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by

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* Maximilian Heigermoser is doctoral researcher, Linde Götz is deputy head and Tinoush Jamali Jaghdani is research associate in the agricultural markets department of the Leibniz Institute of Agricultural Development in Transition Economies (IAMO) in Halle, Germany. E-Mail: heigermoser@iamo.de.

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Over the last two decades, the Black Sea region developed to be a key global exporting region for corn and wheat. However, many market participants grapple with insufficient knowledge of factors that drive Black Sea spot prices, while effective futures markets that could facilitate price discovery and risk management are still missing. In our study, we identify market-specific drivers of volatility of Ukrainian corn and Russian wheat prices. We use daily Black Sea spot price indices for both grains to estimate non-parametric realized volatility measures. These are regressed on several potential drivers, namely, respective futures prices, exchange rates, oil prices and freight rates that serve as a proxy for demand shifts. Estimation results suggest that Ukrainian corn price volatility is well explained by futures price movements and demand shifts, while Russian wheat markets are rather isolated from futures price movements and mostly depend on own lagged volatility and exchange rate movements. Additionally, we find asymmetric responses to price movements at the CBoT: both Black Sea markets react significantly stronger to price increases at the CBoT than to price decreases.

Keywords: Realized volatility, physical markets, futures markets, Black Sea region, grain

Introduction

Over the last two decades, the Black Sea region became a key grain exporting region. In season 2017/18, Russia was the world's biggest wheat exporter, surpassing the decade-long top exporter, the USA. Regarding corn markets, Ukraine was the fourth largest exporter globally and the biggest exporter that is not located on the Americas (USDA 2018). While new export markets are developed, the grain export sector is modernized and especially port capacities are extended in the Black Sea region, there is still a big difference to grain markets in the USA or the EU: An effective futures market that could facilitate price discovery and risk management does not exist. Therefore, many market participants use traditional US futures contracts to hedge their business in the Black Sea region which can involve substantial basis risk: In the third quarter of 2017, Archer Daniel Midlands (ADM), one of the world's largest agricultural trading companies, attributed a quarterly loss of 20 million USD in their Black Sea trading operations to a 'lack of correlation' between hedges off 'North American [futures] exchanges' and the 'underlying movement' on Black Sea wheat and corn spot markets (ADM 2017).

As the importance of Black Sea grain markets is a rather recent phenomenon, there is a lack of knowledge about factors that determine the export price movements in the Black Sea region. In this paper, we investigate the functioning of Black Sea grain markets by focusing on the analysis of price volatility. Against this background, we formulate two sets of research questions: Firstly, what are the characteristics of Black Sea grain price volatility and how does it evolve over time? And secondly, what drives Black Sea grain price volatility? And more specifically: how is Black Sea grain price volatility related to volatility on major grain futures markets?

High volatility, i.e. high uncertainty about future price movements, can disrupt food systems in various ways. Firstly, it can increase the risk and thus the cost of trading operations and lead to losses, or even bankruptcies. Second, it can hamper investment in respective food sectors which will lead to higher food prices in the longer run. Thirdly, it can threaten food security by causing food price inflation and thus poverty in import-dependent low-income countries.

Volatility is inherently unobservable and thus has to be estimated before it can be analyzed. The most common approach to estimating volatility is to employ parametric generalized autoregressive conditional heteroscedasticity (GARCH) models (Bollerslev 1986). To further study inter-dependencies and spillovers between volatilities of multiple series, multivariate M-GARCH models are frequently applied (Hernandez et al. 2014, Serra 2011, Trujillo-Barrera et al. 2012).

However, GARCH models have certain disadvantages with respect to our markets of interest: Firstly, they generally require a fairly large data set and a high (at least weekly) data frequency. Secondly, they are restrictive in the sense that the researcher has to assume a – potentially inadequate – distribution to the modelled price returns to estimate the volatility by maximum likelihood. Thirdly, it is not possible to estimate volatility at a frequency that is lower than the one of the underlying data without losing valuable information. Fourth, while we use 1100 high-frequency daily Black Sea wheat and corn export prices as data basis, there is however no movement from one to the next day in 55 and 57 percent of the cases, respectively. This circumstance is difficult to capture for a standard GARCH model that is designed for highly liquid stock markets.

These shortcomings motivate us to employ the novel, non-parametric realized volatility estimator proposed by Andersen et al. (2003). Following this appraoch, we construct RV measures at a half-monthly frequency, without losing information on the intra-period (daily) returns. While approximately two weeks seems to be a reasonable time horizon to assess price movements on physical grain markets, this appraoch also has the advantage that rather indirect effects of (lagged) variables can be identified more precisely. Capuring effects of slowly-evolving lagged variables on present volatility would imply to a fairly complex lag structure if analyzed on a daily frequency (Karali and Power, 2013).

Thus, to answer the first set of research questions, we construct, describe and compare half-monthly RV measures for Black Sea wheat and corn spot market prices, as well as for nearby futures prices recorded at the Chicago Board of Trade (CBoT) and the Euronext in Paris (EPA) for a time period ranging from March 2014 to June 2018. To answer the second set of research questions, the two Black Sea RV series are regressed on several potential drivers, namely respective grain futures prices, exchange rates, oil prices and freight rates that serve as a proxy for demand shifts.

Previous research by Brümmer et al. (2016) investigated volatlity drivers in oilseeds and vegetable markets using GARCH models and a vector autoregressive (VAR) framework. Brümmer et al. find exchange rate volatility to be a significant volatiltiy driver, while concluding that volatlilty drivers should be considered as market-specific. Karali and Power (2013) explicitly investige the effect of slowly-evolving macroeconomics variables on price volatility of various US commodity futures. They find that the wheat and corn price volatlities show seasonal patterns and are responsive to changes in inventories as well as to USD appreciations. McPhail et al. (2012) investigate CBoT corn futures price volatility using a structural VAR model, finding that energy prices and global demand drive corn prices in the long run.

This paper is structured as follows. In section two, the employed methodology and our estimation strategy is described. A detailed description of the data used in our analysis in provided in section three. Empirical findings are presented in section four and section five gives main conclusions and an outlook on future resarch.

Methodology and Estimation Strategy

Our strategy to estimating the realized volatility of Black Sea grain prices and to identifying its major drivers consists of five consecutive steps. First, we calculate returns for each price series under consideration. A price return at period *t* is the difference between the log prices at period *t* and at period *t-1* for $t = 1, 2, 3 \ldots T$. It thus depicts the relative price changes from one to the next time period. As price returns are commonly not free from autocorrelation, each individual series is, secondly, modelled as an autoregressive moving average (ARMA) process filtering out the “expected part” of the price changes. The respective lag lengths, *p* and *q*, for the autoregressive and the moving average components are determined by first estimating the ARMA(p,q) model with the lowest Bayesian Information Criterion (BIC) value. If there is still autocorrelation in the model residuals under this specification, the lag length is increased until the null hypothesis of no autocorrelation of the Ljung-Box test is no longer rejected at conventional significance levels for up to 300 lags. The residuals from each respective univariate ARMA(p,q) model represents the “unexpected part” (or the uncertainty) within the respective return series.

These series of residual with a daily frequency are utilized to, thirdly, calculate realized volatility (RV) estimates with a half-monthly frequency. Proposing the RV estimator, Andersen et al. (2003) used intraday returns recorded every half hour for several exchange rates to construct RV measures at a daily frequency. Generally, the construction of RV measure at any frequency must be based on data recorded at a higher frequency. Regarding this study, spot price data is available at a daily frequency and we choose to construct RVs at a half-monthly frequency. This is due to several reasons: Firstly, at a weekly frequency each RV estimate would be estimated from a low number of only five (or less) intra-period returns (i.e. business days within one week). Secondly, while a monthly frequency addresses this issue, it leads to a fairly short series of 52 monthly RV observations. Selecting a half-monthly frequency, each RV estimate is based on a reasonable number of 10 to 11 intra-period returns. The resulting series ultimately contain 102 half-monthly observations for our period of investigation, ranging from the second half of March 2014 to the first half of June 2018. Moreover, an evaluation period of 15 days seems to be a reasonable time horizon if physical markets are considered as these move rather slowly compared to futures markets. The estimator used to generate half-monthly RV measures can be written as follows:

$$\hat{\sigma}_t^2 = \sum_{j=1}^{N} \varepsilon_{tj}^2 \quad (1)$$

Where $\hat{\sigma}_t^2$ denotes the realized variance which is the squared realized volatility at period *t* that is our variable of interest. To generate the RV estimate at time *t*, we sum *N* squared, mean-adjusted intra-period returns, $\varepsilon_{t,j}^2$, i.e. the residuals from the preceding ARMA(p,q) estimations on returns, over the respective half month. As discussed above, $N \sim 11$ because there are around eleven business days within one half-month. The RV measures estimated at this stage will serve as basis to answering the first research question. To make visual inspection and basic statistics of the estimates better comparable with other research, all RV estimates are annualized by multiplying each observation with the square root of the number of half-months within one year, $\sqrt{24}$.

To determine the drivers of Black Sea grain price volatility, the fourth step is to estimate two univariate autoregressive models with the series of half-monthly RVs of Black Sea wheat and corn as dependent variables, respectively. This approach is largely in line with previous research on volatility drivers by Brümmer et al. (2016) and McPhail et al. (2012). The autoregressive model can be written as:

$$\sigma_t = \alpha_0 + \sum_{i=1}^{p} \beta_{1i}\sigma_{t-i} + \sum_{i=1}^{p} \beta_{2i} r_{t-i}^{+} + \sum_{i=1}^{p} \beta_{3i} r_{t-i}^{-} + \sum_{j=1}^{K}\sum_{i=1}^{p} \gamma_{1ji} X_{jt-i} + \sum_{j=1}^{K}\sum_{i=1}^{p} \gamma_{2ji} R_{jt-i}^{+} + \sum_{j=1}^{K}\sum_{i=1}^{p} \gamma_{3ji} R_{jt-i}^{-} + \varepsilon_t \quad (2)$$

This equation is estimated two times, with Black Sea wheat and Black Sea corn RV as dependent variable, respectively. σ_t represents the half-monthly RV of Black Sea the respective Black Sea grain prices obtained from equation (1) at period t, with *t = 1, 2, 3, ... T*. α_0 denotes a constant. β_{1i} is a coefficient that represents the effect that own RV lagged by *i* periods has on σ_t, for *i = 1, 2, 3, ... p*. Further, the coefficients β_{2i} and β_{3i} measure the effect that positive and negative half-monthly returns of the considered Black Sea price at period *t-i* (r_{t-i}^{+} and r_{t-i}^{-}) have on present Black Sea RV. Similarly, γ_{1ji}, γ_{2ji} and γ_{3ji} denote the effects that RV (*X*), positive returns (R^{+}), and negative returns (R^{-}) of the explanatory variable *j* (with *j = 1, 2, 3, ... K*) at time period *i* have on σ_t, respectively (see section three for details on the considered explanatory variables).

We include lagged signed returns in our model in line with Patton and Sheppard (2015) who show that the response of volatility to lagged returns depends on the sign of the returns. The lagged signed returns of the dependent variable and the *K* explanatory variables, r^{+} and r^{-} as well as R_j^{+} and R_j^{+} are thus understood as interaction terms between a series of half-monthly returns and a dummy variable that equals one if the respective return is positive (negative) and zero if it is negative (positive). Half-monthly returns are constructed as relative price changes from the last business day in period *t-1*, to the last business day in period *t*. By incoroporating signed returns into our model, we control for leverage effects, or asymmetric responses of Black Sea grain price volatility towards upwards or downwards movements in other markets (Patton and Sheppard, 2015). If coeffcients γ_{2ji} and γ_{3ji} show opposite signs, the effect of the explanatory variable *j* lagged by *i* periods on σ_t is symmetric. Conversely, the latter responds asymmetrically to returns of different sign, if the respective coefficients show the same sign. This approach is also relying on Karali and Power (2013). Finally, ε_t denotes a vector of errors that are i.i.d. and normally distributed with zero mean and constant variance.

As this model specification will result in a fairly large number of coefficients, the fifth and last step is an iterative, general-to-specific model selection process similar to Brümmer et al. (2016) and Hoover und Perez (1999). Following this approach, equation (2) is initially estimated in an unrestricted way, such that RVs and signed returns of the dependent variable as well as all considered explanatory variables are included in the model. Then, the variable with the lowest explanatory power (with the highest p-value of the respective coefficient) is omitted from the model and the equation is re-estimated. This procedure is repeated until the exclusion of one variable does not further decrease the Bayesian Information Criterion (BIC) value. As we present the results of our estimations in section 5.2, we only report the coefficients obtained from estimating the restricted model.

Data

At the center of our empirical investigation are daily FOB spot price indices for Russian wheat and Ukrainian corn (see Table 1). Each business day, these spot prices are assessed by collecting dozens of price quotes from numerous traders, brokers, millers and processors active on the respective markets. Following a strict methodology, each gathered price quote is then converted to the most commonly traded loading location (port), loading window, cargo size, protein content and quality specification to generate a daily spot price index. The volatility of these spot price indices is regressed on a set of potential drivers that are subdivided into four groups.

The first group contains four series of grain futures prices. We include daily settlement prices of nearby futures contracts traded at the CBoT in Chicago and the Euronext in Paris for wheat, as well as for corn, respectively. Due to their high liquidity, the two CBoT contracts are widely accepted as global pricing benchmarks for the respective grains. The USA is further a major competitor to Russia (Ukraine) on global wheat (corn) export markets. Euronext No. 2 milling wheat futures are chosen because recent research has shown that they gain importance for global wheat price discovery, in parallel with the Black Sea region becoming the center of global wheat exports (Janzen und Adjemian, 2017). Euronext corn futures are included because the European Union is the most important export market for Ukrainian corn. These futures contracts are, however, not very actively traded. A nearby futures contract usually loses liquidity and thus informational content in the weeks prior to its maturity when positions are rolled over to e.g. the second-nearest contract. To benefit from settlement prices that contain a maximum of information, we construct a series of continuous futures prices by switching from the nearest to the second-nearest contract on the business day exactly one month prior to the maturity date of the nearest contract. Certainly, this procedure will create artificial price jumps in the resulting series that equal the spread between the two front contracts at the rollover date. However, Carchano and Pardo (2009) showed that this effect does not bias subsequent estimations, irrespective of the chosen rollover methodology.

Table 1: Daily data series used in the econometric analysis

Type	Specification	Country	Mean model	Source
		Spot price indices		
Black Sea wheat	FOB spot price index Novorossiysk, USD/t	Russia	ARMA(1,4)	Platts (2018)
Black Sea corn	FOB spot price index, deep sea ports, USD/t	Ukraine	ARMA(4,4)	Platts (2018)
		Grain futures prices		
CBoT SRW wheat futures	Closing price of nearest contract, ct/bsh	USA	ARMA(10,10)	AHDB (2018)
Euronext No. 2 milling wheat futures	Closing price of nearest contract, EUR/t	EU (France)	ARMA(5,5)	AHDB (2018)
CBoT corn futures	Closing price of nearest contract, ct/bsh	USA	ARMA(1,1)	AHDB (2018)
Euronext corn futures	Closing price of nearest contract, EUR/t	EU (France)	ARMA(5,5)	AHDB (2018)

		Exchange rates		
Ruble vs. USD	USD/RUB	Russia	ARMA(9,9)	Russian Central Bank (2018)
Hryvnia vs. USD	USD/UAH	Ukraine	ARMA(15,15)	National Bank of Ukraine (2018)
		Oil prices		
Europe Brent	Crude Oil spot FOB, USD/barrel	Norway	ARMA(12,12)	Energy Information Administration (2018)
		Freight rates		
Dry Bulk Freight Grains, 25k tons	Handysize vessels, Nikolaev-Alexandria, USD/t	Ukraine, Egypt	ARMA(1,1)	Platts (2018)
Dry Bulk Freight Grains, 60k tons	Panamax vessels, Odessa- Alexandria, USD/t	Ukraine, Egypt	ARMA(1,1)	Platts (2018)

Note: Daily data frequency for all series. Sample ranges from March 17, 2014 to June 19, 2018, including 1100 observations. For freight rates, data is available starting December 1, 2014 including 915 observations.

The second group consists of currency exchange rates relevant to Black Sea grain markets, namely U.S. dollar (USD) versus Russian Ruble (RUB) and versus Ukrainian Hryvnia (UAH) rates. While domestic ex-warehouse prices for wheat and corn in Russia and Ukraine are usually recorded in Ruble and Hryvnia, the export price indices are denoted in USD, the currency that most international grain trade is relying on. As recent research has found imperfect pass-through of exchange rate changes to export prices, i.e. pricing-to-market behavior by Black Sea wheat exporters (Uhl et al. 2016, Gafarova et al. 2015), exchange rates are especially relevant for our study. Investigating the linkage between exchange rate and export price movements, it is advantageous that we can use simple exchange rates, instead of trade weighted dollar indices aggregated from a set of exchange rates that is frequently used as many studies investigating volatility drivers focus on agricultural markets in the USA (McPhail et al. 2012).

One series of Brent crude oil spot prices represents the third group. A growing body of literature examines linkages between energy and agricultural markets (Trujillo-Barrera et al. 2012, Serra 2011, Nazlioglu et al. 2013). Volatility spillovers between these markets are frequently found in the period of global food crises between 2006 and 2011. High crude oil prices potentially drive grain prices because they increase the costs for inputs in agricultural production (fertilizer, fuel, etc.). Further, they incraese the demand for ethanol (i.e. bio fuel) leading to higher demand for its input, corn (McPhail et al. 2012).

The last group contains dry bulk freight (DBF) rates for Handysize and Panamax vessels with loading capacities of 25,000 and 60,000 tons of grains. The rates refer to shipping routes from the Ukrainian ports of Nikolaev and Odessa to the Egyptian port of Alexandria, respectively. Freight rates serve as a proxy for demand shifts in our study. As the supply of cargo ships is relatively inelastic in the short-run, changes in freight rates are assumed to largely stem from shifts in the demand for the grains that the vessels transport (Kilian 2009).

All series are available at a daily frequency and are recorded on five business days per week. Missing values resulting from holidays amount to less than 5 percent for each series and are linearly interpolated. The sample ranges from March 17, 2014 – the first day for which the Black Sea grain price indices are available – to June 19, 2018 and thus contains 1100 observations. Freight rates are only recorded starting December 1, 2015. It is important to note that Black Sea wheat and corn price indices do not move from one day to the next in 57 and 55 percent of the cases. These zero returns do not occur for futures, oil prices, or exchange rates.

Results and Discussion

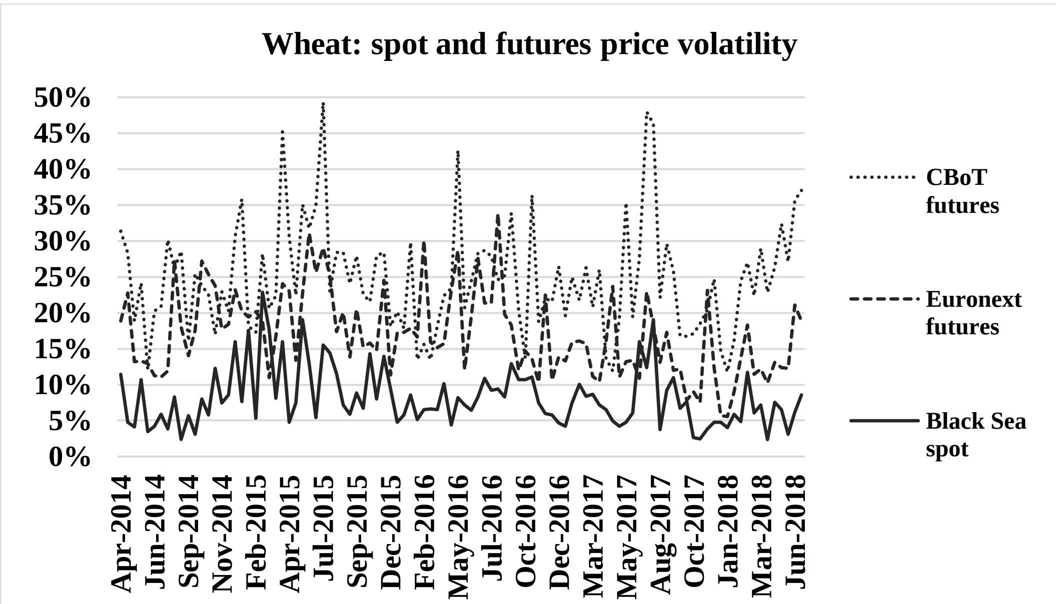
Characteristics of Black Sea grain price volatility

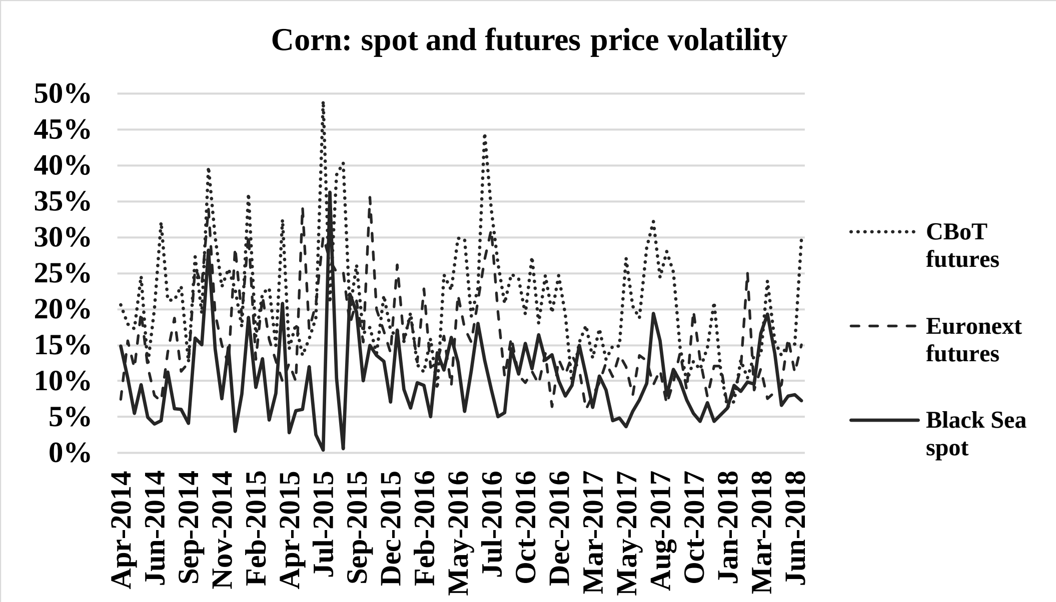
Following the estimation strategy laid out in section 2, we firstly construct daily returns for each variable. Examining the returns, both Black Sea return series show exceptionally large price decreases from Friday, June 13 to Monday, June 16, 2014. These stem from a movement of the assessed loading window to a time period in the second half of July when wheat from the new crop is offered at very competitive prices. The respective returns are erased from the series as they would otherwise have an unproportioned effect on the following estimations. Additionally, the Ruble and Hryvnia exchange rates exhibit exceptional returns on December 17 and 18, 2014 and February 6, 2015, respectively. These result from interventions in foreign exchange markets by the respective national banks and are similarly set to equal zero.

Secondly, univariate ARMA(p,q) models are estimated to deal with autocorrelation that is present in all return series. The lag lengths are presented in Table 1. Respective coefficient estimates are available upon request. The residuals from the ARMA models are utilized to, thirdly, construct half-monthly realized volatility measures. The annualized realized volatilities for spot and futures grain prices are presented in

Figure ***1***. Descriptive statistics for the RV estimates can be found in Table A ***1*** in the annex.

Figure 1. Annualized half-monthly Realized Volatility for Black Sea grains





Note: All series contain 102 half-monthly observations calculated from 1099 daily returns.
Source: Authors' estimations.

Figure ***1*** shows that futures markets – the CBoT in particular – are on average more volatile than Black Sea spot markets. The mean annualized realized volatility for futures prices ranges between 15.4 and 24.8 percent for Euronext corn and CBoT wheat futures, respectively. Mean volatility for Black Sea wheat is 8.2 percent, while corn markets are on average slightly more volatile with 10.3 percent per annum (see Table Table **A *1*** in the annex). Black Sea corn volatility also shows a higher standard deviation compared to Black Sea wheat.

Visual inspection seems to suggest that Black Sea and CBoT corn volatilities co-move to some degree, while co-movement is less apparent regarding wheat markets. The highest volatility on the Black Sea wheat market (22.9 percent) is observed in February 2015, when the Russian government introduced a wheat export tax to dampen domestic food price inflation which subsequently lead to discussions about reviews of the policy continuing throughout the month (Reuters 2015). To capture this effect, we include a dummy variable that equals one in the first and second half of February 2015 and equals zero otherwise, in the following estimations.

Drivers of Black Sea grain price volatility

Examining the drivers of Black Sea grain price volatility, we firstly state that the realized volatility of Black Sea wheat prices primarily depends on own volatility and movements on foreign exchange markets (Table 2). Own volatility at period *t-2* affects the present volatility with the largest effect size among all drivers. The volatility and returns of the USD/RUB exchange rate drive present volatility more immediately with a lag of one period. We do not find asymmetric responses of Russian wheat export prices to upwards and downwards movements in foreign exchange markets. Both, lagged appreciations and lagged depreciations of the Russian Ruble lead to a decrease of present volatility. The two respective coefficients have the same effect size of 0.08 and are statistically significant at the 5 percent level. Positive and negative returns at the CBoT at period *t-1* both increase Black Sea spot volatility. However, the reaction to past upwards movements is stronger, while the coefficient measuring the response to downward movements is also not statistically significant at any conventional significance level. The export tax of the Russian government significantly increased volatility in the wheat market resulting in a positive coefficient.

Table 2. Drivers of Realized Volatility on Black Sea spot markets

Variable	Coefficient Estimate	Standard Error	t-value	p-value
		Wheat		
Constant	0.010	0.003	3.795	0.000
RV $Black_{t-2}$	0.226	0.091	2.470	0.016
RV $FxRub_{t-1}$	0.139	0.039	3.602	0.001
$Return^+$ $XrRub_{t-1}$	-0.084	0.036	-2.327	0.023
$Return^-$ $XrRub_{t-1}$	0.084	0.037	2.293	0.025
$Return^+$ $CBoT_{t-1}$	0.086	0.024	3.507	0.001
$Return^-$ $CBoT_{t-1}$	-0.037	0.032	-1.171	0.246
RV $freight60_{t-2}$	-0.036	0.020	-1.770	0.081
Export tax	0.020	0.005	4.140	0.000
$R^2 = 0.50$	*LB test (10 lags): p = 0.332*	*OLS-Cusum test: p = 0.120*	*JB-normality test: p = 0.049*	*BP test: p = 0.78*
		Corn		
Constant	0.009	0.004	2.646	0.010
RV $CBoT_{t-2}$	0.152	0.073	2.088	0.040
$Return^+$ $CBoT_{t-1}$	0.137	0.054	2.563	0.012
$Return^-$ $CBoT_{t-1}$	0.095	0.057	1.659	0.101
$Return^+$ EPA_{t-1}	0.097	0.060	1.621	0.109
$Return^-$ EPA_{t-1}	-0.135	0.066	-2.041	0.045
RV $freight60_{t-1}$	0.195	0.078	2.484	0.015
$Return^+$ $freight60_{t-1}$	-0.109	0.054	-2.02	0.047
$Return^-$ $freight60_{t-1}$	0.164	0.057	2.890	0.005
$R^2 = 0.39$	*LB test (10 lags): p = 0.978*	*OLS-Cusum test: p = 0.954*	*JB-normality test: p = 0.238*	*BP test: p = 0.81*

Note: EPA denotes Euronext Paris. CBoT denotes Chicago Board of Trade. Null hypothesis of the Ljung-Box (LB) test is no autocorrelation. Null hypothesis of the OLS-Cususm test is model stability. Null hypothesis of the Jarque-Bera (JB) test is normality. Null hypothesis of the studentized Breusch-Pagan (BP) test is homoscedasticity.
Source: Authors' estimations.

Regarding the volatility of Black Sea corn markets, we determine futures market movements and freight rates (i.e. demand shifts) to be the most significant drivers. We find an asymmetric response of Black Sea corn spot price volatility towards price movements at the CBoT. An upward price movement at period *t-1* at the CBoT increases, while a downward movement decreases the volatility on the Black Sea corn spot markets. The latter effect is not statistically significant at the 10 percent level, however, by a narrow margin. The response of corn price volatility to returns at the Euronext exchange (EPA) is symmetric as positive and negative returns both increase Black Sea corn RV. However, negative price returns at period *t-1* have a stronger and statistically significant effect on spot price volatility relative to positive returns. Furthermore, demand shifts with positive and negative sign lagged by one period have a decreasing effect on present volatility. Yet, the RV of freight rates at *t-1* does increase present volatility on the corn spot markets in the region. This effect shows the largest size with a coefficient of 0.195.

Several standard diagnostic tests are ran on both model residual series. Regarding corn price volatility, we do not reject test hypotheses of stability, homoscedasticity, no autocorrelation and normality of the model residuals, respectively (see Table 2). Turing to wheat markets, we find no evidence for autocorrelation in the model residuals. Using the OLS-based CUSUM test we do not reject the null hypothesis of model stability. However, the respective p-value approaches the 10 percent significance level ($p = 0.12$). The Jarque-Bera test for normality suggests non-normality of the model residuals at the 5 percent level of significance. However conflictingly, we do not reject the null hypothesis of normality employing the alternative Shapiro-Wilk test ($p = 0.14$). More detailed results of diagnostic tests regarding both model residuals are available from the authors upon request.

Conclusions

In this paper, we estimated and analyzed the volatility of Black Sea wheat and corn spot prices. Employing the non-parametric realized volatility estimator, we find Ukrainian corn markets to be on average more volatile than wheat markets in the region. The highest volatility value regarding the Russian wheat market is observed in February 2015, after the Russian government implemented an export tax. The considered futures markets, the CBoT and the Euronext Paris, show a higher average volatility than Black Sea spot markets. This can be traced back to the higher activity on futures markets that usually see many transactions each minute, while spot markets even show no trading activity at all on certain days.

Investigating the drivers of Black Sea wheat and corn price volatility, we find clear differences between the two grains. Corn spot price volatility is largely explained by movements on respective futures markets (especially at the CBoT) and by shifts in demand (freight rate returns). Black Sea wheat price volatility on the other hand is relatively more isolated, but not independent from futures markets. It is mostly driven by own lagged volatility and movements of foreign exchange markets.

Including signed returns to control for leverage effects and asymmetries proved valuable in our study. We find that a past upwards movement at the CBoT has a larger volatility-increasing effect on present Black Sea spot price volatility than a past downward movement. Regarding corn markets, we even find that the present volatility of Ukrainian corn decreases if there was a downwards movement at the CBoT that represents the USA, Ukraine's main competitor on global corn markets.

Our research adds to the ongoing research analyzing drivers of volatility on agricultural markets. While most such research focuses on futures markets located in the USA, we determine market specific drivers of wheat and corn spot markets in the increasingly important Black Sea region. Future research should focus on seasonal drivers of grain price volatility, i.e. weather shocks and stocks-to-use rations. As especially Black Sea wheat markets seems to be rather uncoupled from traditional futures markets, our research helps to better understand this spot market that still lacks an effective futures market to facilitate price discovery.

References

ADM. 2017. "ADM presentations." *Transcript of Q3 2017 Archer Daniels Midland Company Earnings Conference Call.* October 31. Accessed March 8, 2019. https://www.adm.com/investors/presentations.

AHDB. 2018. *AHDB Market Data Centre.* Accessed Novermber 13, 2018. https://cereals.ahdb.org.uk/market-data-centre/marketdatacentre.aspx.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys. 2003. "Modelling and Forecasting Realized Volatility." *Econometrica* 71: 529-626.

Bollerslev, Tim. 1986. "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics* 31 (3): 307-327.

Brümmer, Bernhard, Olaf Korn, Kristina Schlüßler, and Tinoush Jamali Jaghdani. 2016. "Volatility in Oilseeds and Vegetable Oils Markets: Drivers and Spillovers." *Journal of Agricultural Economics* 67 (3): 685-705.

Carchano, Oscar, and Angel Pardo. 2009. "Rolling Over Stock Index Futures Contracts." *The Journal of Futures Markets* 29 (7): 684-694.

Energy Information Administration. 2018. *Historic spot prices.* Accessed November 13, 2018. https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm.

Gafarova, Gulmira, Oleksandr Perekhozhuk, and Thomas Glauben. 2015. "Price Discrimination and Pricing-to-Market Behavior of Black Sea Region Wheat Exporters." *Journal of Agricultural and Applied Economics* 47 (3): 287-316.

Hernandez, Manuel A., Raul Ibarra, and Danilo R. Trupkin. 2014. "How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets." *European Review of Agricultural Economics* 41 (2): 301-325.

Hoover, Kevin D., and Stephen J. Perez. 1999. "Data mining reconsidered: encompassing and the general-to-specific approach to specification search." *Econometrics Journal* 2: 167-191.

Janzen, Joseph P., and Michael K. Adjemian. 2017. "Estimating the Location of World Wheat Price Discovery." *American Journal of Agricultural Economics* 99 (5): 1188-1207.

Karali, Berna, and Gabriel J. Power. 2013. "Short- and Long-Run Determinants of Commodity Price Volatility." *American Journal of Agricultural Economics* 95 (3): 724-738.

Kilian, Lutz. 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market." *American Economic Review* 99 (3): 1053-1069.

McPhail, Lihong Lu, Xiaodong Du, and Andrew Muhammad. 2012. "Disentangling Corn Price Volatility: The Role of Global Demand, Speculation, and Energy." *Journal of Agricultural and Applied Economics* 44 (3): 401-410.

National Bank of Ukraine. 2018. *Official exchange rates.* Accessed November 13, 2018. https://www.bank.gov.ua/control/en/curmetal/detail/currency?period=daily.

Nazlioglu, Saban, Cumhur Erdem, and Ugor Soytas. 2013. "Volatility spillover between oil and agricultural commodity markets." *Energy Economics* 36: 658-665.

Patton, Andrew J., and Kevin Sheppard. 2015. "Good volatility, bad volatility: signed jumps and the persistence of volatility." *The Review of Economics and Statistics* 97 (3): 683-697.

Platts. 2018. *Market Data.* June 30.

Reuters. 2015. "As food prices rise, Moscow and Kiev consider export controls." *Reuters News.* February 24. Accessed February 28, 2019. https://www.reuters.com/article/food-wheat-russia-ukraine/as-food-prices-rise-moscow-and-kiev-consider-export-controls-idUSL5N0VR1K220150224 .

Russian Central Bank. 2018. *Official exchange rates.* Accessed Novermber 13, 2018. https://www.cbr.ru/eng/currency_base/daily/.

Serra, Teresa. 2011. "Volatility spillovers between food and energy markets: A semiparametric approach." *Energy Economics* 33 (6): 1155-1164.
Trujillo-Barrera, Andrés, Mindy Mallory, and Philip Garcia. 2012. "Volatility Spillovers in U.S. Crude Oil, Ethanol, and Corn Futures Markets." *Journal of Agricultural and Resource Economics* 37 (2): 247-262.
Uhl, Kerstin, Oleksandr Perekhozhuk, and Thomas Glauben. 2016. "Price Discrimination in Russian Wheat Exports: Evidence from Firm-level Data." *Journal of Agricultural Economics* 67 (3): 722-740.
USDA. 2018. *PSD Online.* Accessed February 18, 2019. https://apps.fas.usda.gov/psdonline/app/index.html#/app/home.

Annex

Table A 1. Descriptive statistics of annualized half-monthly realized volatility series

	Mean (%)	Standard Dev. (%)	Min. (%)	Max. (%)	Skewness	Kurtosis
Black Sea spot prices						
Black Sea wheat	8.2	4.1	2.4	22.9	1.18	4.21
Black Sea corn	10.3	5.7	0.4	36.3	1.36	6.59
Grain futures prices						
Euronext milling wheat	17.1	5.9	5.6	33.8	0.53	2.80
CBoT SRW wheat	24.8	7.7	11.8	49.3	0.92	4.14
Euronext corn	15.4	6.9	6.1	35.6	1.05	3.48
CBoT corn	20.6	8	6.3	49	1.02	4.27

Source: Authors' estimations.