test Statistic	Value	*k*		
F-statistic	1.842810	6		
Critical Value Bounds				
Significance	I0 Bound	I1 Bound		
10%	2.12	3.23		
5%	2.45	3.61		
2.5%	2.75	3.99		
1%	3.15	4.43		

Source: authors' elaboration using Eviews software.

The bounds test unequivocally indicated that the null hypothesis should be accepted, which states that there is no co-integration relationship since the *F*-statistic value was less than the I0 bound at 5% significance. As a result, the authors drew the conclusion that there was no long-term link.

The short-term relationship can be characterised by estimating a short-term ARDL model, also called the first differenced ARDL, as follows.

Table 6. Short term ARDL model

Dependent Variable: D(UTF)
Method: ARDL
Date: 02/01/25 Time: 09:53
Sample (adjusted): 1/16/2018 8/27/2024
Included observations: 346 after adjustments
Maximum dependent lags: 1 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (1 lag, automatic): D(LOPINT) D(LOPO) D(LSHOPO) D(LSPR) DUM1 DUM2 DUM3
Fixed regressors: C
Number of models evalulated: 128
Selected Model: ARDL(1, 0, 0, 1, 0, 0, 1, 0)

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.*
D(UTF(-1))	0.272901	0.050811	5.370903	0.0000
D(LOPINT)	0.015007	0.064511	-0.232623	0.8162
D(LOPO)	0.036505	0.021371	-1.708194	0.0285
D(LSHOPO)	-0.032426	0.062397	-0.519680	0.6036
D(LSHOPO(-1))	-0.144720	0.048061	3.011200	0.0028
D(LSPR)	0.016790	0.026369	0.636718	0.5247
DUM1	0.005889	0.007611	0.773843	0.4396
DUM2	0.182362	0.051685	3.528333	0.0005
DUM2(-1)	0.185010	0.051824	-3.569934	0.0004
DUM3	0.000776	0.009407	0.082444	0.9343
C	-0.000379	0.004231	-0.089628	0.9286

R-squared	0.154936	Mean dependent var	0.000575
Adjusted *R*-squared	0.129710	S.D. dependent var	0.055170
S.E. of regression	0.051468	Akaike info criterion	-3.064439
Sum squared resid	0.887398	Schwarz criterion	-2.942154
Log likelihood	541.1480	Hannan-Quinn criter.	-3.015745
F-statistic	6.141980	Durbin-Watson stat	1.952560
Prob(F-statistic)	0.000000		

*Note: *p*-values and any subsequent tests do not account for model selection.

Source: authors' elaboration using Eviews software.

4. Results and Discussion

An impact is present even when the coefficient of determination R^2 is less than 20%. Insofar as an upward trend in prices encourages buying in the same direction in anticipation of a future increase in prices, and vice versa, the short-term relationship showed a positive effect of the historical values of the price of a barrel of oil on the behavior of financial speculators, which is entirely normal and logical.

With a probability of 0.0285, which was less than 5%, the authors also discovered the significant short-term impact of the DLOPO variable. With a lower coefficient equal to 0.03650, this indicated that a rise in buying positions would have inspired financial speculators more strongly and influenced their behavior similarly to past prices increases. Consequently, the behaviour of traders who are risk -averse is positively impacted by this since the market will then send out a positive buying signal, any change in the speculators' buying position can result in a wave of following this trend, encouraging the appearance of speculative buying which cause prices to rise dramatically. This result is entirely consistent with the research findings of (Chatziantoniou et al., 2021).

The DLSPR variable characterising the spread and DLOPINT characterising the open interests appear to be insignificant, which may be interpreted by a zero effect on the behavior of financial speculators, whereas the DSHOPO variable describing short positions (selling positions), negatively affects the behavior of financial speculators with a coefficient of (-0.032426). This means that the increase in selling positions would have caused financial speculators to become risk-averse with regard to investing in financial assets indexed to the price of a barrel of oil and future price trends, manifested in a reluctance to buy these financial assets, and leading to a sharp fall in prices if the number of financial speculators is large. This seems to be the case at present with increased financialisation and the interdependence of futures markets. Regarding the dummy variables introduced to characterise recent events, in this case the Covid-19 pandemic, the war in Ukraine and the war in the Middle East, it turned out that only the Dum2 variable for the war in Ukraine was significant, with a positive effect and a coefficient equivalent to 0.182362 on the behavior of financial speculators.

Therefore, it can be concluded that the Covid-10 pandemic had no effect on the behavior of financial speculators, either because containment was not anticipated or because financial speculators were caught off guard, hence they chose to take a standby stance and wait for the anticipated economic downturn. The same observation was made concerning the war in the Middle East, where the lack of involvement of Iran, a major petroleum producer, in the conflict could be the reason for the lack of significance. However, the most anticipated political event was the conflict in Ukraine, which all financial speculators were expecting after the region's events escalated and relations between Russia and Ukraine deteriorated. Since these are two significant providers of energy, especially oil, financial speculators sought to capitalise on this situation and, as was evident, this led them to take long positions in expectation of future price increases. Commercials are very sensitive to prices evolution, and the long/short financial speculators’ positions variation have an important impact on the behavior of commercials which engage them in herd behavior, hence the soaring or the sharp drop of oil prices. In general, one can conclude that in a period of rising prices, and in a situation of uncertainty, market players are betting on further rises and often opt to take a herd position on the market, therefore become more aggressive, buying and selling more quickly, with the possibility of rebuilding stocks. Sellers sell their goods more slowly, which explains the delay in the effect of the variables chosen in this model. In addition, their behavior, described as both cautious and greedy, contributed to a more pronounced rise in prices. The same observation can be made in a period characterised by falling prices. In this respect, the more unstable the market, the greater the uncertainty, and the more profitable the situation becomes for financial speculators, assuming that the risk aversion of professionals increases. In turn, this increases the risk premium to the detriment of the certainty equivalent, incorporated into futures prices, which does not rule out the indirect effect of financial speculation on prices.

5. Conclusion

The aim of other studies was to determine whether current events or financial speculation have a direct impact on the evolution of oil prices without making a difference between professionals and non-professionals. Introducing the behaviour or psychological impact of recent events on speculative behaviour on the financial markets and, therefore on the physical markets, makes this study unique. Thus, rather than focusing on the direct impact of financial speculation on oil prices, the authors aimed to capture the indirect influence, and verify the notion that traders' (professionals’) risk aversion connected to the game played by financial speculators, causes them to act in ways that destabilise the market. This led to the use of ARDL modelling combined with the theory of uncertainty and the VNM expected utility theory in order to capture this indirect effect, originally linked to the risk aversion of the various market players, while taking into account the difference between professionals and non--professionals in data analysis. This feature is very important because it allows for predicting more precisely future market behavior and trends, hence considering the appropriate regulatory policies by acting on the risk-averse behavior of professionals without affecting speculation, which is supposed to provide the necessary liquidity to the futures market. This also applies to other commodities markets.

The lack of a long-term co-integration connection makes it evident that, despite its short-term effects, financial speculators’ risk-averse behaviour had no effect, which can be interpreted by informational symmetry and the oil market's ability to regulate itself in the long term. This situation is synonymous with an efficient oil market, according to the efficient market hypothesis. Such efficiency can be explained in part by the drastic means implemented by the control and monitoring bodies for buying and selling operations on the futures and physical markets, given the importance of this market, and the impressive development of algorithms and information technologies. However, it is impossible to rule out the co-integration hypothesis and the possibility of a long-term link, especially if the variables selected had intraday or daily values, due to professionals being risk-averse. In other words, any change in the speculators' buying/selling position can trigger a wave of speculative buying leading to a sharp rise/fall in prices, because in this case the market will send out a positive buy/sell signal. Given that there is no daily or intraday data available and that financial speculators make their buying and selling decisions in milliseconds, which are frequently left to microcomputers, this is one of this study's shortcomings and a weak point in the analysis. The inability to determine the intentions of different market players (buying or selling, speculating, risk hedging) is the other disadvantage of this approach, which makes it extremely challenging to discern between professionals and non-professionals.

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Analiza wpływu zachowań stadnych spekulantów finansowych na niestabilność cen surowców. Dowody z tygodniowych danych z rynku ropy naftowej WTI z wykorzystaniem teorii niepewności (2018–2024)

Streszczenie

Cel: Celem niniejszego artykułu jest modelowanie zachowań stadnych spekulantów finansowych w celu wykazania ich wpływu na niestabilność cen surowców, w szczególności cen ropy naftowej WTI, w następstwie ostatnich wydarzeń: pandemii COVID-19, wojny na Ukrainie i wojny na Bliskim Wschodzie.

Metodologia: Nasze podejście opiera się na wprowadzeniu teorii niepewności i oczekiwanej użyteczności VNM, a następnie na modelowaniu ARDL w latach 2018–2024 przy użyciu słabych danych dostarczonych przez CFTC.

Wyniki: Ustalenia wskazują na znaczący wpływ zmiennych, pozycji kupna i sprzedaży spekulantów finansowych oraz wojny w Ukrainie, co oznacza wzrost mimetycznego zachowania wpływu spekulantów finansowych na ceny. Wynik ten jest cenny w relacji krótkoterminowej. Nie ma jednak związku długoterminowego, co oznacza brak kointegracji, co można interpretować jako efektywność rynku ropy naftowej WTI w długim okresie.

Wnioski i zalecenia: Ceny niektórych towarów stały się w ostatnim okresie nieprzewidywalne, a wpływ czynników fundamentalnych staje się coraz mniej istotny w obliczu decyzji spekulantów na rynkach finansowych. W związku z tym ważne jest, aby wziąć pod uwagę wpływ mimetycznych zachowań spekulantów finansowych i uregulować ich działalność.

Oryginalność/wartość: W przeciwieństwie do wcześniejszych badań, wprowadzenie zachowania lub psychologicznego wpływu ostatnich wydarzeń na zachowania spekulacyjne na rynkach finansowych, a w konsekwencji na rynkach fizycznych, jest tym, co czyni nasze badanie wyjątkowym. Dlatego też, zamiast skupiać się na bezpośrednim wpływie spekulacji finansowych na ceny ropy naftowej, niniejsze badanie ma na celu uchwycenie wpływu pośredniego. Zastosowanym narzędziem statystycznym jest modelowanie ARDL w połączeniu z teorią niepewności i teorią oczekiwanej użyteczności VNM w celu uchwycenia tego pośredniego efektu, który jest pierwotnie związany z awersją do ryzyka różnych uczestników rynku. Ta cecha jest bardzo ważna, ponieważ pozwala nam przewidywać przyszłe zachowania i trendy rynkowe.

Słowa kluczowe: spekulanci finansowi, zachowania stadne, ceny ropy naftowej WTI, teoria niepewności, modelowanie ARDL