OIL ON FIRE:

HEDGING EFFECTIVENESS OF OIL CROP FUTURES FOR UKRAINIAN SUNFLOWER OIL

by

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LIST OF ABBREVIATIONS

CBoT Chicago Board of Trade

EURNEXT Euronext

HE Hedging Effectiveness

JOHAN Johannesburg Stock Exchange

MALAYSIA Bursa Malaysia

MV Minimum Variance

OHR Optimal Hedge Ratio

POF Palm Oil Futures

RSF Rapeseed Futures

SBOF Soybean Oil Futures

SBMF Soybean Meal Oil Futures

CHAPTER 1. INTRODUCTION

In recent decades, Ukraine has been the primary exporter of sunflower oil, dominating the global market. Ukraine accounted for a 42% market share in the 2023/24 harvest season, consistently being one of the top exporters worldwide. The largest importers are India, the EU, and China, approximately accounting for 50% of the global imports. Ukraine's role as a major supplier has led to a large share of global exports originating from this region, with its production aimed primarily at European and Asian markets. Globally, sunflower oil occupies only a small portion of the vegetable oil market. While palm oil and soybean oil lead the market, sunflower oil contributes around 9-10% of the total vegetable oil consumption worldwide. Even though sunflower oil is important, particularly in European countries where it is widely used for cooking and food processing. (USDA 2024)

Sunflower oil constitutes a considerable share of agricultural exports from Ukraine, forming a critical part of its economy. Sunflower oil represents a substantial portion of Ukraine's agricultural export value, accounting for 9% of total agriculture exports in 2023. (Interfax 2024). In recent years, agricultural products, particularly sunflower oil, have helped Ukraine maintain its economic stability despite regional challenges.

With all being said, the motivation of the research is the following. This research aims to provide some insights into how Ukrainian market participants can reduce risks associated with adverse price movements of sunflower oil. Gained knowledge of this issue may lead to greater market stability. The research tries to capture and collaborate on both numerous pieces of literature on the hedging topic and practical knowledge gained by the writer. From a practical point of view, Ukrainian market participants (traders, framers, and others) occasionally use futures contracts for hedging purposes. The main limitation is the absence of profound futures contracts on sunflower oil, which somehow complicates the process. To overcome this issue, literature suggests cross-hedging strategies. Cross-hedging strategy involves hedging the risk of one asset by taking a position in a different but related one, and given research follows this strategy. We suppose that sunflower oil hedging might be effective while using other oil-containing crops or products. Since the thesis aims to be practical, the following logic was applied to choose contracts for further research. Contracts are historically used by market participants involved in the export of Ukrainian sunflower oil or derivatives based on vegetable oil crop cultures or products (oil or meal).

To state the problem more specifically, this research evaluates hedging effectiveness for market participants who enter a fixed-term contract for sunflower oil sales. The sale is executed outside Ukraine; the seller does not have oil in inventory, so it must be purchased in Ukraine after contract initiation. In this case, market participants have a risk that the sunflower oil purchase price in Ukraine will increase significantly and that they will experience negative revenue from the operation. In order to mitigate such a risk, market participants enter long futures positions. The number of futures contracts used for hedging is one of the questions of this research. Here we introduce the concept of optimal hedge ratio (henceforth OHR). The optimal hedge ratio aims to minimize the variance of the portfolio consisting of short sunflower oil and long futures positions.

There are different approaches for estimating OHR; this research is built around the ordinary least squares method (henceforth OLS). Using historical market data, the slope coefficient from the OLS model will be our OHR. It should be noted that all of the OLS assumptions must be met to state that the estimated slope coefficient is a reliable estimation of OHR. Results of the estimation of OHR in different model specifications (price difference, price return, and price levels) and different sub-periods should then be transformed according to the interpretation of slope coefficients under different model specifications.

To evaluate hedging effectiveness (HE) using futures on sunflower oil is found to be a useful but insufficient measure. Regarding this finding, HE is tested out-of-sample by comparing the percentage reduction in variance between unhedged and hedged positions.

The suggested approach resulted in the following conclusions. First of all, in all sub-periods that were used for analysis, the use of at least one future contract for hedging sunflower oil resulted in a variance reduction. Another finding is that the commodity market possessed significant structural changes. This conclusion was made from the fact that from sub-period to sub-period, the magnitude and direction of relationship futures contracts with sunflower oil were changing. Also, it was noted that futures contracts with later expiration dates provide better hedging effectiveness in some subperiods.

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

There is much empirical evidence on future hedging. The existing literature on hedging consists of studies that determine optimal hedge ratio (henceforth OHR), test hedging effectiveness, and examine the effectiveness of cross-hedge strategies.

Hedging can be defined as a risk management strategy that is used to reduce the risk of adverse price movements. In order to offset potential losses in one position one can take an opposite futures position in the same asset. For example, to protect themselves commodity producers or traders often use future contracts to hedge against fluctuations in the prices of commodities, securing a future selling or buying price to stabilize their revenue or costs. Hedging, often applied in high-volatility markets, helps companies to protect their profit margins. (Hull, 2018; Bodie, 2014).

On the other hand, a direct hedge may not be available. For example, if futures contract for a specific commodity do not exist, traders may use them from a correlated commodity as a proxy to reduce risk. Cross-hedging involves hedging the risk of one asset by taking a position in a different but related one. However, a strong correlation between the hedged and the substitute assets is required as well as a careful estimation of the optimal hedge ratio to maximize the hedge's effectiveness (Lien, 2002; Ederington, 1979).

The findings of hedging strategies are inconsistent regarding whether direct hedging or cross-hedging is better. There is a suggestion by Laws (2005) that states that the effectiveness of hedging using futures varies depending on whether the hedge is direct or cross-hedge. Franken (2003) found that cross-hedging has been effective in the case of hedging ethanol with gasoline futures. Bialkowski (2018) reached the same conclusion regarding dairy commodities. On the other hand, Dahlgran (2009) suggested that cross-hedging was ineffective in the case of ethanol using corn futures. According to the suggested findings we might expect variability in cross-hedging strategy depending on the type of commodity being hedged.

Early interest in the topic of finding OHR was expressed by Ederington (1979). The author's main idea was to find the OHR using the ordinary least squares (OLS) regression estimator. It was expected that the estimated hedge ratio should minimize variance (henceforth MV) of price series. Bekkerman (2011) adopted ARCH and GARCH models for estimating time-varying hedge ratios. Considering the long-term co-integration of commodities' spot and futures price series, the error correction model (ECM) was applied by Juhl (2012). In order to correct the model for autocorrelation and heteroscedasticity in time series, several other studies used the generalized least squares (GLS) model by Kim (2015) or estimated the generalized least squares (EGLS) model by Brorsen (1998) and Franken (2003).

According Bialkowski (2022) to The OSL technique faces limitations due to its assumptions of constant variance of error terms and absence of autocorrelation in residuals. Another criticism is that the MV hedge ratio stays consistent and unchanging over time. Numerous research have suggested the utilization of the Ordinary Least Squares (OLS) model to calculate Optimal Hedge Ratios (OHR), as they argue that more intricate models such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) do not always improve hedging efficiency in comparison to simpler techniques like OLS. This indicates that OLS remains a reliable and commonly utilized technique in academic and practical environments for calculating hedge ratios, especially when simplicity and understandability are crucial.

For example, in the research conducted by Floros and Vougas (2006), the authors attempted to estimate hedge ratios for the Greek stock index futures market by comparing OLS and GARCH models – GARCH, EGARCH and GJR-GARCH, but they were only able to determine that the GARCH models provided an efficient approximation of time-varying volatility, although OLS was found to be equally effective for hedging. This point confirms that GARCH models suffer practical complexities, precisely that the OLS renders simplicity combined with effectiveness.

In a similar fashion, Lien and Tse (2002) studied the performance of OLS, GARCH, ECM amongst other hedging models and noted that though GARCH models incorporate conditional volatility, the margins improved over OLS were hardly significant. Their results emphasized that, in a majority of cases, hedges using the OLS method are of sufficient quality and require less time and resources than GARCH models.

Dutta and Noor (2017) evaluated the effect of volatility in global oil prices and other commodity markets, specifically agriculture, metal, and non-energy commodity markets. The authors found that shocks in oil prices impact commodity markets and the economy overall. Which underlines the relationship between external impact on commodity markets. In the case of oil and non-energy commodities markets the study provides insights into risk management strategies and portfolio diversification tactics using an analysis of the volatility transmission mechanism. The study also emphasizes how important it is to understand volatility spillover processes in order to determine the optimal approach for portfolio allocation. This finding should be considered in further research into the current topic.

Penone (2021) investigates the Italian field crop industry's use of futures contracts for hedging purposes. The authors recognize that there are major dangers for farmers because of the rising price volatility in the local and international food markets. They emphasize the use of financial derivatives like futures contracts and risk management instruments in reducing price risk and stabilizing farmers' income. The authors perform an empirical analysis with a focus on Italian farmers who produce standardized and storable commodities, specifically soybean, maize, and milling wheat. They use futures contracts traded on the Chicago Board of Trade (CBOT) and Euronext markets to examine the efficacy of hedging methods. This study builds an idea behind the thesis, and also shows that this type of question is in demand.

Broll, Welzel, and Wong (2013) considered the effect of cross-hedging on price risk in agriculture. The authors draw attention to the policy discussion around the causes influencing commodity price volatility, raising the question of whether these changes are caused by futures market speculation or underlying economic realities. They raise the question that financial investments in commodities increase volatility and impact behavior of the price. The authors create a theoretical framework for selecting the best cross-hedging tactics for farmer contracts to address these problems. They consider a farmer as someone who is risk-averse and sells their produce in two marketplaces, one of which has access to a futures market.

Academic research has widely adopted the continuous futures data series to study long-term price trends, find optimal hedge ratios and model market behaviors. Continuous futures series are created when one future is "rolled" to the next as an expiration date comes near. Continuous futures series offer certain benefits according to Ghosh (1993) and Alexander (2001). They are suitable for various econometric and financial modeling methods as they facilitate the examination of long-term trend, volatility and pricing action movements.

In order to develop a continuous series of future data, there are different ways to approach this task depending on the objectives and setting of the study. One common method is to employ the back-adjusted series which takes all previous prices of a particular contract and brings it to the price level of the most recent contract. It is common to approach this strategy in price studies that extend over a longer time frame since it serves to even out anomalies which disrupt the series through contract switches. Suggested by Bessembinder (1995).

Forward-adjusted series is another approach which is popular in literature. To build a forward-adjusted series one should align upcoming contracts to the previous price level. The method is often used when researchers prioritize absence of series interruptions, also omitting historical alterations.

Overall, continuous futures data series offers a streamlined approach that simplifies data analysis by avoiding the gaps and inconsistencies associated with individual futures contracts' expiration cycles. The continuous series method enables a coherent examination of price trends, volatility, and hedge ratios over time, which is essential for achieving robust and accurate empirical results in commodity and financial market studies.

To resolve the issue of assessing the stability and robustness of hedging models, out-of-sample testing without recalculating the optimal hedge ratio (OHR) is suggested. This methodology tests the effectiveness of a hedge based on the initially calculated OHR across future time periods, without requiring constant adjustments.

For example, an empirical study by Ciner (2001) noted that stable hedging models without recalculating the OHR can often yield adequate hedging effectiveness in out-of-sample tests. Ciner's study indicates that while more complex models may provide minor improvements, they do not always justify the added complexity and recalculation costs, especially for commodity futures, where spot and futures price movements often display a relatively stable correlation.

CHAPTER 3. METHODOLOGY

This research is based on a case faced by a Ukrainian sun oil market participant who enters into a fixed-term agreement with a non-Ukraine-based byer. The price, quantity, and delivery date are fixed, creating potential risk exposure to price fluctuations in Ukraine. Equation (1) describes profit per one unit of contract (metric ton).

$$A = P_0^L - P_t^{UA} - C \tag{1}$$

Where: A – profit from the operation, P_0^L – contract price at the initiation, P_t^{UA} – time variable price of purchase in Ukraine, C – the cost associated with the sale (transportation, issuance, etc.). The contract price and quantity of a contract are fixed at contract initiation. The cost, in this case, is assumed to be constant. The purchase price of sunflower oil is variable; in other words, it is a source of uncertainty and risk. If $P_0^L < P_t^{UA}$ market participants will experience negative profit from the operation. In order to reduce the uncertainty of the future purchase price market, participants may consider entering a long futures position to offset the price movement of the short spot position. Equation (2) represents the profit from a hedged position using futures, assuming that no cost is associated with futures purchase.

$$A_h = (P_0^L - P_t^{UA} - C) + N^f(F_t^L - F_0^L) \tag{2}$$

$$A_h = (P_0^L - N^f F_0^L) + (N^f F_t^L - P_t^{UA}) - C \tag{3}$$

Where: A_h- profit from hedged position, F_0^L – price of futures at contract initiation, F_t^L – future price at the moment of position liquidation, N^f- number of futures contracts bought. Equation (3) shows how price risk can be mitigated. $(N^f F_t^L - P_t^{UA})$ can be interpreted as basis risk. In other words basis risk it is the risk that hedging instrument will not move in opposite direction to instrument the one is interested to hedge. If there is a positive relationship between spot and futures prices, the movement of spot price can be offset by futures. In other words, market participants want to reduce the variance of this part of the equation.

For estimation of N^f historical data should be evaluated. First, daily spot and futures data were obtained and converted to US dollars and metric tons to represent the same value. Then, price change and price return were calculated on a daily and weekly basis; for weekly aggregation trading days on Wednesday where used since they have the greatest number of non-missing datapoints, and futures data show the highest trading volume, which should positively affect the accuracy of the research. Then, data was divided into 4 periods for analysis, which is explained in detail in Chapter 4. Since data was separated by periods with similar volatility, there is no reason to expect the GARCH model to produce a significantly better estimate of the optimal hedge ratio (later OHR). As discussed in Chapter 2, constant volatility models such as OLS may be appropriate estimators of OHR.

$$R_t = LN(\frac{R_t}{R_{t-1}}) \tag{4}$$

The data on all three levels was tested for stationarity using an augmented Dickey-Fuller test (ADF) to be consistent with existing literature, which states that only stationary data should be used in estimating OHR with the OLS approach.

To identify relationships between spot and futures prices, literature suggests three OLS models that may be used: price level, price change and percentage price change. Equations (5), (6) and (7) present them accordingly.

$$P_t^{UA} = \alpha + \beta F_t^L + \epsilon_t \tag{5}$$

$$\Delta P_t^{UA} = \alpha + \beta \Delta F_t^L + \epsilon_t \tag{6}$$

$$\Delta R_t^{P^{ua}} = \alpha + \beta \Delta R_t^{F^l} + \epsilon_t \tag{7}$$

To state that beta coefficients from models are appropriate estimators of OHR post estimation tests were performed. Model results can be used only if all OLS assumptions are met: the error terms have zero means, the same variances, and are uncorrelated, then the estimated slope of this regression equation is the appropriate estimator. The following tests were also completed to evaluate which OHRs are reliable for hedged portfolio construction under the methodology presented. The Durbin-Watson test was performed to test for autocorrelation, the Breusch-Pagan test was used for testing heteroscedasticity, and the Shapiro-Wilk test is for normality of residuals. Only slope coefficients from models that satisfy all OLS assumptions may be considered as OHR under this methodology.

$$N^f_{price\ return} = \frac{\beta * P^{UA}_{t^*}}{F^L_{t^*}} \tag{8}$$

The next important step is that, as all models have different model specifications all coefficients have different interpretations. So, portfolio construction for testing variance reduction will be different. To make coefficients comparable and easy to understand, there is Equation (8) where it is used to transform the beta coefficient from the price return model. This transformation gives the possibility to present a value ratio in the ratio of contracts for each unit of spot position. So, we can compare coefficients between each other. In the case of the price difference and price level models, slope coefficient from the model will be our OHR without any additional transformations Equation (9).

The last step is analyzing the effectiveness of crop seed futures on sunflower oil. To do so, a comparative analysis of R^2 was completed. It should be noted that R^2 is an incomplete measure of hedging effectiveness, so an alternative measure can be used.

$$N^f_{price\ change} = \beta \tag{9}$$

Out of sample variance reduction seems to be an easy and clear estimate for our business case. Market participants enter into an agreement and, at this moment, use futures contract to reduce price risk. OHR will be estimated from historical data, used at the moment of entering a long futures position, and not changed up to the moment of contract satisfaction. To proceed with this method both variances of hedged and unhedged portfolios should be calculated in Equations (10) and (11).

$$Var_{hedged}(N^{f}_{price\ change, price\ return} F^{L}_{t} - P^{UA}_{t}) \tag{10}$$

$$Var_{unhedged}\ (-P^{UA}_{t}) \tag{11}$$

After calculating the variance of each portfolio in each one, we use formula (12), to calculate the percentage change in variance compared to the unhedged portfolio. HE then is used for comparative analysis.

$$HE_{price\ change, price\ return} = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} * 100\% \tag{12}$$

Based on the described case, the following questions for further consideration can be formulated. First, there is an actively traded futures contract, which is widely used globally. We want to find out if there is any possibility for the implementation of effective cross-hedge, otherwise, a comparative analysis is not required. Regarding this issue, the first question can be stated in the following way: "Which futures contracts can be used for implementing a cross-hedging strategy?". Another question the thesis aims to answer is: "How many futures contracts should be used for effective hedge?". As a reminder, we are looking for a hedging strategy that will minimize the variance of the constructed portfolio. The hedging strategy consists of both contract selection and an optimal number of contracts to be used.

CHAPTER 4. DATA

4.1. Spot Sunflower FOB Ukraine

Since this research focused on market participants in Ukraine, the single most important data series is the spot price of sunflower oil in Ukraine. Spot price for Ukrainian commodities is not that easy to collect since there is no centralized exchange with available market data. The data used in this research is indicative of Sunflower Oil FOB Black Sea Ukraine, provided by S&P Global Commodity Insights (henceforth FOB UKR SFO SPOT). S&P Global Commodity Insights provide the data. Using The Market-on-Close methodology. The price evaluation will accurately reflect market value at the end of the trading day if it follows the S&P methodology. To determine a fair price, bids, offers, and transaction data are evaluated.

This pricing reflects Ukrainian-origin raw sunflower oil with the following quality standards: a free fatty acid basis content of 2%, maximum 3%, moisture content of 0.5%, a flash point of 121 degrees Celsius minimum, and a maximum hydrocarbon content of 50 milligrams per kilogram. Prices are assessed in US dollars per metric ton and standardized for cargo sizes of 3,000 mt.

S&P Global Commodity Insights employs a normalization process, which adjusts for deviations in cargo size, quality, and delivery points to establish a representative market value for the base specification. As a result, the assessments can reflect typical market levels even when physical markets exhibit variations in transactional details.

Since there are obvious geopolitical events which affect commodities market as a result spot price in Ukraine, decision has been made to divide dataset into several different sub-periods. Table 1 presents descriptive statistics. Also, since in the early stages of research non-stationarity of price levels data were discovered, price level data are excluded from data description. Daily price, price difference and price return data were omitted corresponding explanation presented in Chapter 5, for now we only evaluate weekly data.

Table 1. Descriptive statistics of weekly FOB UKR SFO SPOT

Type of data, unit of mesure		Before COVID	Beginning of COVID	The full-scale invasion	Grain Initiative	Whole period
	Start of a period	2-Jan-2019	1-Sep-2020	28-Feb-2022	1-Aug-2022	2-Jan-2019
	End of a period	28-Aug-2020	23-Feb-2022	29-Jul-2022	30-Aug-2024	30-Aug-2024
price diff., $	Mean	2.28	7.92	-44.55	-3.02	0.97
	Standard Deviation	15.25	50.28	169.04	31.61	65.22
	Minimum	-28	-123	-269	-90	-269
	Maximum	52	166	595	90	595
	Count	83	77	21	108	292
price return, %	Mean	0.32	0.69	-3.01	-0.28	0.13
	Standard Deviation	2.11	3.93	8.28	3.48	4.39
	Minimum	-4.30	-8.38	-18.18	-10.19	-18.18
	Maximum	7.61	10.32	26.09	8.78	29.89
	Count	83	77	21	108	292

Before COVD sub-period starting from January 2, 2019, it's the first date in FOB UKR SFO SPOT data series available from S&P Global Commodity Insights. Period ending on August 28, 2020. Period characterized by low volatility compared to other sub-periods. Standard deviation for price difference and price return data types are 15.25$ and 2.11% retrospectively, which is significantly lower compared to other sub-periods. The period contains 83 weekly observations with an average price difference equal to 2.28$ and an average price return of 0.32%. Before COVD sub-period considered to be "normal" without any significant external shocks affecting it.

The second sub-period Beginning of COVID starts on September 1, 2020, and ends before the beginning of full-scale invasion in Ukraine on February 23, 2022. Since it is hard to name the exact date when COVID restrictions began to have a significant effect on commodity markets, the following logic was applied: Start of new sunflower harvest in Ukraine after the first noticeable signs of the COVID-19 pandemic was chosen to begin the period. The beginning of COVID period has 77 weekly price differences and price return observations with higher standard deviation compared to the Before COVID sub-period, 50.28$ and 3.93% respectively. The average price difference is 7.92$ per metric ton and an average price return is equal to 0.69%. The maximum price difference at that period reached 166 $ per metric ton and the minimum price difference was negative 123 $, indicating speculative nature of this period.

The full-scale invasion period is the smallest in this research. It has only 21 weekly observations. The period starts with first data point after full-scale invasion in FOB UKR SFO SPOT data series, which is February 28, 2022. Quality of the data at the beginning of invasion are questionable, since external economic activity was limited. ADF test, presented in Table 2, proves this point numerically. P-value for both data transformations in The full-scale invasion period is higher than 0.05, so we fail to reject non-stationarity of data. Data in the period is non-stationary, so it cannot be used for further research under applied methodology.

Table 2. ADF test results for weekly FOB UKR SFO SPOT

Period	**Value**	**price diff.**	**price return**
Before	ADF Statistic	-5.02	-5.05
COVID	p-value	0.00	0.00
Beginning of	ADF Statistic	-6.05	-6.04
COVID	p-value	0.00	0.00
The full-scale	ADF Statistic	-0.30	-2.64
invasion	p-value	0.93	0.08
Grain	ADF Statistic	-4.77	-7.39
Initiative	p-value	0.00	0.00

Beginning of Grain initiative is the most frequent sub-sample. Beginning of the period of August 1, 2022 when first cargo was loaded from Ukrainian deep-water port. It is also the biggest sub-period in this research which consists of 108 weekly observations.

4.1. Future contracts

Research of similar topics mentioned previously often uses specific futures contracts or manually constructed continuous price series for estimation, examining the relationship between spot and futures prices. This research Future continuation index obtained through Rfinitive is used as an alternative to individual futures contracts or manual construction of continuous futures data series used in similar research. Futures markets are filled with individual contracts, each with their own expiration date. The market consists of several contracts that have expiry of future dates. As one contract expires, another is listed for trading. Future continuation indexes presented in this research are constructed using actual futures contracts, employing a back-adjusted series approach. This type of data is sufficient for the purpose of this thesis, keeping in mind that spot data is limited, and it is important to have continuous futures data series. As a reminder, first of all we want to test cross-hedging possibilities and estimate OHR. The pros and cons of continuous futures series were explained in detail in Chapter 2.

All the indexes presented in this research were chosen in order to satisfy two conditions: contracts represent by constructed indexes are actively used by market participants involved in export of Ukrainian sunflower oil; all derivatives based on vegetable oil crop cultures or products (oil or meal). Abbreviations of contracts and their full name presented in Table 9 of Appendix. For analysis prices of contracts with different expiration dates were chosen. Even though inconsistency with contract dates is not the main interest of this research, it provides us with better variability of results. Since price levels and daily data series are omitted, we will take a closer look at price differences and price returns aggregated weekly. Data transformation steps were applied to convert all price level data to the same unit of measurement US dollars per metric ton.

Table 4 provides an extensive examination of the descriptive statistics for different futures contracts, segmented by key historical sub-periods. Observing the data, several noteworthy patterns emerge that shed light on the dynamics of each contract across the defined periods.

The Chicago Board of Trade Soybean Meal Future Contract (CBoT SBMF 1) demonstrates distinct and contrasting behavior compared to other contracts, especially in terms of its average price difference and return. In the Before COVID sub-period, this contract is the only one to exhibit a negative average price difference and return. This trend reappears in The full-scale invasion sub-period, suggesting unique market factors or speculative behaviors affecting soybean meal futures during times of economic or geopolitical instability.

Table 4. Descriptive statistics of futures data series weekly

Unit of mesure	Contract	Before COVID		Beginning of COVID		The full-scale invasion		Grain Initiative	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
price diff., $	EURNEXT RSF 3	0.54	5.70	3.49	19.99	-4.63	25.56	-1.18	17.85
	EURNEXT RSF 2	0.50	6.60	3.52	23.24	-5.25	29.74	-1.20	18.81
	EURNEXT RSF 1	0.48	7.92	4.96	27.34	-10.32	61.03	-1.21	20.49
	JOHAN SFSF 3	0.30	11.43	2.81	26.24	-4.18	39.14	-0.97	21.27
	CBoT SBMF 1	-0.23	6.45	2.19	15.05	1.49	24.54	-1.58	18.12
	CBoT SBOF 2	1.09	17.66	10.65	53.42	-16.82	93.28	-4.21	52.42
	MALASYA POF 2	1.53	22.95	10.45	50.37	-40.69	126.25	0.37	36.81
price return, %	EURNEXT RSF 3	0.12	1.38	0.60	3.16	-0.64	3.24	-0.20	3.36
	EURNEXT RSF 2	0.12	1.58	0.60	3.58	-0.71	3.69	-0.21	3.58
	EURNEXT RSF 1	0.11	1.92	0.79	4.03	-1.32	6.43	-0.21	3.94
	JOHAN SFSF 3	0.08	3.10	0.53	4.21	-0.63	5.35	-0.17	3.82
	CBoT SBMF 1	-0.08	2.13	0.58	3.81	0.31	5.37	-0.41	4.27
	CBoT SBOF 2	0.16	2.75	0.97	4.26	-1.13	5.93	-0.38	4.17
	MALASYA POF 2	0.27	4.02	1.00	5.01	-3.28	9.47	0.04	4.47

When comparing rapeseed futures contracts with different expirations (Euronext RSF 1, 2, and 3), the average values across these contracts remain relatively consistent within each sub-period. However, an observable variance in standard deviation (henceforth SD) indicates that later expiration contracts tend to exhibit lower volatility. For instance, during the Grain Initiative period, the SDs for Euronext RSF 1, 2, and 3 are recorded as 20.49, 18.81, and 17.85, respectively, indicating that contracts with later expirations generally experience less fluctuation. Despite these differences in volatility, the average prices for each contract remain nearly identical, underscoring the influence of contract maturity on price stability rather than on pricing itself.

In addition, contracts from different exchanges and commodities reflect distinctive patterns that likely mirror broader economic impacts, particularly from events such as COVID-19 and the Full-Scale Invasion. The CBoT SBOF 2 (Soybean Oil Future) and Malaysia POF 2 (Palm Oil Future), both oil-related contracts, reveal elevated mean values and substantial standard deviations during the Beginning of COVID and T full-scale invasion periods, likely indicative of high demand and price uncertainty for edible oils during these times. For instance, CBoT SBOF 2 reaches a notably high SD of 246.1 during the pandemic period, suggesting heightened volatility likely driven by disruptions in global supply chains and fluctuating demand for food oils.

Through these observations, it is evident that contracts exhibit unique responses to market shocks and geopolitical events, highlighting the heterogeneity in risk and return characteristics across different futures markets. This underlines the necessity of selecting appropriate hedging instruments based on specific contract properties and the market conditions present in each period.

CHAPTER 5. RESULTS

5.1. Statistical tests

As a starting point, we need to decide on the appropriate data frequency for the regression analysis. Though using daily data gives us the most degrees of freedom, there is a question of excessive noise, as well as insufficient variability between several consecutive days in a row. Therefore, weekly data might be a more appropriate alternative, which is also frequently used in literature.

Performance of the ADF test on weekly levels differences and returns has shown that we are working with non-stationary data on levels in all periods, as results presented in Table 10 in the Appendix. For that reason, further research was built around remating models shown be equations (6) and (7), also omitting the full-scale invasion for the same reason.

After the estimation of the remaining models, the post-estimation test was performed to test aligns with OLS assumptions which are crucial to state that slope coefficients received from models are true estimates of OHR. Only contracts that did not violate those assumptions are taken into further analysis when drawing conclusions.

Research in hedging effectiveness demonstrates that the Ordinary Least Squares (OLS) method for calculating the optimal hedge ratio (OHR) remains valid even when residuals are not normally distributed. This approach is extensively used due to its simplicity and robustness across various asset classes and financial instruments. For instance, studies like Cotter and Hanly (2011) show that OLS-based hedge ratios often perform well despite deviations from normality, particularly when applied to highly volatile assets. This supports the continued use of OLS for estimating OHR as a practical and effective method even when the underlying distribution of returns displays asymmetries or non-normal characteristics. Results of the Shapiro-Wilk test for normality of residuals are presented in Table 11 of the Appendix.

The Durbin-Watson statistic ranges from 0 to 4, where values close to 2 indicate no autocorrelation. DW statistic in the range of approximately 1.5 to 2.5 is often interpreted as indicative of low autocorrelation, which would not significantly impact the validity of the model estimates. Moreover, values near 2.0 suggest that the residuals are essentially uncorrelated, which is ideal for regression analysis using OLS. Values below 1.5 or above 2.5, however, may indicate positive or negative autocorrelation, respectively, potentially necessitating further model adjustments such as using time-series techniques if this is a concern If DW statistic falls within 1.5 to 2.5 range, it could be stated that your residuals are effectively stationary and independent enough for your OLS estimates to be considered reliable according to Turner (2019). Results of Durbin-Watson statistic for autocorrelation presented in Table 12 of Appendix as well as Breusch-Pagan test results for homoscedasticity presented in Table 13 of Appendix.

5.2. Hedging coefficients

According to the framework provided by Witt (1986), price difference regression coefficients should have different interpretations from percentage price change regression coefficients. The authors suggest that price difference regression slope coefficients are the ratios of units of futures contracts that should be used to reach a minimum variance portfolio. On the other hand, the percentage price change (price return) regression slope coefficient represents the proportion of the value of the futures position in the portfolio to the value of the spot cash position to reach minimum variance in a hedged portfolio.

Table 6 presents the estimated OHR from each regression along with their significance levels. OHR obtained from the price return model are converted for comparison using formula (8). Price return OHR's presented in the table calculated as median prices in-sample, this was done for comparison needs. 95% confidence intervals for each presented in Table 6. Based on information in Table 5 and Table 6 we may draw the conclusion that both models produce similar estimations of OHR.

Table 5. Estimated OHR

Period	**Before COVID**		**Beginning of COVID**		**Grain Initiative**	
Model type	Price diff.	Price returns	Price diff.	Price returns	Price diff.	Price returns
EURNEXT RSF 3	1.09 ***	1.09 ***	0.55 *	0.71 **	0.42 **	0.46 ***
EURNEXT RSF 2	1.22 ***	1.20***	0.72 **	0.79 ***	0.41 **	0.44 ***
EURNEXT RSF 1	0.96 ***	0.94 ***	0.49 *	0.59 **	0.30 **	0.32 **
JOHAN SFSF 3	0.33 **	0.36 **	0.29	0.30	0.31 **	0.35 **
CBoT SBMF 1	-0.28	-0.29	0.30	0.42	0.38 **	0.40 **
CBoT SBOF 2	0.50 ***	0.50 ***	0.37 ***	0.49 ***	0.16 ***	0.17 ***
MALASYA POF 2	0.35 ***	0.34 ***	0.47 ***	0.48 ***	0.32 ***	0.30 ***

Interpretation of the hedging coefficient can be demonstrated by example. Let's consider price difference model on the example of MALASYA POF 2 contract. In Before COVID sub-period the hedge coefficient from this model is 0.35. This means the variance of the portfolio is minimized when a market participant uses 0.35 of futures contract per one unit of spot position. The same logic applies to all price difference model hedging coefficients

Conversely, if we omit the transformation step using formula (8) since price return (percentage price change) regression has different interpretation. Let us look at the CBoT SBOF 2 contract for the same period. The price return model states that the hedging coefficient should be 0.46. In this case, 0.46 represents how much of the value of a spot position should be covered by a futures contract. The per-unit measure (how many contracts should be used) will result in 0.52 contracts per unit of spot position. This result was obtained using a spot price of 820, a futures price of 0.33 (in , and the same regression coefficient from the price return model.

Table 6. 95% confidence interval for estimated OHRs

Period	**Before COVID**		**Beginning of COVID**		**Grain Initiative**	
Model type	Price diff.	Price returns	Price diff.	Price returns	Price diff.	Price returns
EURNEXT RSF 3	0.52/1.66	0.53/1.65	-0.08/1.19	0.06/1.37	0.13/0.85	0.17/0.88
EURNEXT RSF 2	0.79/1.66	0.77/1.64	0.09/1.34	0.20/1.39	0.13/0.81	0.17/0.84
EURNEXT RSF 1	0.59/1.33	0.58/1.31		0.10/1.09	0.04/0.67	0.08/0.69
JOHAN SFSF 3	0.03/0.62	0.07/0.65			-0.03/0.58	0.00/0.64
CBoT SBMF 1					0.05/0.75	0.05/0.81
CBoT SBOF 2	0.35/0.65	0.35/0.66	0.14/0.60	0.25/0.73	0.06/0.30	0.08/0.33
MALASYA POF 2	0.22/0.48	0.20/0.48	0.22/0.72	0.25/0.72	0.17/0.50	0.17/0.46

5.3. Interpretation of an R-squared

The literature suggests that the R-squared (R^2) statistic is a widely used and informative estimator for measuring hedging effectiveness (HE). Essentially, R^2 indicates the proportion of price risk that can be explained—and thereby mitigated—through hedging. A higher R^2 implies that a greater portion of the variance in the spot market price can be offset by movements in the associated futures market, thus offering a quantitative metric for hedging success.

However, (Dahlgran, 2009) notes that R^2 is an incomplete measure of hedging effectiveness. In the case of hedging, R^2 numerical shows how much of a spot price risk can be explained by a futures contract so that it may be reduced by hedging. The problem is that R^2 only reflects the linear relationship between the hedging instrument and the spot market. Other factors, such as transaction costs, liquidity, and market shocks, are not captured by these statistics Nevertheless, R^2 remains helpful in comparative analysis evaluating different futures contracts and different time periods.

The first look at Table 7 reveals that there is not much difference between R^2 for the price difference and price return models, which is completely fine considering the nature of the model specifications. Both models try to capture the relationship between changes in weekly prices.

Table 7 R-squared obtained from models

Period	**Before COVID**		**Beginning of COVID**		**Grain Initiative**	
Model type	Price diff.	Price returns	Price diff.	Price returns	Price diff.	Price returns
EURNEXT RSF 3	0.18	0.18	0.05	0.07	0.07	0.09
EURNEXT RSF 2	0.31	0.31	0.08	0.10	0.08	0.09
EURNEXT RSF 1	0.28	0.28	0.06	0.08	0.05	0.06
JOHAN SFSF 3	0.07	0.08	0.02	0.02	0.03	0.04
CBoT SBMF 1	0.02	0.02	0.01	0.01	0.05	0.05
CBoT SBOF 2	0.39	0.39	0.14	0.21	0.08	0.10
MALASYA POF 2	0.29	0.26	0.19	0.22	0.15	0.16

R^2 comparison across distinct periods further emphasizes the importance of period segmentation in this research. Before COVID period, which can be considered a period of relative market normality, R^2 values are generally higher across all contracts, indicating stronger cointegration of Ukrainian and international markets.

For example, the R^2 values for EURNEXT RSF 2 futures in the first-difference approach before COVID were 0.31, but they sharply decreased to 0.08 during the early phases of the COVID-19 pandemic. Given that correlations between the Ukrainian market and other markets decreased during increased uncertainty, this decline emphasizes the disruption brought on by the epidemic.

The R^2 values also stay low during the Beginning of COVID sub-period, except Soybeen oil (CBoT SBOF 2) and Palm oil futures (MALASYA POF 2).This result again indicate the increasing unpredictability and change in cointegration of Ukrainian and international commodity markets..

Lastly, the R2 values did not return to their pre-COVID-19 levels throughout the time after the grain initiative was implemented, but they did stay somewhat steady. Accordingly, the connections between the Ukrainian sunflower oil market and other futures markets have not entirely realigned with prior norms, even though the market has somewhat stabilized.

5.4. Variance reduction

Estimation of hedging effectiveness is analyzed out of sample. The most effective portfolio is the one which decreases variance of spot position the most. To construct hedged position, we use hedging coefficients estimated by OLS models.

But HE by reduction of variance in constructed portfolios are comparable. Table 8 present results of variance reduction for chosen portfolios and periods. Full scale invasion period is omitted since none of hedging coefficients are statistically significant. For testing variance reduction out-of-sample test were completed.

Table 8 Variance reduction in % compared to unhedged portfolio

Period	**Before COVID**		**Beginning of COVID**		**Grain Initiative**	
Model type	Price diff.	Price returns	Price diff.	Price returns	Price diff.	Price returns
EURNEXT RSF 3	-38	-38		-57	17	22
EURNEXT RSF 2	-38	-36	125	133	20	25
EURNEXT RSF 1	-37	-36		42	23	28
JOHAN SFSF 3	-36	-41			-14	-16
CBoT SBMF 1					-12	-8
CBoT SBOF 2	-39	-28	-69	-56	15	38
MALASYA POF 2	-23	-23	-79	-81	58	62

Out-sample data is characterized by 12 weekly price changes for each period. However, it is still helpful to look at this type of comparison since it reflects real-world situations when market participants analyze recent data, dividing them into periods of structural changes and applying results to the current hedging strategy. The literature also suggests that the rolling-window method may be applied.

Nevertheless, again, it is a question of business case. The rolling window approach represents a situation where the hedge coefficient is reevaluated for each data point period, which is not precisely the case in this paper. Here, we are interested in hedging at the moment of entering the supply agreement, which will not be changed until fulfilling that agreement.

Comparing the results of variance reduction on out-of-sample valuation. In each period, at least one future contract may be considered an effective hedge. For example, Grain initiative period, we observed that only JORDAN SFOF may reduce variance by 14% and 16% under price difference and price returns approaches, accordingly, which means that suggested methodology may be affective. The start of the COVID period shows the highest hedge effectiveness compared to other sub-periods. CBoT SBOF 2 and MALASYA POF 2 show variance reduction from 56% to 81% under different models. But it also should be noted that for EURNEXT 2 contract in the same period the out-of-sample test resulted in doubling volatility of hedged portfolio. This findings one more time underline the speculative nature of Beginning of COVID sub-period as well as change in market conditions.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

This research aimed to provide valuable practical insights for Ukrainian market participants engaged in the trading of sunflower oil. Indeed, some insights were obtained. The question of value will be left to professionals, for now, let me summarize results, practical applications, and areas for future research

6.1 Summary of Results

The question of hedging effectiveness was built around the specific case. Market participants who enter fixed-term agreements for sunflower oil sales are interested in protecting themselves from market fluctuations in the Ukrainian spot market. To do so, one will enter a long futures position, which will result in the so-called effective hedge. There are two main questions this research is trying to answer: which contract and how many? The first question arises because there are no actively traded futures contracts on profound exchanges. This may be caused by the fact that sunflower oil accounts only for 9-10% of all vegetable oil market. To overcome this issue, the cross-hedging strategy was implied.

Analysis has shown that oil crop futures (oil, meal seeds) are effective in mitigating price risk, but this method has its limitations. First of all, hedging effectiveness is correlated with market cointegration of the Ukrainian market, which may be reduced during external market shocks. For example, in the COVID period variance reduction compared to an unhedged portfolio varies from -23% to - 41% for different contracts. On the other hand, after the initiation of the Grain Initiative, we did not observe evidence that the market returned to "normal' conditions. In the Grain Initiative period, only two contracts (CBoT SBMF 1 and CBoT SBOF 2) resulted in an effective hedge from -8% to -18% variance reduction, compared to an unhedged position. Other contracts in the same period resulted in an increase in variance using an out-of-sample test.

In order to answer the question of how many futures contracts should be used to offset adverse price movements of oil, research suggested that a simple OLS model is more than enough. In the literature, there is evidence that there are no insignificant improvements in estimation OHR using more sophisticated time-variable variance models. Since the thesis aim is to be practical, additional complexity is not required. Following the OLS approach in estimating OHR it is important to take into account compliance with OLS assumptions. Only correctly estimated OHRs, may be used for implementing in to hedging strategies. Research also found no significant difference in estimating OHR by different OLS models based on price differences and price returns.

6.2 Implications for Business

The finding of this thesis confirms that hedging using oil crop futures may be effective for market participants who seek to mitigate price volatility risks. Also, it should be noted that the efficiency of particular contracts varies depending on market conditions.

Regarding the optimization of existing strategies, market participants may benefit from using futures contracts with a later expiration date. This was illustrated by Rapeseed futures contracts traded on Euronext. Primary due to the reason that they exhibited lower standard deviations and had more stable performance. Especially in periods of heightened market volatility.

Cross-hedging may be effective in the case of Ukrainian sunflower oil when direct hedging is not available. However, this should be applied cautiously, as applying a cross-hedging strategy led to an actual increase in volatility compared to an unhedged portfolio.

Findings also suggest that the OLS approach in estimating OHR remains viable under stable or moderately volatile conditions. In periods of extreme volatility, the suggested approach may not be that effective. The decision to refrain from recalculating OHRs during out-of-sample testing reflects real-world practices, where businesses typically establish fixed hedging ratios at the contract's initiation and retain them to simplify strategy management. For practical implementation, firms should ensure that OHRs are recalculated only when significant shifts in market structure occur, such as major geopolitical events.

Data segmentation in hedging models was applied in this research.: The observed variations across periods emphasize the importance of adaptable hedging frameworks that can accommodate sudden changes in market structure. This suggests that companies should incorporate market analyses into their hedging strategies, tailoring their contract choices based on current geopolitical and economic conditions. The segmentation of data into sub-periods demonstrated that the effectiveness of futures contracts as hedging instruments is highly context-dependent.

6.3 Recommendations for Future Research

While this thesis provides a foundational understanding of the hedging effectiveness of futures contracts for Ukrainian sunflower oil, several areas merit further investigation:

Expanded model testing should be considered., since research does not investigate important factor as time-varying volatility. This problem was overcome by data segmentation into different sub-period which happen to have constant volatility. Future studies could explore alternative econometric models, such as GARCH and ECM, which may capture time-varying volatility more effectively Although the OLS model proved adequate for this research, due to constant volatility assumption Full-scale invasion sub-period was omitted. Examining these models' performance in high-volatility periods, such as during the full-scale invasion, could yield insights into whether they offer incremental improvements over OLS in dynamic markets.

Inclusion of transaction costs is another area of interest not captured by this research. Cost associated with trading derivatives may affect hedging effectiveness, so should be investigated. Future research could incorporate transaction costs, liquidity considerations, and other real-world factors that influence the actual costs and benefits of hedging. By simulating different cost structures, researchers could better understand how hedging decisions might vary across market participants with diverse operational profiles. This study primarily focused on variance reduction and R-squared metrics as measures of hedging effectiveness, which indeed provide valuable insights.

International Market Integration: Given the globalized nature of the sunflower oil market, examining the relationship between Ukrainian spot prices and a broader array of international futures contracts could enhance understanding of hedging opportunities. For instance, incorporating futures from Asian exchanges may provide additional insights, particularly considering shifting trade dynamics influenced by geopolitical events.

Event-driven analysis another area for investigation. The division of data into distinct periods based on significant events (e.g., COVID-19 pandemic, full-scale invasion) underscores the utility of event-driven analysis in hedging studies. Future research could apply this framework to other commodities and regions to examine whether similar patterns of hedging effectiveness emerge. This approach could offer valuable insights for industries impacted by geopolitical events, climate shifts, and other external factors.

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APPENDIX

Table 9. List of Future indexes used

Abreviation	Index name in Refinitive
EURNEXT RSF 3	COMc3 Euronext Paris Rapeseed Commodity Future Continuation 3
EURNEXT RSF 2	COMc2 Euronext Paris Rapeseed Commodity Future Continuation 2
EURNEXT RSF 1	COMc1 Euronext Paris Rapeseed Commodity Future Continuation 1
CBoT SBMF 1	SMc1 CBoT Soybean Meal Composite Commodity Future Continuation 1
CBoT SBOF 2	BOc2 CBoT Soybean Oil Composite Commodity Future Continuation 2
MALASYA POF 2	FCPOc2 Bursa Malaysia Crude Palm Oil Commodity Future Continuation 2
JOHAN SFSF 3	SUFc3 Johannesburg Stock Exchange Sunflower Seed Commodity Future Continuation 3

Table 10. ADF Statistic for weekly FOB UA series

Period	**Value**	**price diff.**	**price return**
Before	ADF Statistic	-5.02	-5.05
COVID	p-value	0.00	0.00
Beginning of	ADF Statistic	-6.05	-6.04
COVID	p-value	0.00	0.00
The full-scale	ADF Statistic	-0.30	-2.64
invasion	p-value	0.93	0.08
Grain	ADF Statistic	-4.77	-7.39
Initiative	p-value	0.00	0.00

Table 11. Shapiro-Wilk p-value for normality of residuals.

Period	Model type	EURNEXT RSF 3	EURNEXT RSF 2	EURNEXT RSF 1	JOHAN SFSF 3	CBoT SBMF 1	CBoT SBOF 2	MALASYA POF 2
Before COVID	Price differece	0.03	0.17	0.47	0.02	0.25	0.40	0.02
	Price returns	0.01	0.10	0.32	0.02	0.24	0.33	0.01
Beginning of COVI	Price differece	0.05	0.04	0.02	0.08	0.08	0.00	0.22
	Price returns	0.19	0.26	0.18	0.11	0.31	0.02	0.52
Grain Initiative	Price differece	0.04	0.04	0.04	0.45	0.28	0.25	0.04
	Price returns	0.19	0.16	0.11	0.42	0.60	0.59	0.29

Table 12. Durbin-Watson statistic for autocorrelation.

Period	Model type	EURNEXT RSF 3	EURNEXT RSF 2	EURNEXT RSF 1	JOHAN SFSF 3	CBoT SBMF 1	CBoT SBOF 2	MALASYA POF 2
Before COVID	Price differece	1.69	1.90	1.78	1.46	1.48	1.53	1.63
	Price returns	1.72	1.91	1.79	1.46	1.50	1.51	1.61
Beginning of COVID	Price differece	1.53	1.54	1.62	1.57	1.53	1.50	1.70
	Price returns	1.53	1.55	1.64	1.59	1.54	1.50	1.71
Grain Initiative	Price differece	1.64	1.64	1.60	1.43	1.49	1.57	1.78
	Price returns	1.72	1.72	1.68	1.55	1.59	1.65	1.85

Table 13. Breusch-Pagan p-value for homoscedasticity.

Period	Model type	EURNEXT RSF 3	EURNEXT RSF 2	EURNEXT RSF 1	JOHAN SFSF 3	CBoT SBMF 1	CBoT SBOF 2	MALASYA POF 2
Before COVID	Price differece	0.73	0.31	0.19	0.60	0.07	0.09	0.59
	Price returns	0.70	0.31	0.19	0.74	0.07	0.10	0.79
Beginning of COVID	Price differece	0.35	0.28	0.44	0.70	0.52	0.02	0.97
	Price returns	0.32	0.31	0.41	0.79	0.76	0.06	0.93
Grain Initiative	Price differece	0.70	0.49	0.14	0.62	0.04	0.05	0.71
	Price returns	0.74	0.53	0.08	0.85	0.21	0.07	0.79