Paper prepared for the 123rd EAAE Seminar

PRICE VOLATILITY AND FARM INCOME STABILISATION

Modelling Outcomes and Assessing Market and Policy Based Responses

Dublin, February 23-24, 2012

Price volatility and accuracy of price risk measurement depending on methods and data aggregation: The case of wheat prices in the EU countries

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Abstract

In this paper we use weekly milling wheat price series for nine selected EU countries to evaluate levels and components of volatility in the period from July 2004 to April 2011 and to examine how sensitive the results can be to spatial aggregation of the price data. The prices were analyzed in levels and logarithmic rate of returns. To asses price risk, apart from basic measures of price variability, the price series were decomposed using multiplicative model in order to determine shares of seasonal and random components in the total variance of the prices. We also applied ARMAX model to separate the stochastic components of the price series to properly evaluate real price risk exposure and tested for ARCH and GARCH effects. We found considerable differences when comparing various price volatility measures calculated for the analyzed countries indicating that wheat price risk exposure may vary across the EU.

Keywords: wheat prices, volatility, price risk, data aggregation

JEL classification: C22

1. INTRODUCTION

Volatility of the world agricultural commodity prices has been recently drawing a lot of attention mostly from the point of its sources and consequences to producers and consumers (World Bank, 2007, World Bank, 2009, Prakash, 2011). Numerous studies aimed at identifying causes of this phenomenon have been already conducted motivated mainly by the 2008 price spike and relatively high price levels of major agricultural commodities such as corn, rice and wheat after 2009, e.g. Abbot et al. (2008), Dong et al. (2011), Cooke and Robles (2009), Ghosh (2010), Gilbert (2010a,b), Mayer (2009). Mitchell (2008), Ledebur and Schmitz (2009) and Wu (2011). However, because of complexity of changes in factors underlying demand and supply no single reason can easily be identified as responsible for increasing volatility of the world agricultural prices. As presented in some FAPRI and IFPRI studies as well as in OECD-FAO Agricultural Outlook 2007-2017 the recent trends on the international commodity markets should be viewed as a structural break which will create tensions on the markets and most likely increase the volatility of commodity prices for the next 10-15 years (Blein and Longo, 2009). The list of the factors causing this tension and influencing volatility of agricultural commodity prices include:

- the impacts of climate change on agriculture, land degradation, and the intensification of floods and droughts in tropical areas;
- world population growth and increasing urbanization;
- increasing and more inelastic food demand due to per capita incomes rising globally including many poor countries;
- the growing demand for land in developing countries by outside investors, the degradation of land due to unsustainable agricultural practices, and ineffective management of water resources for agricultural use;
- transmission of price volatility from energy to agricultural markets as a consequence of increasing links to energy markets through both inputs such as fertilizer and transportation, and through biofuel feedstock;
- short-sighted agricultural public policies in response to food price increase and the associated risk of a return to agricultural protectionism resulting in trade restrictions, which amplify price volatility in international markets;
- low inventory levels and the slow rate of restocking at the household, state, regional and international levels;
- exchange rates and currency movements by affecting domestic commodity prices; and
- speculative influences related to the interests of financial investors diversifying their financial portfolios using commodity markets.

No matter how convincing these explanations are the real issue is whether participants of the agricultural commodity markets will be facing in near future permanently greater price volatility. The debate that hitherto has been conducted in literature seems to be dominated by arguments supporting the view that an increase in agricultural prices volatility should be treated as a fact (European Commission, 2009). Although some authors point out that evidence for increase in grains price volatility is weak (e. g. Gilbert and Morgan, 2010), an assumption that agricultural commodity markets will exhibit greater price volatility than it used to be may be plausible.

In general, increasing price volatility translates into greater price risk exposure. Therefore, appropriate measurement of price volatility and assessment of related price risk become very important for the market participants interested in mitigating negative impacts of price changes. This issue is central for markets agents interested in maximizing their utility functions regardless what market level they operate (global, regional, local). It is rather well understood that in the face of high price volatility an in-depth price risk analysis is needed to make right market decisions. Related discussions are usually focused on assessment of the price risk exposure using different methods and data sources (e.g. Figiel and Hamulczuk, 2010, Pop and Ban, 2011). Much less attention is paid to the issue how the use of various methods and types of data may influence results of an analysis, and hence market agents decisions.

Variability of agricultural commodity prices is natural as related to the functioning of market mechanism and is desirable as it reflects the process of markets adjusting to changes in supply and demand conditions (O’Connor and Keane, 2011). In addition, spontaneous reactions of numerous suppliers of agricultural commodities producing on their own account and assuming market risk inevitably lead to market anomalies. Reactions to the past prices create every time different market situations, each of them being a new search for equilibrium price and quantity. It should be noted that not all price changes can be treated as reflection of risk what often undermines the sense of price risk analysis based directly on time series without their appropriate decomposition. For instance, most market participants are aware of seasonal fluctuations, therefore, this type of price variability should not be taken into account while assessing pure price risk. Long term price developments such as trends also can't be treated as indications of risky situations. This is because market participants have time to adjust to such changes described as technological trends. Predictable components can be found both in cash and futures price series (Bester, 1999, Karali and Thurman, 2010). Thus, only parts of price variability can be considered as sources of price risk.

It can be assumed that market agents in the process of decision making try to predict future values of some economic variables. Agricultural producers gather and process market information in order to form their price expectations. Even if they do not exploit all of the information available in forming rational expectations they base the expectation of future outcomes on historical evidence. In other words producers are rational in the sense that their expectations of price levels and volatility reflect some form of adaptive or rational expectations (Moschini and Hennessy, 2001, Moledina et al., 2004) Such assumption is of course problematic as it is difficult to find out how widely and properly agricultural producers exploit available information and how well they know the mechanism generating changes. Nevertheless, it is justifiable to presume that the expected distribution of future price is a function of past realizations.

There are many ways of analyzing price variability beginning with simple measures of variation in price levels through analysis of differences and ending with relatively more sophisticated methods of time series analysis such as ARCH or GARCH (Alexander 1996, Andersen et al., 2005, Bollerslev, 1986). In any case results of price volatility analysis may be strongly dependent on both the type data used (especially the level of their spatial or temporal aggregation) and the methods applied for measuring price movements. Therefore, good understanding how the use of various data sets and analytical methods influences such results seems to be crucial for appropriate price risk assessment. Inappropriate measurement of price variability and consequently related price risk may result in use of irrelevant and inefficient policy instruments meant to stabilize agricultural prices and producers incomes. Also may have an impact on parameters determining value of market derivates used for hedging price risk.

The purpose of this paper is to evaluate price volatility and related price risk in the selected EU countries wheat markets using different methods and to examine how sensitive the results can be to spatial aggregation of the price data connected to the data collection system and averaging. The main reasons for choosing wheat prices for analysis were the availability of long enough time series and importance of this commodity for the UE agriculture.

2. DATA AND METHODS

In this paper we use weekly milling wheat procurement price series for nine selected EU countries to evaluate levels and components of volatility in the period from July 2004 to April 2011. The data source was the EU Commission on the basis of information communicated by Member States. The countries included in the analysis are: Belgium, France, Germany, Hungary, Italy, Lithuania, Poland, Slovakia and Spain. The data sets for these countries were the most complete with the number of gaps ranging from 1.69% to 13.34%. To equalize the length of the price series the lacking observations were interpolated. In addition, the average prices for the whole EU were also taken into account. Altogether 10 wheat price series consisting of 356 data points each constituted the basis for estimations.

To analyze wheat price volatility we applied several methods. The prices were analyzed in levels and logarithmic rate of returns. The first step was to plot a graph of the price movements and calculate descriptive statistics for the price levels such as mean, median, standard deviation, coefficient of variation and average relative changes of the prices over one year period. The price series (Y_t) were also decomposed into long term trend (TC_t), seasonal (S_t) and random fluctuations (I_t) using multiplicative model: $Y_t=TC_tS_tI_t$. Seasonality effect was identified using dummy variables (0, 1). The long term trend was estimated through smoothing using Henderson’s 13-element moving average (Findley et al., 1998). This part of the analysis allowed also to evaluate the share of seasonal and random fluctuations in the total variance of the price series. Price series usually behave as non-stationary processes, so in order to verify this presumption each of the series was tested for stationarity using the Augmented Dickey Fuller (ADF) test and the models with the best lag structure (Lütkepohl, 2004).

The next step was to examine the log returns for each price series calculated as:

$$r_t = \ln(\frac{Y_t}{Y_{t-1}}) \tag{1}$$

where r_t is the rate of return and Y_t denotes value of price variable in period t.

In this context a synthetic measure of risk can be annualized standard deviation σ_T defined as follows:

$$\sigma_T = [T * (\frac{1}{n-2})\sum_{t=2}^{n}(r_t - \bar{r})^2]^{0,5} \tag{2}$$

where $\bar{r}$ is the average rate of return in the period from 1 do n (number of observations, in our case 356) and T is the number of periods in year (52).

In another step of the analysis we separated predictable and unpredictable components of the price series according to the formula: $r_t=\mu_t+ \varepsilon_t$, where μ_t is the expected value in time t (predictable component) and ε_t is a random term (unpredictable component). Based on this approach when assessing price risk only stochastic unpredictable component is supposed to taken into consideration, not the predictable one. To estimate the latter we used ARMAX model such as:

$$r_t = \phi_0 + \sum_{i=1}^{k} \delta_i x_{i,t} + \sum_{i=1}^{p} \phi_i r_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3}$$

where r_t is the rate of return; ϕ_0, δ_i ϕ_i and θ_i are structural parameters; $x_{i,t}$ denotes seasonal dummy variables; and ε_t is the error term. So, in the estimations the model was limited to its autoregressive parts and seasonal components. The error term values were analyzed in respect of their distributions and existence of ARCH effect. We performed the Engle test for residual heteroscedasticity based on the LM test statistic (Engle, 1982) defined as:

$$LM = nR^2 \tag{4}$$

where n is the number of observations and R^2 is the coefficient of determination calculated for the following equation:

$$\varepsilon_t^2 = \alpha_o + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + u_t \tag{5}$$

where: α_0, α_i are the model parameters; ε_t^2 are residuals as described by equation (3); and u_t is the error component.

For price series with time-varying variance we applied GARCH modeling. A GARCH(p,q) model for rate of returns r_t can be written as follows (Bollerslev, 1986):

$$r_t = \mu_t + \varepsilon_t \tag{6}$$

$$\varepsilon_t = z_t \sigma_t \tag{7}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{8}$$

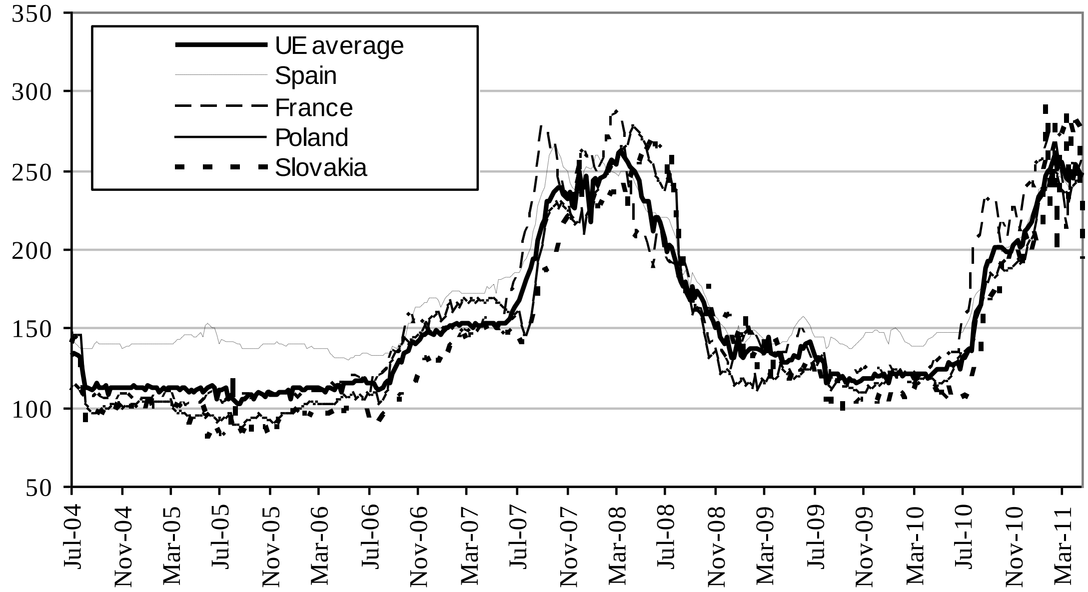
where: μ_t – represents expected value; ε_t is the error component from the model describing expected value with conditional normal distribution $N(0,\sigma_t^2)$; z_t denotes i.i.d. random variables with mean 0 and variance 1 following normal, Student-t or other distribution assumed; q is the degree of the ARCH(q) process; p is the degree of the GARCH(p) process; and ω, α, β are parameters of the model and must be non negative.

A conditional variance equation (8) makes variability dependent on the past values and squares of the rates of returns. The parameters β_j reflect expectations that the price volatility process will follow similar patterns as observed in the past, whereas, the parameters α_i show the influence of new information on price volatility development as expressed by σ_t^2. Seasonality of the variance was not modeled. Seasonal fluctuations were included only in the mean equation.

3. RESULTS

The analyzed wheat price series as the most agricultural commodity price series exhibit complex structure (Figure 1). Trends, cyclical movements, seasonal and random fluctuations caused by number of different factors can be especially seen in a longer time period. Seasonality often attributed to agricultural production was a less important part of the examined wheat prices variability than it could be expected. As reported in Table 1 the share of variance connected to seasonal variability in the total variance of the wheat price series is low ranging from 0.92 to 3.01%. It means that unconditional wheat price volatility is dominated by a longer time changes, mainly that of cyclical nature.

Figure 1. Milling wheat prices in selected EU countries in 2004-2011 [euro/ton]



Source: own calculations on the basis of the UE Commission data

Table 1. Descriptive statistics of weekly wheat prices series in selected EU countries

Country	Mean (euro/ton)	Median (euro/ton)	Average price change in a one year (%)	Standard deviation (euro/ton)	Coefficient of variation (%)	Share of seasonal component in the total variance (%)	Share of random component in the total variance (%)
Belgium	158.80	138.16	37.07	51.63	32.5	0.92	0.31
France	155.65	134.80	38.91	52.97	34.0	1.28	0.43
Germany	153.45	133.37	40.31	52.53	34.2	1.03	0.33
Hungary	137.11	113.01	45.80	55.33	40.3	2.51	0.75
Italy	168.12	144.72	32.18	48.97	29.1	2.94	0.40
Lithuania	139.49	124.32	39.82	48.16	34.5	2.76	1.16
Poland	147.73	124.15	39.82	52.20	35.3	1.80	0.29
Slovakia	142.60	124.39	44.86	54.29	38.1	3.01	1.47
Spain	169.79	147.90	26.42	39.46	23.2	1.83	0.27
EU	152.67	132.91	35.90	47.65	31.2	1.91	0.35

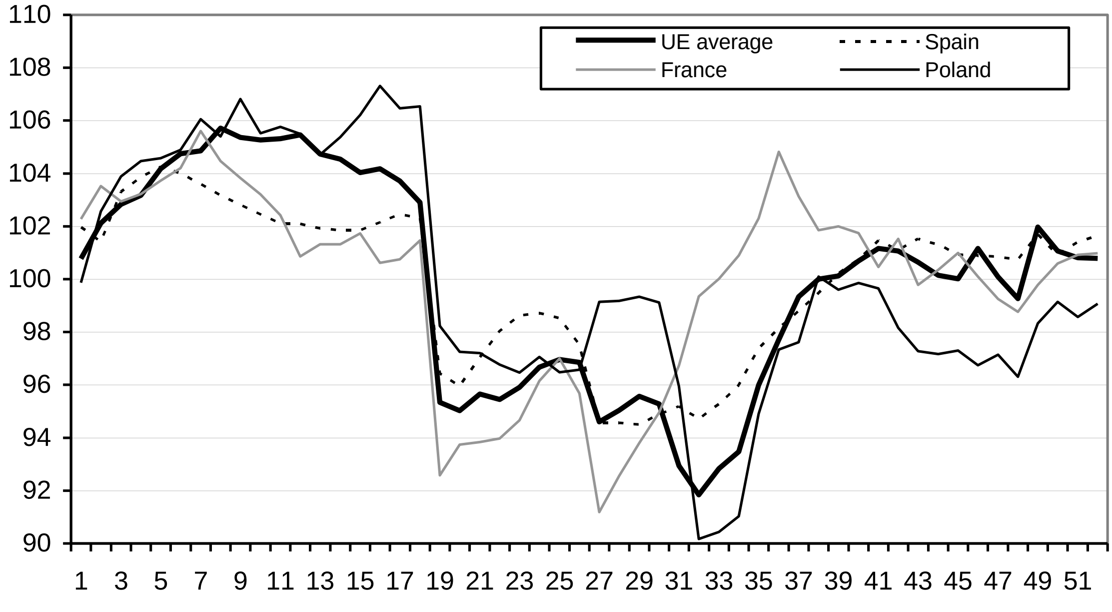
Source: own elaboration on the basis of the UE Commission data

On average wheat prices in the analyzed period where the highest in the Southern European countries (Italy and Spain) and the lowest in countries which became members of the EU in 2004. Comparison of coefficients of variations and relative magnitude of average price changes in a one year suggests that price risk in the wheat market was the greatest in countries like Hungary and Slovakia. The risk was somewhat lower in Germany, France, Lithuania and Poland and the lowest in Belgium, Italy and Spain. An alternative way of looking at price risk is to compare shares of random component in the total price variance. They were the highest for Hungary, Lithuania and Slovakia what may mean that more price risk occurs in smaller territorial markets. However, it can also be related to the level of the price data aggregation in particular countries depending on the number of the NUTS-2 units.

In general wheat prices have changed over time in a similar fashion in all countries considered. Values of correlation coefficients between single country prices and the EU average price exceeded 0.95 what can be viewed as a sign of a high degree of the wheat market integration in the EU and an evidence for the law of one price to hold in this market.

Wheat price seasonality indices calculated for France, Poland, Spain and the whole EU are presented in Figure 2. Patterns of seasonal fluctuations for other countries are similar and in most cases highly correlated, especially for the groups of geographically neighboring countries such as Eastern, Southern or Western Europe, where market proximity induces almost identical price movements.

Figure 2. Seasonal indices of wheat prices in selected EU countries in 2004-2011 [%]



Source: own calculations on the basis of the UE Commission data

Before analyzing log returns of the considered wheat time series each of the series was tested for stationarity using the ADF test. The results indicated that all series are non-stationary processes integrated of order 1. Consequently, for a better insight into the dynamics of respective price series we calculated the log returns for each of them. The descriptive statistics of them are included in Table 2. Applying Jarque-Bera test we found out that none of the log return series displayed normal distribution. The log return series distributions appeared to be leptokurtic what indicates higher than under normal distribution probability of larger price changes, hence greater price risk.

Table 2. Descriptive statistics of the log returns for wheat prices series in selected EU countries

Country	Mean	Minimum	Maximum	Standard deviation	Annualized standard deviation (52)	Skewness	Kurtosis
Belgium	0.002	-0.140	0.111	0.030	0.213	-0.549	4.758
France	0.002	-0.148	0.144	0.034	0.245	0.279	3.137
Germany	0.002	-0.151	0.178	0.033	0.236	0.051	5.306
Hungary	0.003	-0.297	0.215	0.054	0.386	-0.385	3.660
Italy	0.002	-0.198	0.211	0.029	0.212	0.388	13.408
Lithuania	0.002	-0.321	0.378	0.061	0.442	-0.012	6.699
Poland	0.002	-0.197	0.124	0.032	0.233	-1.542	8.579
Slovakia	0.001	-0.359	0.395	0.073	0.526	-0.263	8.532
Spain	0.002	-0.083	0.080	0.019	0.134	0.303	4.172
EU	0.002	-0.124	0.117	0.028	0.203	-0.086	3.334

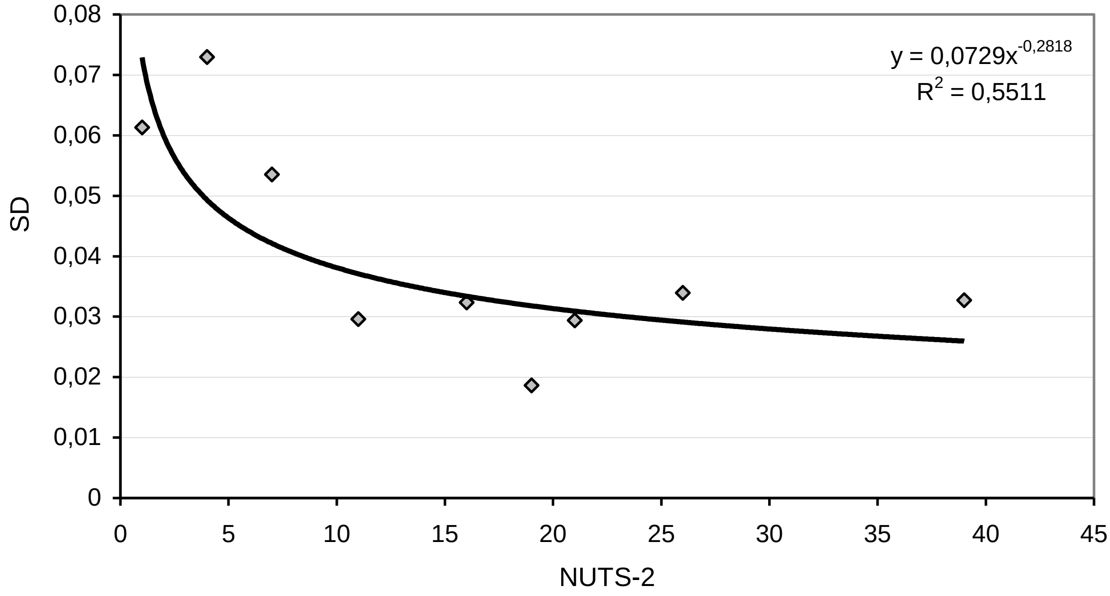
Source: own elaboration on the basis of the UE Commission data

An examination of results reported in Table 2 shows the greater price volatility associated possibly with the degree of data aggregation at the country level. The largest standard deviations are for Hungary, Lithuania and Slovakia. In case of Slovakia estimated probable price change in a one year amounts to 52.6%, which is over twice as much as in Poland or in the entire EU.

To further verify whether a relationship between volatility of weekly wheat prices and the degree of the price data aggregation exists we run a simple regression using number of NUTS-2 units in each country included in the analysis as a proxy variable reflecting the degree of the price data aggregation. Figure 3 shows the relationship between standard deviation of the log returns for weekly wheat prices and the number of the NUTS-2 units in a particular country, namely: Belgium – 11; France – 26; Germany – 39; Hungary – 7; Italy – 21; Lithuania – 1; Poland – 16; Slovakia – 4; Spain – 19. The total number of NUTS-2 units in the EU-27 is 271. The observed decrease in volatility measured by standard deviation of the log returns along with the increase in number of the NUTS-2 units as suggests that assessment of the price risk exposure based on the annualized standard deviation (Equation 2) may be biased. Especially, the larger the country is the more doubtful conclusions about price risk can be drawn based on the aggregated data collected at NUTS-2 level.

Assuming that agricultural producers are able to identify deterministic components such of price process such as trend or seasonality fluctuations these parts of price variability should not be considered as sources of the price risk (Dehn, 2000, Moledina et al., 2004). To estimate predictable components of the analyzed wheat price series we used the ARMAX type of model as described by Equation (3). Such model explains linear relationships existing in the log return time series. In the final calculations we included only lags and seasonal dummies which were statistically significant. Table 3 presents the results.

Figure 3. Relationship between standard deviation of the log returns for weekly wheat price series and the number of NUTS-2 units in the analyzed EU countries



Source: own calculations on the basis of the UE Commission data

Table 3. Summary statistics for the ε_t values of the ARMAX model of the log returns for weekly wheat price series in the analyzed EU countries

Country	Minimum	Maximum	Standard deviation	Annualized standard deviation (52)	Skewness	Kurtosis
Belgium	-0.111	0.097	0.026	0.185	-0.468	3.548
France	-0.143	0.142	0.033	0.236	0.173	2.457
Germany	-0.124	0.169	0.030	0.220	-0.030	5.536
Hungary	-0.282	0.192	0.050	0.360	-0.351	3.488
Italy	-0.197	0.172	0.028	0.201	-0.244	11.167
Lithuania	-0.306	0.208	0.055	0.395	-0.389	3.677
Poland	-0.131	0.134	0.028	0.205	-0.426	4.497
Slovakia	-0.308	0.415	0.066	0.477	0.046	8.598
Spain	-0.078	0.089	0.017	0.125	0.386	5.786
EU	-0.128	0.113	0.025	0.182	-0.099	3.966

Source: own elaboration on the basis of the UE Commission data

It appeared that the conditional mean model explains behavior of the log returns only to a small extent. Allowing for producers predictions of the prices reduced the estimated values of the annualized standard deviation in all cases but rather slightly (by 0.009 for France and Spain up to 0.049 for Slovakia). Also the distribution of the residuals have not significantly changed compare to the distribution of the log returns.

The fact that linear relationships do not explain much of the variability as well as non-normal distribution of the residuals indicate possibility of nonlinear relationships in the analyzed wheat price series. This means that price variability as a symptom of price risk might be changing over time. As consequence there will be successive periods of relatively low or high price risk exposures. To detect this we tested for ARCH effect applying Engle test for residual heteroscedasticity based on the LM test statistic (Equation 4). Results included in Table 4 show that the ARCH effect was confirmed with lag 1 for all countries apart from Hungary. In case of Belgium, France and Poland this effect seems to be weakening with the larger number of lags included.

Table 4. Summary of Engle test for residuals of the log returns of weekly wheat prices series in the analyzed EU countries (Equation 3)

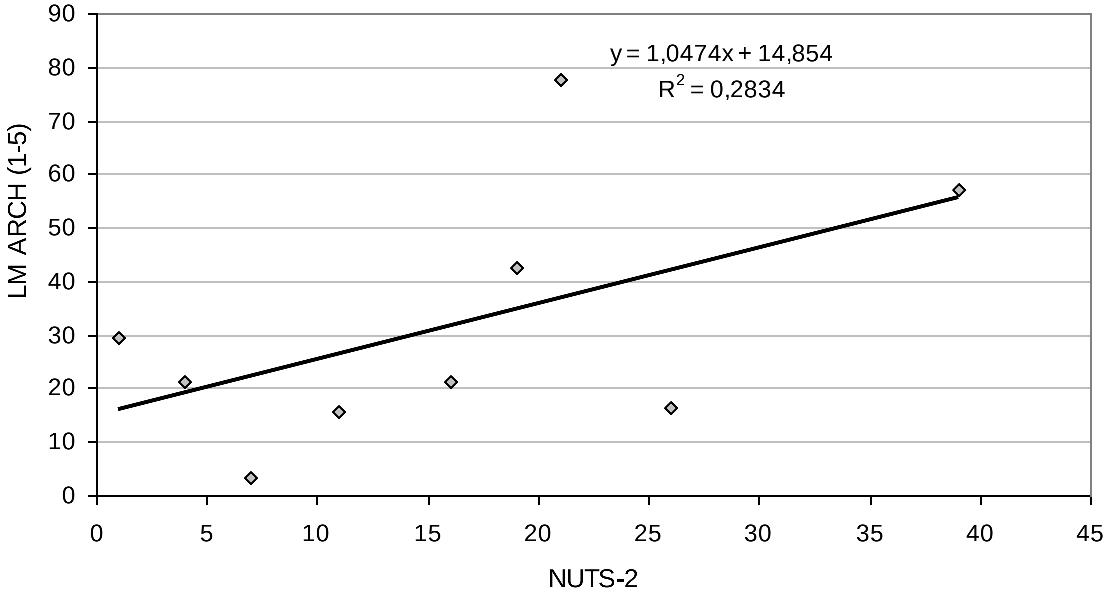
Country	Lag 1		Lags 1-5		Lags 1-10		Lags 1-25	
	LM_{ARCH}	P value	LM_{ARCH}	P value	LM_{ARCH}	P value	LM_{ARCH}	P value
Belgium	6.3331	0.0119	15.5220	0.0084	22.8441	0.0113	31.6105	0.0476
France	9.8826	0.0017	16.3308	0.0060	16.4568	0.0873	29.1987	0.0839
Germany	49.9169	0.0000	57.2541	0.0000	58.1498	0.0000	57.5052	0.0000
Hungary	2.9237	0.0873	3.2242	0.6655	3.9290	0.9505	5.7560	0.9992
Italy	65.3498	0.0000	77.5559	0.0000	78.5010	0.0000	78.7623	0.0000
Lithuania	27.9526	0.0000	29.5743	0.0000	36.1998	0.0000	38.6378	0.0074
Poland	35.7122	0.0000	21.3963	0.0007	26.8244	0.0028	30.6631	0.0598
Slovakia	9.2677	0.0023	21.1137	0.0008	42.0112	0.0000	46.9445	0.0006
Spain	40.0331	0.0000	42.5439	0.0000	44.2434	0.0000	49.1257	0.0000
EU	11.7539	0.0006	22.1578	0.0005	24.9290	0.0055	28.9163	0.0894

Source: own elaboration on the basis of the UE Commission data

Based on these results we can suppose that probability of consecutively occurring bigger price changes is higher than probability for the smaller ones while directions of these changes can differ. Such behavior of the weekly wheat price series is similar to price patterns observed in the financial markets, thus the type of price risk the participants of agricultural markets are exposed to should not be seen as much different (Holton, 2004). It is also worth to notice that how strongly the ARCH effect revealed was related to the size of the country markets in question, namely, the bigger number of the NUTS-2 units in the country the higher is the value of the LM_{ARCH} statistic. This relationship is shown in Figure 5 and it once again suggests that spatial data aggregation may play a role in shaping the results of the analysis.

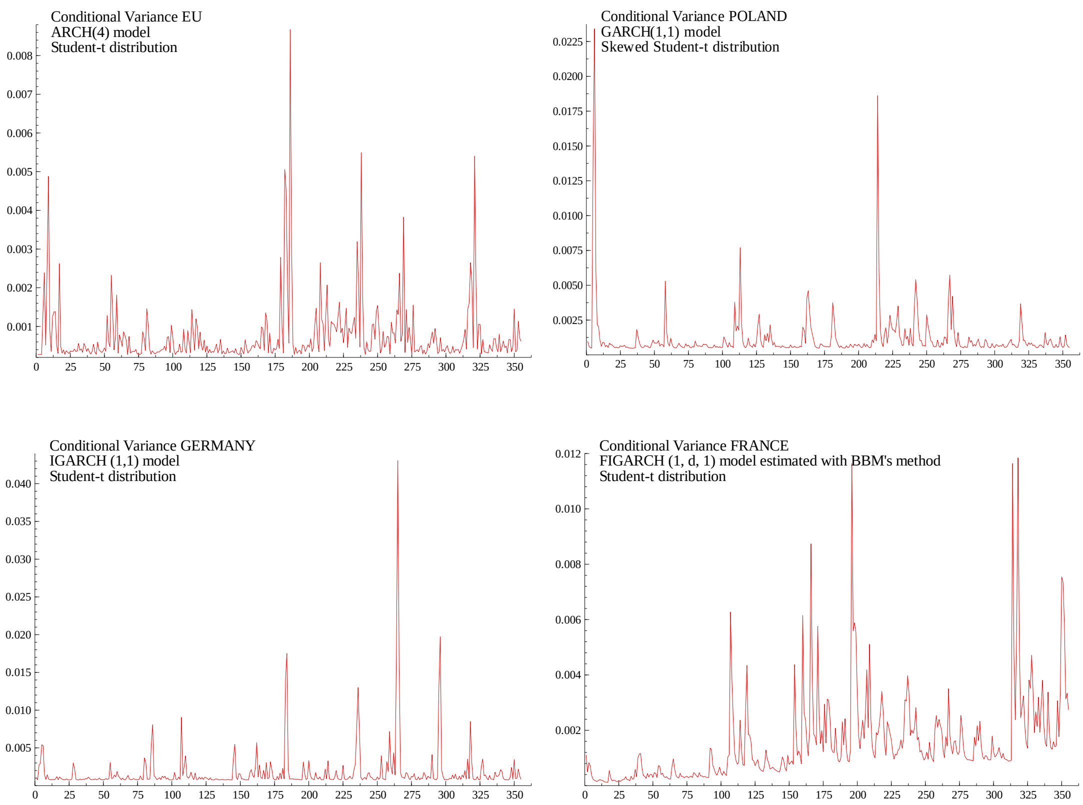
We also tried to parameterize ARCH effect using various ARMAX-GARCH models. The seasonality parameters were eventually omitted due their instability and relatively little importance of the seasonal component in explaining the total variance of the examined wheat price series. So, the models were simplified and became ARMA-GARCH. It appeared that Student-t or skewed Student-t distributions are more appropriate for the examined wheat price series than normal distribution of the innovations. GARCH (1,1) models were acceptable only in case of wheat prices in Hungary, Lithuania and Poland. Conditional volatility of the average wheat prices for the entire EU was explained best with the model simplified to the form of ARCH(4). For the rest of the wheat price series more suitable to capture conditional price volatility were such models as IGARCH (Germany, Italy and Spain) or FIGARCH (Belgium, France and Slovakia). Selected results of this modeling are shown in Figure 6.

Figure 5. Relationship between values of the LM_{ARCH} statistic and the number of NUTS-2 units in the analyzed EU countries



Source: own calculations on the basis of the UE Commission data

Figure 6. Selected results of the modeling conditional volatility of the wheat price series



Source: own calculations on the basis of the UE Commission data using G@RCH software

As it can been seen wheat prices conditional volatility patterns in the EU countries are different and no single model can be applied to describe them properly. For example in Germany short term effect prevailed (α = 0.93) whereas for example in Spain the persistence in volatility was higher (α = 0.63). An increase in wheat prices conditional volatility in the analyzed period is best visible in the case of French market. This volatility was also highly persistent. There is no strong evidence for existence of a clear relationship between the number NUTS-2 and wheat price volatility persistence although the values of the β parameter in the tested models were higher in larger countries except for Germany. So, convincing explanation why the wheat price conditional volatility patterns assessed on the basis of the EU Commission weekly data differ across the EU countries can't not be easily provided.

4. CONCLUSION

Comparing various price volatility measures calculated for weekly wheat price series in the selected EU countries we found considerable differences. This means that patterns of wheat price behavior in these countries are not the same, what implies different price risk exposure. However, proximity of the countries is related to similarity of the price movements indicating higher degree of price integration between neighboring markets. Price volatility levels appeared to be negatively correlated with the size of a country. On one hand this can be attributed to the market size, but on the other we suppose that this is also an effect of a country spatial aggregation of price data taking place at the NUTS-2 level (the bigger number of the NUTS-2 units in a country the lower level of price variability). Therefore, using country average may be inappropriate in assessing price risk exposure for market participants operating in various regions.

Another important finding refers to detecting the ARCH effect in weekly price series for almost all countries included in the analysis, contrary to some other studies based on monthly price series. However, it is worth to notice that how strongly the ARCH effect revealed was positively correlated to the number of NUTS-2 units in a particular country. When modeling GARCH effect it appeared that Student-t or skewed Student-t distributions are more appropriate for the examined wheat price series than normal distribution of the innovations. Simple GARCH (1,1) models were acceptable only in case of three out of ten modeled wheat price series. Apart from the average wheat prices for the entire EU more suitable to capture conditional volatility of the examined wheat price series were IGARCH and FIGARCH type of models as showing its non-stationary character. Thus, it can be stated that conditional volatility patterns of the weekly wheat prices in the EU countries are different and no single model can be applied to describe them in a satisfactory manner. This also means that market participants are likely to be exposed to different price risk depending on country and possibly region of their operations.

ACKNOWLEDGEMENTS

The paper includes results of a study conducted as a part of the research within the Multi-Annual Programme 2011-2014 "Competitiveness of the Polish food economy in the conditions of globalization and European integration" at the Institute of Agricultural and Food Economics – National Research Institute, Warsaw, Poland.

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