COMMODITY FUTURES VOLATILITY AND UNCERTAINTY DURING COVID-19 PANDEMIC

by

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Abstract

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The 2020 year has changed our life significantly. The world remembered the word "Pandemic" and was faced with a new one "lockdown". There was an increase in uncertainty in the world and volatility in the financial markets. Commodity futures volatility is our variable of interest. This study aims to discover the connection between uncertainty and commodity futures volatility in that period. We decomposed world uncertainty into three elements: economic, financial, and emotional uncertainties.

We used trading data for six commodity futures from the New York Board Trade for the last two years 2019 and 2020. One year before the pandemic and one year during the pandemic. Also, Google trends data, Consensus forecast, and VIX to compose an index of economic, emotional, and financial uncertainties.

We estimated the relationship by the panel data controlling for the futures contracts. We used an unbiased extreme value volatility estimator and standard deviation as two measures of volatility. Results stay that emotional and financial uncertainties had a significant effect on the futures volatility. The connection with economic uncertainty is no so clear.

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The warmest words I want to say to my parents for their belief in me. They always stand behind my back. I know that I will have support and help from them for all my future steps and plans.

Chapter 1

INTRODUCTION

COVID-19 Pandemic has significantly changed our lives. We are now used to people wearing masks, to washing our hands every hour and even stay at home with a light cough. This is really of our modern life. However, coronavirus had an effect not only on our daily habits but on all parts of our life. Financial markets are a crucial part of it; maybe not everyone feels or understands the value and impact of it. However, it does not mean that he or she is no affected by it.

We want to discover the effect of the COVID-19 pandemic on commodity futures volatility. In particular, we are interested in disentangling the effects of general financial market turbulence, overall economic instability and emotional uncertainty on the commodity futures volatility.

The world of financial instruments is remarkably diverse and prosperous, and includes stocks, options, warrants, bonds, collateralized debt obligations, and a lot of other assets. Forwards and futures stand out of the other instruments by the target and scope of use. They are the main hedge instruments in business.

Volatility is one of the main characteristics of any financial instrument. As a result, it is one of the most popular subjects in research related to futures. Commodity futures are of interest due to their usefulness and prevalence. For example, Roll (1984) investigated the connection between weather and orange juice futures prices.

"Like the financial futures, the use of commodity futures is also considered to be more generic as it benefits larger stakeholders and the economy as well. The increasing participation in the commodities market by the investors is alarming for their risk-bearing capacity where the benefit of leverage in the futures trading is attracting a greater number of participants." (Kirithiga et al., 2017).

Over the last decade, commodity markets have attracted increasing attention due to the significant volatility that has occurred in these traditionally tranquil markets. Additionally, the performance of the equity markets has been disappointing and due to the historically low correlation between equity markets and commodity markets, the commodity markets have become a viable alternative to investors. (Chiarella et al., 2013).

Economic uncertainty is one factor of financial life and the decision-making process. Investment and financial decisions should be made with consideration of the future. Forecasting the future is a quite difficult and complex task. Investors should take to account future prices, connections between markets and firms, global economic and political situation, and a lot of other things. As the future is foggy, it causes some level of uncertainty, an element that could not be predicted, and it influences all decisions and forecasts.

We will use the term Knightian uncertainty as one of the fundamental terms of economic science. We live only by knowing something about the future; while the problems of life, or conduct at least, arise from the fact that we know so little. This is as true of business as of other spheres of activity. The essence of the situation is action according to opinion, of greater or less foundation and value, neither entire ignorance nor complete and perfect information, but partial knowledge (Knight 1921). In other words, with a more common interpretation of this term, uncertainty is that the future could not be explained or described by some of the distribution functions or mathematical models.

The last spike of economic uncertainty was in the period of the 2008 financial crisis. After this period investors and policymakers learned how to live and consider their decision in the new reality with high economic uncertainty. For the period after dark 2007-2009 years, economic uncertainty is one the hottest research question (Moore 2016, Bahmani-Oskooee & Arize, 2020, Pei-Tha Gan et al. 2013). The main problem of estimating economic uncertainty is the absence of a formal indicator. As a result, economic agents use some dummy indicators for estimating it. The main aim of earlier papers was to develop such a universal estimator of economic uncertainty or discover the effect of economic uncertainty on policymaking.

As was mentioned previously Roll (1984) discovered the effect of weather uncertainty on the orange juice futures prices. Watugala (2015) researched a clear connection between economic uncertainty and commodity futures volatility. He decomposed sources of commodity futures volatility related to the supply and demand side and economic uncertainty. He identified a positive relationship between increasing economic uncertainty and futures volatility. In some sense, this theme is already studied and researched. However, at the beginning of 2020 world was faced with a new global problem: the COVID-19 pandemic and related to its lockdown.

Barrero and Bloom (2020) said that economic uncertainty significantly increased in 2020 due to the reaction to the COVID-19 pandemic. Most of the economic uncertainty indicators reached the highest values. For this, there are three reasons. First, decreasing the economic activity in the world at all and in the different countries partially. Next is the forecasted slower economic recovery. The third is decreasing reaction of the firms on the policy decisions, as firms tend to be more cautious to changes in business conditions.

We want to discover the effect of the COVID-19 pandemic on the commodity futures volatility. It is defined connections between economic uncertainty and commodity futures volatility. However, we want to decompose uncertainty into the three channels and discover their effect on the commodity futures volatility. First one is economics uncertainty which is defined by the inconsistency in the projections of macroeconomics experts. Second is financial uncertainty as Chicago Board Options Exchange's Volatility index. Third is emotional uncertainty which we will capture throw Google trends searches query. We focus on these three channels because they describe all parties which could affect on the futures prices. Financial uncertainty affects traders on the futures exchanges and investors. We connect economic uncertainty with supply side of commodities and emotional uncertainty with demand side.

The world has never faced such a problem as lockdown in recent financial history. For the whole generation of modern investors and financial analysts, it was a new problem. Nobody knew how to make decisions and estimate risks in such a world. There is no evidence for the relationship of global illness expansion and financial instruments volatility in general and commodity futures particularly. This paper could be the instrument for decision-making and risk estimation on the commodity market in the future.

In the literature, no research describes the connection between COVID-19 and futures behavior. It could be the first paper in this sphere. In any case, this scope is not researched yet, and any empirical evidence will create a meaningful impact on economic and financial research.

We can look on the commodity futures from the two prospects of view as financial asset and proxy for the commodity prices. Commodity futures return is decomposed by the three elements: difference between current and previous prices, maturity premium, and difference between futures prices and prices on the spot market. There is problem to get historical spot prices of commodities.

Hence, we use an unbiased extreme value volatility estimator as volatility of the financial assets. We stop on this estimator because it showed better results comparing with range-based and returned-based estimators (Kumar, 2014). In addition, this estimator does not require from us information about futures returns, only trading information. Also, we use simple standard deviation as volatility of the commodity prices.

We choose six commodity futures (Cotton, Sugar, Corn, Coffee, Copper, Soybean) because they showed the clearest trend of increasing volatility during 2020. For estimating economic uncertainty, we will consider using the methodology for economic uncertainty estimation introduced by Ozturk & Sheng in 2018. Estimations are based on the panel model with fixed effect.

In our opinion these three uncertainties are the sources of commodity futures volatility. Hence, we expect to find causality between the increase of three types of uncertainty: financial, economic, and emotional due to the COVID-19 pandemic and commodity futures volatility.

The structure of the paper is the following. Section 2 contains literature review. Section 3 discusses methodology. The data is described in section 4. Section 5 contains empirical results. Conclusions are in Section 6.

Chapter 2

LITERATURE OVERVIEW

The volatility of the commodity future is not a new topic in the research papers. Roll (1984) discovered dependence of frozen concentrated orange juice futures price volatility on the weather predictions. There was a significant relationship between changes in juice prices and failure in temperature predictions. There was no significant evidence for influence mistakes in rain predictions. However, the weather could explain only a small part of juice price volatility. Most sources of volatility were not described and researched in the paper. It could be production costs, substitutes, export demand, etc.

Researchers discovered this theme with greater attention to find sources that could explain most of the commodity futures volatility. Wang and Garcia (2011) focused on corn futures. They used the family of GARCH models to estimate long memory, seasonality, and structural changes' effect on the corn volatility. They found that seasonally adjusted GARCH models are better for predicting the future volatility of corn, as the models consider the seasonal component. For a 1-day forecast, there was no significant difference between simple GARCH other long memory models. For the longer forecast periods, there was a significant difference. In general, they confirmed a significant effect of long-memory and structural changes in addition to the seasonality on the corn future volatility.

Another critical characteristic of the futures is the maturity term. Ao and Chen (2020) discovered this effect on Chinese commodity futures. They estimate the effect of maturity controlling at the same time crude oil prices, seasonality, product, and fixed effect. It was clearly defined the effect of the maturity date for most of the Chinese commodity futures. Exceptions are metal and industrial goods.

Mukherjee and Goswami (2017) investigate the volatility of four commodity futures (potato, metal, crude oil, and gold) with three types of contracts (near a month, next near a month, and far month). As volatility estimators, they used simple standard deviations. Such methodology could result in bias estimation as the return of commodity futures is more complicated than the simple difference between buying and selling prices. Nonetheless, they consider that Samuelson's hypothesis does not hold for these commodities on the Indian futures market. Samuelson's hypothesis states that volatility of commodity future increases with lower maturity of it.

Wutugala (2015) connected futures volatility with economic uncertainty. In particular, he decomposed variance of the commodity futures and showed that unexpected changes in the excess basis return depend on future expectations and uncertainty. Future interest rate, convenience yield, and risk premia are the main drivers of volatility. Wutugala (2015) also clearly defined the connection between economic uncertainty and commodity futures volatility. He also showed a connection between changes of demand on the emerging markets with futures volatility. This study clearly defined transmission channels between drivers of economic uncertainty and futures volatility. The methodology is too complicate to be used in this paper.

We think to use a simpler methodology than was presented before by Wutugala (2015). Kumar (2017) used an unbiased extreme value volatility estimator to analyze and forecast energy futures volatility. This author used AFRIMA and AFRIMA-Add RS models to show all advantages of such a method. We think it is the most appropriate way to estimate commodity futures volatility in this paper. Since it is problem to get historical commodity prices from the spot market and defined real futures return.

Joarder (2018) presented a simple panel model for the estimation effect of the macroeconomic fundamentals on the oil and oilseed futures in the Indian market. The study showed that futures volatility depends more on the macroeconomic policies and indicators than on the speculations. The main policy implication is that for stabilizing market volatility government needs to stabilize the macroeconomic situation of the country.

The second important variable of interest in this thesis is economic uncertainty which is well discovered in the literature too. One of the first definitions of economic uncertainty was made by Knight (1921). Uncertainty is future parameters that could not be described by any distribution law. It is a simple and clear definition of uncertainty which is widely used in our days.

Moore (2017) constructed (an) economic uncertainty index for Australia. He researched internal and external factors that drive uncertainty. Elections, unemployment growth, foreign factors, huge international events, and accidents cause some level of uncertainty. Moore discovered the countercyclical behavior of economic uncertainty. An increase in uncertainty affects the unemployment growth, capital investments slump, and savings rate decreasing.

Economic uncertainty is investigated by different authors with a different focus. Bahmani-Oskooee (2020) finds causality between monetary uncertainty and money demand for Africa's countries. Gan et al (2019) introduced an uncertainty index that could serve as a guide for policy decisions. Wu et al (2020) analyze the correlation between economic uncertainty and bank risks in emerging markets. Gan (2014) developed another uncertainty index for countries.

The 2020 year introduced for the world a new type of crisis and global problem – the COVID-19 pandemic. Researchers have already presented a paper on the coronavirus effect on the world. Barrero and Bloom (2020) depicted the reaction of the economic uncertainty indicators to the COVID-19 pandemic. Most of the indicators are on the highest levels for recent years. It was showed that 10-percentile of US firms dropped their subjective forecast from zero sales growth to – 15% after the start of the pandemic. So, most of the firms expect a huge contraction of production.

Google trends uncertainty index is a popular topic in recent years of research. All existing works used a similar approach to construct the Global uncertainty index. We will follow the methodology suggested by Weinberg (2020). Google trends uncertainty index was constructed for the EU region, based on the 6 countries' search queries. We will use the same methodology for our GTU. We will use this methodology because it is quite straight-forward.

We will use in this paper all previous discoveries and combine them to discover different effects on the commodity futures volatility. We will use the volatility estimator which was used by Kamar. The main model would be according to the Joarder methodology panel estimation model with fixed effects. As we present early papers showed the correlation between uncertainty and commodity futures volatility. It gives an opportunity not to focus on all drivers of futures volatility but only on economic uncertainty, financial uncertainty, and emotional uncertainty.

The main contribution of this paper to the literature is the first step in the research of connection volatility and uncertainty during the COVID-19 Pandemic. Decomposition of the uncertainty on the three drivers could show meaningful results and push interest to it in the future.

Chapter 3

METHODOLOGY

Commodity future is the hedging instrument, and volatility is one of the main characteristics of hedge financial instruments. On the other hand, the prices for commodity futures could be used as indicators for the spot commodity prices, as spot market prices are less readily available. Thus, the volatility of futures prices contain information about the volatility of spot prices as well.

Our key point of interest is the effect of uncertainty on commodity futures volatility. As we want to observe different effects of three different types of uncertainties - financial, economic, and emotional - we should provide proxies for all three of them. The easiest one is probably the financial market uncertainty, for which there is a conventional measure in the form of CBOE Volatility Index (VIX).

Emotional uncertainty will be constructed based on the Google search trends. Weinberg (2020) states that people search for something when they are interested in it. Spikes in the search queries show that people are worried about it and they are uncertain in these terms. We use the term Google trends uncertainty (GTU) as this term is common in the literature. For example, Weinberg (2020) and Castelnuovo et al. (2017) used the same term in their papers.

Weinberg (2020) stated that people search for information about some events and facts when they are not sure about them. Thus, the index which is constructed based on the search frequency of the words could be named GTU. Furthermore, GTU is used to capture the emotional uncertainty of the people.

Google trends data shows the relative popularity of the word in the search. The relative index has a range between 0 and 100 compared with other words in the request. Hence, 100 shows the most popular word in the search, and 0 shows the word which was not met in the search for a specific period.

Previous research on the google trends data showed there is no significant difference between the frequency popularity of the specific word in the search and a full sentence query with the same word. Based on it, we decided to use only five keywords for the GTU index (5 is the limit for one request). GTU index was constructed using the next list of the words: "coronavirus"; "lockdown"; "crisis"; "pandemic"; "COVID-19". These words were chosen as they show interest in the Pandemic and they also captured the interest of people in the crisis. We summed up frequencies for all the words. Hence GTU has a potential range from 0 to 500.

The next part of the research is the economic uncertainty index. It was estimated based on the Ozturk et al. (2017) method. They developed their approach based on the capital asset pricing model (CAPM). Uncertainty is decomposed on the market volatility and company-specific volatility like a risk under CAPM theory. They suggested evaluating economic uncertainty as volatility of consensus forecast error and individual forecast errors.

The variable-specific uncertainty U_c is constructed by the way:

$$U_c = \sigma_c^2 + D_c \tag{1}$$

where σ^2 measured as the mean difference of the individual experts' forecasts and the consensus forecast for the specific variable and country, D_c is the interquartile range of the experts' inaccuracy comparing with the consensus forecast (idiosyncratic uncertainty). Median and interquartile range were used to avoid the effect of the outliers.

We used the Focus Economics report to get individual and consensus forecasts for the G7 economies. As our main task was to construct a proxy of the economic uncertainty of the world, we decided to build our index based on the economic uncertainties of G7 countries as G7 countries have the most significant political and economic impact on the world.

We should aggregate variable-specific uncertainty to country-specific uncertainty. Furthermore, country-specific uncertainties are aggregated into the common economic uncertainty. For aggregating variable-specific uncertainties, we used the equal weight. For countries, we used weights as their share GDP share in the common G7 GDP.

All measures used fixed event forecasts. Each month forecasters provide their estimation for the end of this and next years. Following Dovern et al. (2012) fixed event forecast were transformed to the fixed horizon forecasts by the following adjustment:

$$\mathrm{F}_{i,t+12|t} = \frac{\mathrm{k}}{12}\mathrm{F}_{i,t+k|t} + \frac{12-\mathrm{k}}{12}\mathrm{F}_{i,t+12+k|t} \qquad (2)$$

Where $\mathrm{F}_{\mathrm{i,t+k|t}}$ and $\mathrm{F}_{\mathrm{i,t+k+12|t}}$ are the two forecasts based on the information set at time t with horizons of k between 1 and 12 and k+12 months, respectively. The average of two event forecast weighted by their share in the forecast horizon. It was used twelve months ahead forecast for composition this economic uncertainty index.

As was mentioned before CBOE Volatility Index (VIX) is used for financial market uncertainty. "The Cboe Volatility Index (VIX) is a real-time index that represents the market's expectations for the relative strength of near-term price changes of the S&P 500 index (SPX)" (Investopedia 2021). It shows the forward projection of the S&P 500 volatility. This projection is based on the 30-days future horizon. We used data for VIX without any changes and corrections.

As we work with futures as the financial instrument and proxy for the commodity prices, we use two different estimations of the futures volatility. Unbiased extreme value volatility estimator will be used for futures as financial instruments due to the lack of data from spot markets. The standard deviation of the daily futures prices in the week will be used for futures volatility as the proxy for the commodity prices volatility.

Financial instruments' volatility measures are based on the deviation of their returns. Return for the commodity futures has three main components: difference of the trading prices, time to the expiration date, and the difference between futures price and price on the spot market. Spot market prices are not available in the free access. Thus, we are faced with the problem of measuring futures volatility.

We decided to use the unbiased extreme volatility estimator proposed by Kumar (2014). It has some advantages. First, it normalizes volatility in the range between 0 and 1. Second, we need only futures trading data to construct it. Trading data are the prices of futures on the market: open price, high price, low price, and close price.

Unbiased extreme value volatility estimator was proposed by Kumar (2014):

$$b_t = log\left(\frac{H_t}{O_t}\right); \tag{3}$$

$$c_t = log\left(\frac{L_t}{O_t}\right); \tag{4}$$

$$x_t = log\left(\frac{C_t}{O_t}\right); \tag{5}$$

Where O – open prices, H – high, L -low, C – close.

$$Add\ ux = \frac{1}{2}(u_t^2 - x_t^2) + x_t^2; \tag{6}$$

$$Add\ vx = \frac{1}{2}(v_t^2 - x_t^2) + x_t^2 \tag{7}$$

Where $u_t = 2 * b_t - x_t, v_t = 2 * c_t - x_t$

Unbiased Add RS estimator is:

$$Add\ RS = \frac{1}{2}[Add\ ux\ +\ Add\ vx] \tag{8}$$

Add RS we will use to estimate futures volatility.

Another estimator standard deviation was constructed based on the daily prices in the week of trading. For each week we measured standard deviations of daily prices and take as the weekly volatility of the futures and commodity prices.

In the estimation methodology we will follow Joarder (2018). We will use the panel regression model to estimate relationship between uncertainties and futures volatility.

As variables have different measures, we use log-log model, because we are interested in the effects of increasing or decreasing of uncertainties on the volatility. It will be simpler for understand and interpretation work with percentage changes than with absolute changes of variables.

So, the main regression models are:

$$\log(Add\ RS_t) = \beta + \ log(VIX_t) + log(EU_t) + log(GTU_{t)} \\ + \ \log(\text{Lags of Add RS}) \tag{9}$$

Where $\log(Add\ RS_t)$ – logarithm of unbiased extreme value volatility estimator, log(VIX_t)- logarithm of CBOE Volatility Index in time t, log(EU) – logarithm of economic uncertainty index, log(GTU_t) – logarithm of Google trends' uncertainty index. $\log(\text{Lags of Add RS})$ – logarithm of the lags of Add RS (number of lags would be choose based on the PACF and ACF functions for special commodity).

$$\log(SD) = \beta + \ log(VIX_t) + log(EU_t) + log(GTU_{t)} \ + \ \log(\text{SD}) \tag{10}$$

Where $\log(SD)$ – logarithm of weekly standard deviation, log(VIX_t)- logarithm of CBOE Volatility Index in time t, log(EU) – logarithm of Economic uncertainty index, log(GTU_t) – logarithm of Google trends' uncertainty index. $\log(\text{SD})$ –

logarithm of the lags of weekly standard deviation (number of lags would be choose based on the PACF and ACF functions for special commodity).

Chapter 4

DATA DESCRIPTION

We composed GTU and Economic uncertainty indexes for the period 2019-2020 years. VIX was collected from yahoo. Finance for the same period. We have 104 observations of the VIX and GTU as these are weekly data. The economic uncertainty index was obtained monthly. Thus it has only 24 observations for two years.

Table 1 Descriptive Statistics of uncertainties indexes

Variable	Obs	Mean	Sd	Min	1-Qu.	Median	3-Qu.	Max
GTU	104	10.87	20.23	0	0	0	11.25	107.00
Economic Uncertainty	24	0.89	0.54	0.42	0.48	0.54	1.47	2.03
VIX	104	22.49	11.50	11.87	14.87	19.02	26.25	82.69

Google trends uncertainty index has a range between 0 and 107. It has quite a significant variation as the standard deviation is 20.23 and higher than the mean of 10.87. Most of the values of GTU are 0. It is easy to explain, as for almost full 2019-year people had no reason for searching "uncertainty" words. Moreover, at the end of 2020 interest in the COVID-19 and economic crisis decreased, and people stopped searching it. A maximum of 107 with a potential maximum of 500 implies that people did not search a lot with the "uncertainty" words.

VIX is characterized by relatively low values for almost all periods. The value of the third quantile is almost the same as the mean. The standard deviation is 11.5 what is only half of the mean of 22.49. By descriptive statistics, it looks like the VIX index with a calm long period and with quite a short period of increasing volatility on the financial markets.

Economic uncertainty is between 0.42 and 2.03. It shows the average mistake of individual forecasters for 7 uncertainty macroeconomics indicators: Real GDP growth, Consumption variation, Investment variation, Industry variation, Unemployment, Inflation, and Key policy rate or 10-year bonds (depends on the country). It is characterized by a longer period of increased uncertainty. Furthermore, Economic uncertainty did not show the trend to significantly decreasing at the end of 2020.

Table 2 Correlation between variable-specific uncertainty

	Aggregated EU	Real GDP	Consumption	Investments	Industry	Unemployment	Inflation	Policy rate
Aggregated	1.00							
Real GDP	0.81	1.00						
Consumption	0.87	0.72	1.00					
Investments	0.76	0.54	0.81	1.00				
Industry	0.84	0.81	0.70	0.52	1.00			
Unemployment	0.89	0.58	0.79	0.69	0.54	1.00		
Inflation	0.22	0.11	0.16	-0.07	0.12	0.24	1.00	
Policy rate	-0.25	0.00	-0.39	-0.40	-0.06	-0.32	0.02	1.00

Correlation of the variable-specific uncertainty, idiosyncratic uncertainty, and common uncertainty is in Tables 2-4. There is a strong correlation between almost all variable-specific common uncertainty. The exception is the only pair of Key policy rates and Inflation with a correlation of -0.37.

Table 3 Correlation between variable-specific idiosyncratic uncertainty

	Aggregated EU	Real GDP	Consumption	Investments	Industry	Unemployment	Inflation	Policy rate
Aggregated EU	1.00							
Real GDP	0.92	1.00						
Consumption	0.93	0.97	1.00					
Investments	0.93	0.86	0.93	1.00				
Industry	0.93	0.94	0.89	0.84	1.00			
Unemployment	0.93	0.86	0.88	0.92	0.81	1.00		
Inflation	0.79	0.76	0.66	0.64	0.77	0.75	1.00	
Policy rate	-0.67	-0.66	-0.75	-0.81	-0.60	-0.66	-0.37	1.00

Signs and strength of correlation are similar to the normal economic series. Thus, we can see a strong linear relationship between errors of forecast in the Real GDP growth, Consumption variation, Investment variation, and Industry growth.

Variable-specific uncertainty is characterized by the low correlation between all variables. Hence, most of the connection for common uncertainty goes from the idiosyncratic variable-specific uncertainty. It is logically straightforward as the share of idiosyncratic uncertainty is the highest in the common variable-specific uncertainty.

Table 4 Correlation between variable-specific common uncertainty

	Aggregated EU	Real GDP	Consumption	Investments	Industry	Unemployment	Inflation	Policy rate
Aggregated EU	1.00							
Real GDP	0.90	1.00						
Consumption	0.91	0.97	1.00					
Investments	0.90	0.89	0.95	1.00				
Industry	0.89	0.93	0.86	0.83	1.00			
Unemployment	0.95	0.88	0.92	0.95	0.82	1.00		
Inflation	0.78	0.72	0.63	0.61	0.76	0.73	1.00	
Policy rate	-0.68	-0.64	-0.75	-0.81	-0.52	-0.74	-0.34	1.00

Aggregated Economic uncertainty has a positive and high correlation with all variable-specific uncertainties. The exception is only Key Policy rate uncertainty which has a negative correlation with all other variable-specific uncertainties. Hence, forecasters could provide more precise predictions for the policy rates of the countries in the period of uncertainty.

For discovering the connection between different uncertainty indexes, we normalized them between values 0 and 1, and draw them on one graph 1. Where the red line is Economic uncertainty, green is VIX and blue is GTU.

As we can see from the figure 1 GTU and VIX have a similar pattern for the last two years. It is in line with the Weinberg (2020) research for the EU google trends uncertainty and volatility index for European financial markets. In our study, VIX has higher spikes than GTU for most of the cases. Spikes of the VIX for the 2019 year show that short-time periods of volatility on the financial markets. This volatility could be explained by the specific news for the markets or some disturbances which are connected straight to the financial market specifics.

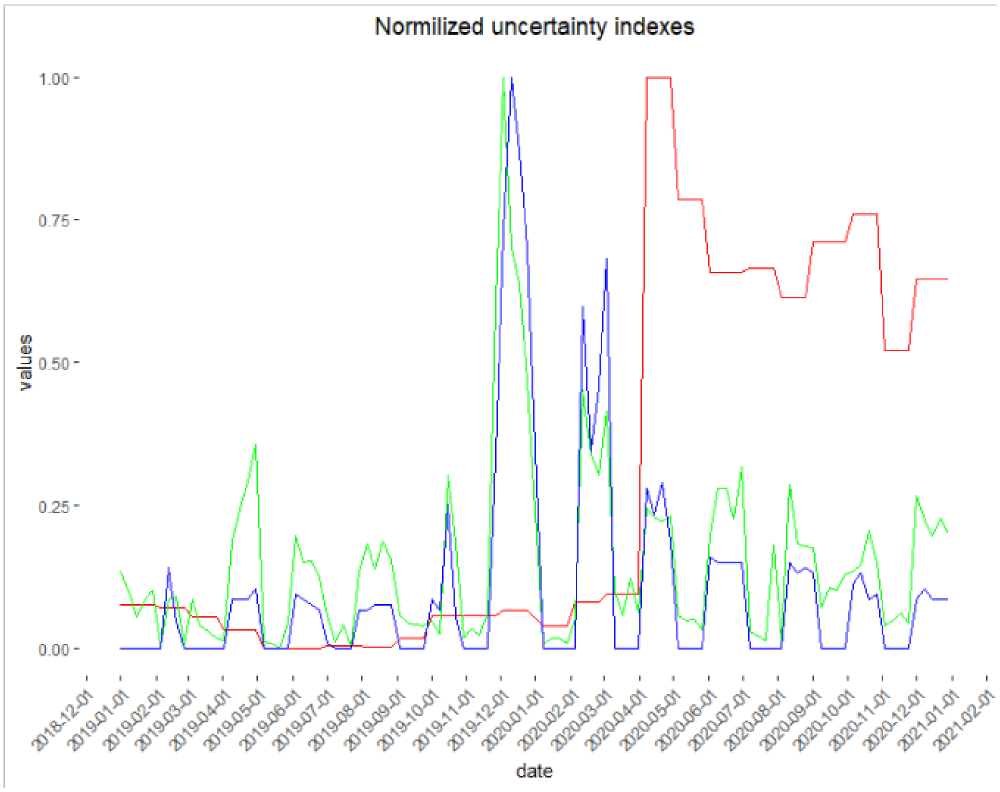

Figure 1 Normalized uncertainty indexes

Small spikes of the GTU in 2019 show us that people started to search the word "crisis" in periods of high market volatility. It is another piece of evidence about the effectiveness of prediction possibilities of GTU for uncertainty in the world.

The economic uncertainty index has a different pattern for the last two years. It was on the low level for all of 2019. It was expected as in 2019 there was no evidence or expectations about real economic/financial crisis. However, after the beginning of 2020 Economic uncertainty significantly increased more than three times. All 2020 year was unpredictable, and analysts could not forecast future with the previous levels of confidence. This tendency is observed from the trend on the economic uncertainty index for the world. Till the end of 2020 economic uncertainty did not return to the pre-COVID-19 values. The trend does not show the pattern for future deceasing of it.

From the figure 2 we conclude the same results as after visual analysis. There is strong linear connection between GTU and VIX with correlation of 0.87. Correlation of GTU and VIX with Economic uncertainty is moderate.

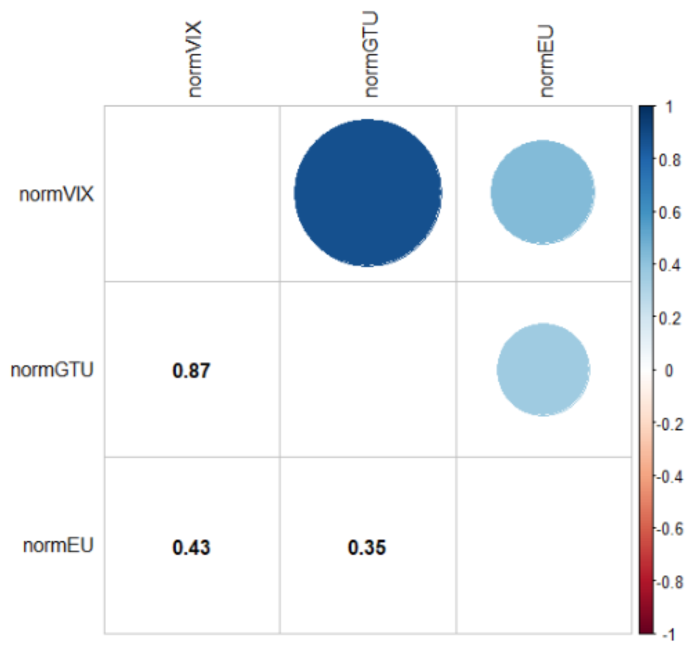

Figure 2 Correlation between normalized uncertainty indexes

Next key variables of our analysis are the commodity futures volatility. We will discover standard deviation of the daily prices and unbiased extreme estimator.

Table 5. Descriptive statistics of the standard deviation of futures prices

Variable	Obs	Mean	Sd	Min	Max
Cotton sd	396	3.54	2.62	0.25	17.44
Sugar sd	297	0.87	0.56	0.16	3.48
Corn sd	416	14.45	10.85	0	67.16
Coffee sd	396	13.48	8.58	3.1	45.45
Copper sd	416	0.19	0.11	0.02	0.59
Soybean sd	104	57.77	36..17	13.2	195.66

There are different numbers of observations for different commodities due to their futures dates of expirations. For example, for copper and corn, there are six expiration dates during the year when for soybean only one. Futures are traded on the New York Board Trade. We take daily data to construct weekly standard deviation, and then we annualized it. Weekly trading data was used to calculate the extreme value estimator. The largest number of futures contracts is for Corn and Copper. Thus, they have 416 observations.

The least volatile commodity is copper. There is almost no variation during the observed period with the mean of 0.19, the standard deviation of 0.11, and the maximum value of 0.59. On the other hand, Soybean is the most volatile commodity. It has the highest standard deviation of 36.17 and a range between 13.82 and 195.66.

Sugar has a similar pattern to copper but with a higher variation. The mean and standard deviation for the sugar is four times higher than for copper. At the same time, the maximum is significantly different with copper, 3.48 and 0.59, respectively.

Cotton, corn, and coffee are in the middle of the in terms of volatility. They have means in the range of 3.54 and 14.45. Standard deviations and maximum are significantly higher than for the sugar and copper. However, all characteristics are far from the soybean.

Table 6. Descriptive statistics of the unbiased extreme value estimator

Variable	Obs	Mean	Sd	Min	Max
Cotton sd	396	0.03	0.06	0	0.62
Sugar sd	297	0.06	0.1	0	0.79
Corn sd	416	0.02	0.01	0	0.26
Coffee sd	396	0.12	0.14	0	0.8
Copper sd	416	0.04	0.08	0	0.95
Soybean sd	104	0.06	0.06	0	0.27

For the unbiased extreme estimator, descriptive statistics are in table 6. The maximum value for all commodities is not higher than 0.12. All commodities have a minimum of 0. In contrast with standard deviation, maximum values are relatively closer. According to the unbiased extreme value estimator, the least volatile commodity is Cotton, the most volatile commodity is Coffee.

From Figure 3, we can conclude that this estimator has variation and captures an increase of the volatility at the beginning of 2020. For cotton, sugar, corn, and copper there is a clear spike of volatility at the beginning of 2020. Nonetheless, these spikes have different periods. Copper has the shortest spike when the other three commodities have a relatively long period of high volatility.

Estimator captures the high volatility for the coffee for the entire 2020 year. For the precise conclusions, we need to highlight that coffee has higher volatility for the 2019 year too. Thus, there is no clear connection in the visual analysis between increasing volatility and the start of the COVID-19 Pandemic.

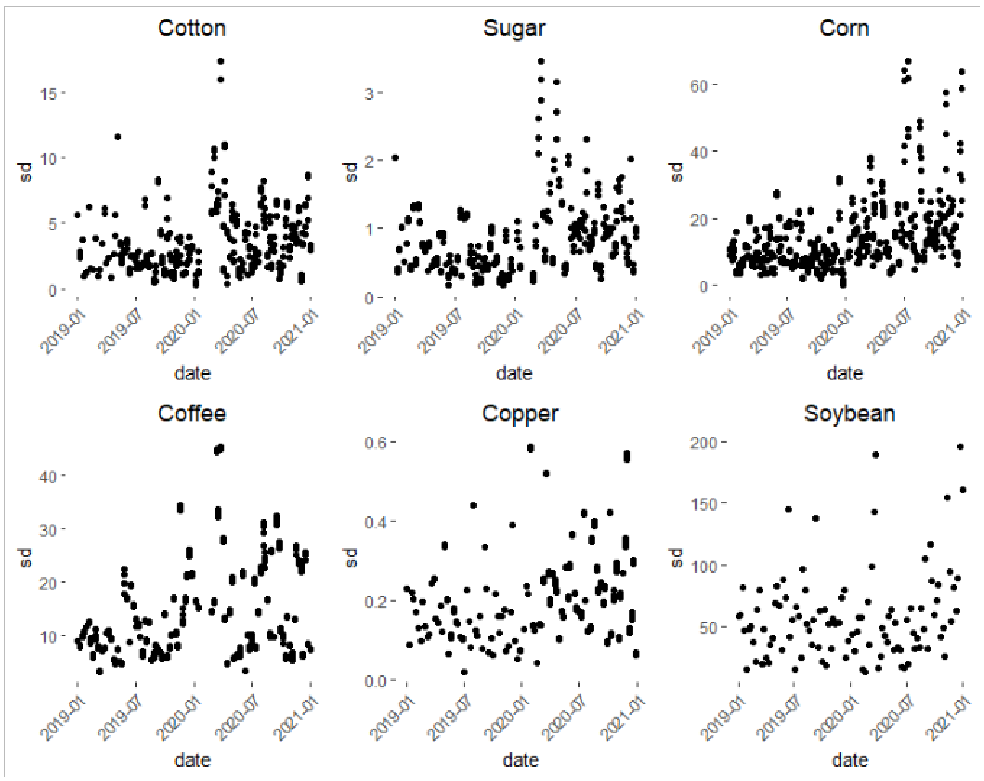

Figure 3. Unbiased extreme estimator.

Soybean has no clear pattern for the 2020 year and the start of the COVID-19 pandemic. It has high volatility for the full observed period.

Figure 4 depicts standard deviations of the futures. It shows similar patterns as the RS estimator. Nonetheless, standard deviation shows more spikes and a longer period of high volatility. It is expected as the standard deviation was calculated based on the daily data when RS on the weekly.

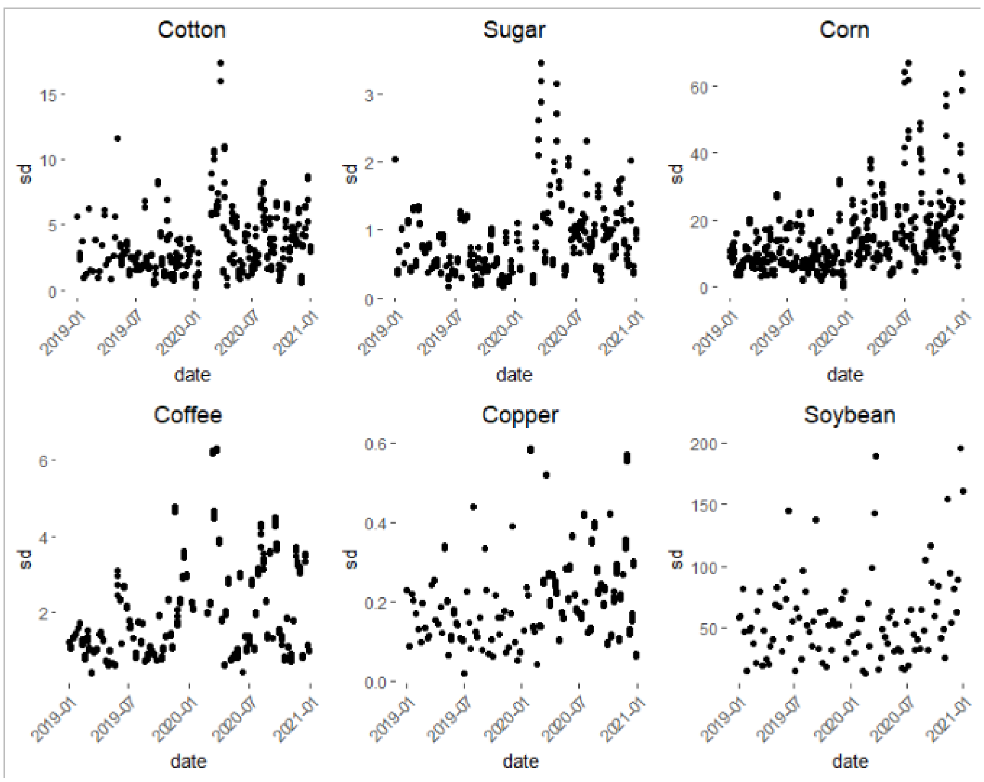

Figure 4. Standard deviation.

Chapter 5

ESTIMATION RESULTS

We estimate panel regression with fixed effect for the whole sample of futures. There are 2440 observations in total. We take logs for all key variables.

Table 7**.** Panel model estimation

Commodity Futures Volatility and Economic Uncertainty During COVID-19 Pandemic

	Dependent variable:	
	log(RS)	log(sd)
	Whole sample	Whole sample
	(1)	(2)
VIX	0.774^{***}	0.256^{***}
	(0.119)	(0.067)
GTU	0.239^{***}	0.115^{***}
	(0.040)	(0.023)
Economic Uncertainty	0.206^{***}	-0.015
	(0.061)	(0.034)
Observations	2,440	2,440
R^2	0.337	0.167
Adjusted R^2	0.329	0.158
F Statistic (df = 3; 2413)	408.022^{***}	161.387^{***}
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

From the estimation, we have the expected results. The exception is only Economic uncertainty in the model for standard deviation. However, this coefficient is insignificant.

VIX has the highest impact on commodity futures volatility. If VIX increases on the one percent, it will increase volatility on the 0.774% or 0.256% in terms of Add RS or standard deviation, respectively. As futures is part of financial markets it is obvious that volatility on them will have an impact on the futures prices and volatility.

GTU has a similar effect for both volatility estimators. Coefficients are 0.239 and 0.115. It is stated that GTU should increase by a large percent to have a significant effect on the volatility of the futures. However, GTU is the most volatile uncertainty index which we used. It could skyrocket in a few days if there is some hot topic. Thus, these coefficients are logical and predictable.

The last one is economic uncertainty. It is insignificant for standard deviation. However, for Add RS it has a coefficient of 0.206. This effect on the level with the with GTU. As economic uncertainty has in general two levels for the period. It was low in 2019 and high in 2020, the coefficient near it captures the effect of the monotonous effect on the futures volatility. As was mentioned, volatility in the 2019 year was lower than in 2020 for most of the commodities.

We want to discover the effect on each commodity volatility. In Table 7 results of the regression for each of the commodities are presented. It contains regression with standard deviation as the dependent variable.

First, we want to highlight Soybean. All the uncertainty indexes are insignificant for it. Only VIX is significant on the level of 90%. As Soybean has high volatility during all periods and there is no additional increase of volatility in 2020.

Coffee has an unpredictable coefficient near VIX. If VIX increases by one percent, the volatility of coffee would decrease by 0.4 percent. It is quite an unusual direction for volatility reaction on the increase of the financial market volatility. Further GTU has a positive relationship with coffee volatility. We can conclude that their effect partially compensated for the coffee.

Table 8 Panel model estimation for standard deviation of separate commodities

Futures Volatility and Economic Uncertainty During COVID-19 Pandemic

	Dependent variable:					
	log(sd):					
	Cotton	Sugar	Corn	Coffee	Copper	Soybean
	(1)	(2)	(3)	(4)	(5)	(6)
VIX	0.761^{***}	0.728^{***}	0.032	-0.405^{**}	0.119	0.536^{*}
	(0.200)	(0.187)	(0.148)	(0.169)	(0.134)	(0.302)
GTU	0.032	-0.052	0.145^{***}	0.346^{***}	0.089^{**}	-0.112
	(0.070)	(0.066)	(0.049)	(0.059)	(0.044)	(0.100)
Economic Uncertainty	-0.204^{**}	0.212^{**}	0.144^{*}	-0.444^{***}	0.097	0.050
	(0.099)	(0.093)	(0.078)	(0.084)	(0.071)	(0.159)
Observations	396	297	415	396	416	104
R^2	0.183	0.271	0.207	0.151	0.151	0.037
Adjusted R^2	0.171	0.259	0.195	0.138	0.138	0.008
F Statistic	29.105^{***} (df = 3; 389)	36.140^{***} (df = 3; 291)	35.535^{***} (df = 3; 408)	23.050^{***} (df = 3; 389)	24.182^{***} (df = 3; 409)	1.267 (df = 3; 100)
Note:						*p<0.1; **p<0.05; ***p<0.01

Copper was characterized by low volatility. Thus, GTU is only significant for the Copper volatility. Additionally, it has a small economic effect increase of GTU by one percentage point will lead to the 0.089 percentage point increase in copper volatility.

Cotton and Sugar have a similar connection with VIX as it was in the whole sample regression. Economic uncertainty has a negative effect on cotton volatility when for sugar this connection is positive.

Regression with the standard deviation showed a chaotic result. It is quite hard to find one pattern for all commodities. It is due to that standard deviation was constructed on the daily basis and capture more speculative moves than fundamental.

Table 9 Panel model estimation for Add RS of separate commodities

Futures Volatility and Economic Uncertainty During COVID-19 Pandemic

	Dependent variable:					
	log(RS)					
	Cotton	Sugar	Corn	Coffee	Copper	Soybean
	(1)	(2)	(3)	(4)	(5)	(6)
VIX	0.805**	1.268***	0.466*	-0.910***	0.882***	1.364***
	(0.357)	(0.264)	(0.256)	(0.292)	(0.251)	(0.434)
GTU	0.395***	0.143	0.271***	0.721***	0.105	-0.175
	(0.125)	(0.092)	(0.084)	(0.103)	(0.083)	(0.143)
Economic Uncertainty	-0.134	0.267**	0.714***	-0.435***	0.206	-0.045
	(0.177)	(0.131)	(0.135)	(0.145)	(0.132)	(0.229)
Observations	396	297	415	396	416	104
R^2	0.365	0.575	0.458	0.283	0.266	0.143
Adjusted R^2	0.356	0.567	0.450	0.272	0.255	0.117
F Statistic	74.686*** (df = 3; 389)	131.027*** (df = 3; 291)	115.048*** (df = 3; 408)	51.240*** (df = 3; 389)	49.287*** (df = 3; 409)	5.560*** (df = 3; 100)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 9 contains the results of panel estimations for Add RS estimator for all commodities. These results are more in line with panel regression on the whole sample.

Coffee shows the same unpredictable results in this regression too. Economic uncertainty has a minus sign in addition to the negative effect of the VIX. As it was for the standard deviation growth of GTU increases coffee volatility and compensates the effect of VIX and Economic.

VIX is a significant variable for all of the commodities, even Soybean. The percentage change of the VIX will have the largest effect on the volatility through other variables. The volatility of sugar and soybean will increase by more than one percentage point when VIX increased by one percentage point.

GTU is positively correlated only with cotton, sugar, and coffee. All other commodities do not change their volatility after increasing GTU. As cotton and sugar have small volatility in the 2019 and short-term spike at the beginning of COVID-19 Pandemic. Connection with GTU captured that spike and showed and significant effect.

The Economic Uncertainty index has a positive effect on sugar and corn. The coefficient for corn regression is 0.714, which is associated with increasing corn volatility on the 0.714 percentage point with the uncertainty growth of 1 percent. We can state that corn is the most dependent from the global economic uncertainty.

There is no one clear trend for the connection between uncertainties and different commodities volatility. The most volatile futures are affected by the financial market uncertainty. Soybean is the best example of it. Futures that have high volatility independently from the COVID-19 pandemic and other factors.

Economic uncertainty affects futures with more fundamental pricing, such as sugar and corn. Involatile futures such as copper has no connection with most of the uncertainty indexes. There is a positive connection only with VIX. It showed that only uncertainty for increasing volatility for such futures is volatility and unpredictable future of the financial market.

Google trend uncertainty affects short-term volatility in the time of increasing interest to the world or economic problems from the people who are not systematically read news and articles on the economic-related themes. Experts, forecasters, traders, and other economic and financial professionals are more foreseeing and have a higher impact on the volatility through their effects on the specific uncertainties. Such economists and forecaster increased uncertainty in the world when it is difficult for them to give predictions in the line with consensus. Traders on the exchanges start to quickly buy and sell financial assets. This increases financial market uncertainty and commodity futures volatility.

C h a p t e r 6

CONCLUSIONS

We used a combination of methodologies of Kumar (2014), Ozturk (2018), Joarder (2018), and Weinebrg (2020) to decompose the effect of uncertainty between economic, financial, and emotional uncertainties.

We constructed the Google trends uncertainty index to capture the emotional uncertainty of the people. Then we constructed a global economic uncertainty index and use VIX for financial markets uncertainty.

Evidence from the market and trading futures data we found out increasing of commodity futures volatility. In some cases, it was a short-term spike, others increasing for the whole 2020 year. Corn is an example.

Our estimation showed the effect of all three types of uncertainty on the whole market. Under market, we understand a sample of all futures. When started to investigate the effect of uncertainties on the specific commodities, results were partially unpredictable.

Coffee has a negative relationship with financial and economic uncertainties. Its volatility increased at the end of 2019. Thus it is questionable that this increase was stimulated by the COVID-19. Another interesting case is soybean futures. It has high volatility for all periods of research. Thus, it has a connection only with the VIX.

For other futures, all of the uncertainty types have a positive relationship with their volatilities. Significance and economic strength differ between commodities, but the general trend is the same.

These results were obtained using two different volatility estimators, an extreme unbiased volatility estimator, and a standard deviation. Hence, they are robust and understandable.

It makes sense to construct the GTU index daily and use it as a predictor of the volatility on the commodity and financial markets.

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