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MEASURING PRICE RISK IN COMMODITY MARKETS

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Key words: price risk, measurement methods, commodity markets, Polish wheat market.

Abstract

In the article concepts of price uncertainty and risk as well as econometric methods useful in measuring this type of risk are briefly discussed. Four the most frequently used approaches and related methods of measuring price risk in commodity markets were characterized and their potential application was empirically illustrated on the example of wheat market in Poland. Results of the analysis carried out showed that predictable and unpredictable components of the price series should be distinguished to properly evaluate real risk exposure. Some noticeable changes in the volatility of the wheat prices over the analyzed period indicate that exposure to the price risk in Polish wheat market after accession to the EU has increased.

MIERZENIE RYZYKA CENOWEGO NA RYNKACH TOWAROWYCH

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Słowa kluczowe: ryzyko cenowe, metody pomiaru, rynki towarowe, polski rynek pszenicy.

Abstrakt

W artykule omówiono koncepcje niepewności i ryzyka cenowego, jak również statystyczne metody przydatne w jego mierzeniu. Scharakteryzowano cztery główne podejścia i związane z nimi metody pomiaru ryzyka cenowego na rynkach towarowych oraz zilustrowano ich potencjalne zastosowanie na przykładzie rynku pszenicy w Polsce. Wyniki przeprowadzonej analizy wskazują, że przewidywalne i nieprzewidywalne komponenty szeregów czasowych cen powinny być rozróżniane, aby właściwie ocenić ekspozycję na ryzyko cenowe. Pewne, zauważalne w analizowanym okresie, zmiany w zmienności cen pszenicy wskazują, że po akcesji do UE wzrosła ekspozycja na ryzyko cenowe na polskim rynku pszenicy.

Introduction

Market agents are constantly facing various types of risks, which can be defined according to many different criteria. In fact, there is no single classification of those risks widely accepted as universal one. From managerial perspective several general risk categories can be pointed out such as: business risk, market risk, inflation risk, interest rate risk, credit risk, liquidity and derivative risk. In a globally competitive environment with instant communication cultural and currency risks become also important (HIRSCHEY 2003). In this context price risk is inherent to market risk and becomes especially evident when price volatility exists. Among the markets exhibiting relatively high level of such volatility are commodity markets. In order to effectively deal with price risk born on these markets appropriate understanding and measuring of such risk are crucial.

The purpose of this article is twofold. First, is to briefly discuss concepts of price uncertainty and risk as well as econometric methods useful in measuring this type of risk. Second, is to empirically illustrate application of the discussed methods to evaluate price risk on the example of wheat market in Poland. Polish wheat market represents a typical commodity market of significant size and with prices formed by domestic and international transactions. Thus, it meets criteria for empirical price risk analysis, which can be considered methodologically applicable for other commodity markets and serve as point of reference. The analysis was carried out using Polish monthly wheat procurement prices reported by the Polish Statistical Office (GUS) for the period from January 1996 to August 2010. The length of the price series allowed for assessing EU accession effect on the price risk in the analyzed market.

Notions of price uncertainty and risk

Both risk and uncertainty stem from perception of reality and knowledge about probabilities of events. Interpretations of probabilities can be objective or subjective. According to objective interpretations, probabilities are real and possible to discover by logic or estimate through statistical analyses. According to subjective interpretations, probabilities are human beliefs and they are not intrinsic to nature (HOLTON 2004).

The most famous general definition of risk was provided by KNIGHT (1921) who proposed that risk relates to objective probabilities while uncertainty relates to subjective probabilities. He distinguished *a priori* probabilities derived from inherent symmetries (as in throw of a die) and statistical probabilities obtained through analysis of homogenous data. He was also reluctant to treat opinions formed in the absence of symmetry or homogenous data as probabilities. Knight's definition has been criticized as based on a particular objectivist interpretation of probabilities, and being in fact a definition which addresses only measurable and unmeasurable uncertainty (HOLTON 2004).

According to common usage risk entails not only uncertainty but also exposure meant as possible consequences. This is because people care about the outcomes, and if someone has personal interest in what transpires, that person is exposed. Therefore, risk is exposure to proposition of which one is uncertain. Following this reasoning it can be stated that risk is a condition of individuals who are self-aware. Companies, organizations and government are not self-aware, so they are not capable of being at risk. They are sort of conduits through which individuals (members, employees, investors, voters, etc.) take risk. Consequently, subjective probability, utility as well as state preferences are tools for depicting the uncertainty and exposure components of risk. Using these tools we can only define some aspects of the perceived risk, not risk itself (HOLTON 2004). In the vast body of literature notions of uncertainty and risk are often interchangeable, although we assume that the term uncertainty should be used to describe the environment in which economic decisions are made, and the term risk to characterize the economically relevant implications of uncertainty.

Commodity price risk is one of very clearly perceived risks by producers, processors and traders. Price variability is a key aspect of this risk for all market participants. So, we attribute price risk to the volatility of price behavior to which the participants of a particular market are exposed. Volatility increases the risk of receiving lower or paying higher prices for a specific commodity, and it also makes the use of derivative instruments to hedge against price risk more expensive. Commodity prices in general are known to have a high volatility. Although there is no consensus as to what constitutes too much commodity price variability, it is generally agreed that price variability that cannot be managed with existing risk management tools can destabilize incomes, inhibit producers from making investments or using resources optimally, and eventually drive resources away from the sector. Thus, there is an obvious need for accurate measuring this risk in order manage it effectively.

Methods of measuring price risk

There are various levels and ways of assessing price risk. For instance, price risk can be evaluated at the company level with regard to specific market environment. Another levels would be overall market level (i.e. domestic as well as international markets for certain goods and services), or macroeconomic level (i.e. the economy as a whole). Also the ways of assessing price risk represent very wide spectrum of methods from fairly simple to sophisticated ones. In our article we focus on econometric methods of measuring price risk observable at the market level.

A lot of various concepts and methods of measuring price risk can be found in the literature. Most of them are based on assessment of historical prices volatility, however, there is a lack of consensus about the best solution for measuring risk and uncertainty connected with price changes. Great variety of concepts and methodological approaches could be justified in the context of different assumptions made about price expectations of producers and others market players (MOSCHINI, HENNESSY 2001, MOLEDINA et al. 2003, ANDERSEN et al. 2005).

Estimating price risk on the basis of prices volatility several key choices have to be made, namely:
- use price levels or price returns in the analysis;
- distinguish negative and positive price movements, or not;
- separate predictable and unpredictable components of price series, or not;
- treat variability as time invariant or time varying.

Having these issues in mind, four the most frequently used approaches and related methods of measuring price risk in commodity markets can be characterized. According to the first approach all price movements are treated as indicators of instability. In this type approach it is assumed that market agents behave in a naive way, so, they do not form any forecasts about future prices. Additionally, price levels (P_t) are taken into account to estimate price variability using statistical measures. The most common measures are classical unconditional standard deviation (σ) and coefficient of variation (V). They are computed as follows:

$$\sigma = \left[\frac{1}{n-1}\sum_{t=1}^{n}(P_t - \bar{P})^2\right]^{0.5} \tag{1}$$

$$V = \frac{\sigma}{P} \cdot 100 \tag{2}$$

where:
σ – unconditional standard deviation,
P_t – price in the period of t,
$\bar{P}$ – average price of commodity in the analyzed period,
n – the number of observations,
V – coefficient of variation.

Apart from the above measures another ones could be used, such as: average deviation, nonparametric volatility coefficient, or inter-quartile range. This type of approach is unsatisfactory for a number of reasons, however, the most important one is the fact that in real life we cannot not assume that market agents do not form any price expectations. It seems reasonable to assume that producers or buyers can distinguish regular movements in price behaviors such as seasonality or trend. In other words they are able, at least to some extent, to predict price changes on the basis of the past patterns and *ex ante* knowledge. Consequently, this is why such measures may overestimate degree of risk.

The second approach is to analyze price volatility using, instead of the price levels, price ratios (P_t/P_{t-1}) over a period of time, where P_t and P_{t-1} are price levels in periods t and $t-1$ respectively. In a practice, not ordinary ratios but logarithmic ratios (called rate of returns) are used. Logarithmic rate of returns have numerous advantages in comparison to ordinary returns, what make them very useful in both theoretical considerations and practical analyses. The first advantage is possibility of aggregation of returns in a longer period. The second, is fact that the simple ratio is an asymmetric measure. Positive returns are theoretically unlimited, whereas negative ones are very limited. Hence, logarithmic returns have better statistical properties. Logarithmic rate of return is computed as follows:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3}$$

where r_t is rate of return in a period t.

To analyze volatility on the basis of returns earlier described statistical measures could be used. Typically, it would be standard deviation of logarithmic ratios calculated according to the following formula:

$$\sigma = \left[\left(\frac{1}{n-2}\right)\sum_{t=2}^{n}(r_t - \bar{r})^2\right]^{0.5} \tag{4}$$

where $\bar{r}$ is an average return.

To asses volatility and risk in a longer period of time standard deviation formula can be extended to the form:

$$\sigma = \left[Z \cdot \left(\frac{1}{n-2}\right) \sum_{t=2}^{n} (r_t - \bar{r})^2\right]^{0.5} \tag{5}$$

where Z is the number of observations in the analyzed period (e.g. in case of monthly data and taking into account yearly cycle of agricultural production $Z = 12$).

One of the most important issues in price risk analysis is whether both positive and negative price returns should be treated as indications of such risk. It could be assumed that this depends on the market agent position on a spot market. For example, in case of wheat producer who carry stocks, only the negative returns indicating probability of decrease in prices could be treated as indication of risk. On the other hand processors for whom wheat is a part of the production costs would consider positive returns as indication of risk. Depending on the side of the market transactions (selling or buying) we might consider either downturn or upturn in prices as potential exposure to price risk. Correspondingly, only one kind of returns (negative or positive) should be analyzed in order to measure price risk. An appropriate measurement tool is semi-standard deviation, which is similar to standard deviation, however, the only observations from a data set included in the calculations are those which values are below the mean or a target level ($r_i < \bar{r}_0$). In other words it is a measure of downside risk. The formula for calculating this measure could be written as follows:

$$\sigma_s = \left[\left(\frac{1}{n-2}\right) \sum_{t=2}^{n} (d_t)^2\right]^{0.5} \tag{6}$$

where:
σ_s – semi-standard deviation,
$d_t = 0$, for $r_t \geq \bar{r}_0$,
$d_t = r_t - \bar{r}_0$ for $r_t < \bar{r}_0$,
$\bar{r}_0$ – mean or target value of the returns.

Semi-standard deviation (or semi-variance) includes only the values reflecting the negative direction of fluctuations of commodity prices from the threshold level, which delineates risky price movements from those which are not risky. Semi-standard deviation also could be used to measure upside risk meant as dispersion of all observations that rise above the mean or target value of a data set. The values of semi-standard deviation are always lower than that of total standard deviation of the distribution.

Semi-standard deviations are especially useful for analyzing longer lasting periods when distributions of returns are right skewed, and no single measure of dispersion summarizes the overall risk of the distribution. In case of relatively short investment period (e.g. monthly) distributions of returns are rather symmetric.

Using the two described above approaches we would intrinsically assume that market agents behave in a naive way meaning that they do not have the ability to detect regular features of the price process. It is rather obvious that market decisions of the agents are based on expectations other than naive ones. So, these approaches exaggerate uncertainty an related price risk (DEHN 2000, MOLEDINA et al. 2003).

The third approach to measure price risk eliminates or at least substantially mitigates this problem through decomposition of a price series and identifying its predictable and unpredictable components under assumption that the price volatility remain time invariant. Rationale for such approach seems to be obvious when we closer analyze demand and supply conditions of some of the commodity markets. An example would be agricultural commodity markets, in which the dynamic of prices is very complex (FERRIS 2005). Nevertheless, some price movements can be assumed as regular and thus predictable. The most common feature of agricultural prices is seasonality. The seasonality is being reflected in an upward and downward regular movement in prices during one year. In other words it represents intra-year fluctuations which are repeated more or less regularly year after year. It is difficult to envisage that for example farmers or processors do not have any idea about existence of such fluctuations.

Another type of variation which is supposed to be taken into account by market agents is the tendency of price evolution. When the data exhibit a steady growth or decline over time we can assume that in a long term the phenomenon is characterized by a trend**.** Statistically, a trend component of a price series can be classified as either deterministic or stochastic. Deterministic trend represents a smooth line, which can be described by simple mathematical equation (e.g. linear or exponential trend). Stochastic trend does not imply existence of a monotonically increasing or decreasing function, but simply the lack of a constant mean.

Finally, what might be observable in the price behavior is the cyclical component, which shows recurring values of the variable of interest above or below the trend line over a multiyear time horizon. The cyclical component describes more or less regular fluctuations caused by the economic cycle. Prices of agricultural commodity are affected by so called inventory cycle (e.g. hog cycle). The length of cycles is not constant, as the length of seasonal peaks and valleys, making prediction of economic cycles much tougher. By some analysts cycles are treated as a part of long-term tendency, so called stochastic trend.

In general, the discussed approach is based on assumption that all regular price movements could be predicted. To extract them an econometric model with explanatory variables can be applied. More convenient way is to use time series models, e.g., ARIMA (BOX, JENKINS 1983) or congruent models (ZIELIŃSKI 2002). In our article we present a model with deterministic elements for trend t and seasonality D_k and with autoregressive component r_{t-j} which is close to the second idea. Then, the risk is basically related to a summary measure of the unpredictable elements of the price process, so called error term (ε_t). To determine the level of price risk standard measures of variability such as standard deviation, semi-standard deviation or other could be applied. A relevant model could be estimated using price levels or price returns. The model, similar to that of DEHN (2000), reflecting logarithmic returns of the monthly prices r_t behavior can be written as follows:

$$r_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \sum_{j=1}^{p} \beta_j r_{t-j} + \sum_{k=1}^{11} \gamma_k D_k + \varepsilon_t \tag{7}$$

where:
α_0, α_1, α_2, β_j, γ_k – coefficients of the model,
t – time variable,
r_t, r_{t-j} – logarithmic returns and lagged logarithmic returns for the past periods j,
D_k – dummy variables for seasonal components,
ε_t – error term, a stochastic component of price returns.

The fourth approach to measure price risk, in contrast to the third one, allows us to treat variance as time varying. The approaches with the use of price returns discussed so far, are based the assumption that price volatility is time invariant. But, when observing real price behaviors very often there appear to be periods of higher and lower price volatilities. In a time series of returns we can see so called volatility clusters. They are formed as a result of autocorrelation in variance of returns. It simply means that large price movements are followed by movements of the same nature and the same apply to small kind of movements.

To carry out an analysis we can use either price returns of the r_t (see equation 3) or stochastic component ε_t (see equation 7). In the first case there is no distinction made between predictable and unpredictable component of the series. When volatility is estimated using stochastic component of the price series, then we analyze risk which constitutes a part of the price time series variability. One of the simplest methods which could be applied is exponentially weighted moving average model (EWMA). The following is the recursive formula for the variance of stochastic component:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1 - \lambda)\varepsilon_{t-1}^2 \tag{8}$$

where:
λ – smoothing constant,
σ_t^2 – current variance,
σ_{t-1}^2 – variance for the previous period,
ε_{t-1}^2 – previous value of stochastic component of the price returns.

In such model the estimated risk is time varying and more depends on last most recent returns (or innovations) than on the earlier ones. This is ensured by the use of smoothing constant λ which should be less than one. A higher λ indicates slower decay in the series of returns, or in the stochastic component. On the other hand, if we reduce the lambda, we indicate faster decay because the weights fall off more quickly. The decision about value of λ is rather subjective. According to HAUG (2007) it should be between 0.75 and 0.98. Alexander (1996) suggests smaller smoothing constant ranging from 0.5 to 0.7.

Time varying conditional variances can be also obtained by applying parametric methods such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (BOLLERSLEV 1986). The most commonly used is univariate GARCH(1.1) specification, according to following formula applied to the stochastic component of the equation 7:

$$\sigma_t^2 = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \delta_1\sigma_{t-1}^2 \tag{9}$$

where:
γ_0, γ_1, δ_1 – coefficients of the model.

Parameters of equation 9 are estimated using maximum likelihood methods on the basis of a set of assumed initial values of the squared innovations and the variances. GARCH(1.1) model in comparison to EWMA model is a mean reversion under condition that $\gamma_1 + \delta_1 < 1$. Model reverses to the mean variance which can be calculated using the following formula:

$$\sigma^2 = \frac{\gamma_0}{1 - \gamma_1 - \delta_1} \tag{10}$$

An empirical illustration

We illustrate our theoretical considerations about commodity price risk measurement methods using Polish wheat procurement prices for the period from January 1996 to August 2010. Figure 1 presents behavior of those prices together with calculated trend (T) and long-term tendency, so-called trend-Cycle (TC). The computations were made using Hodrick-Prescott filter and ARIMA X-12 method (FINDLEY et al. 1988).

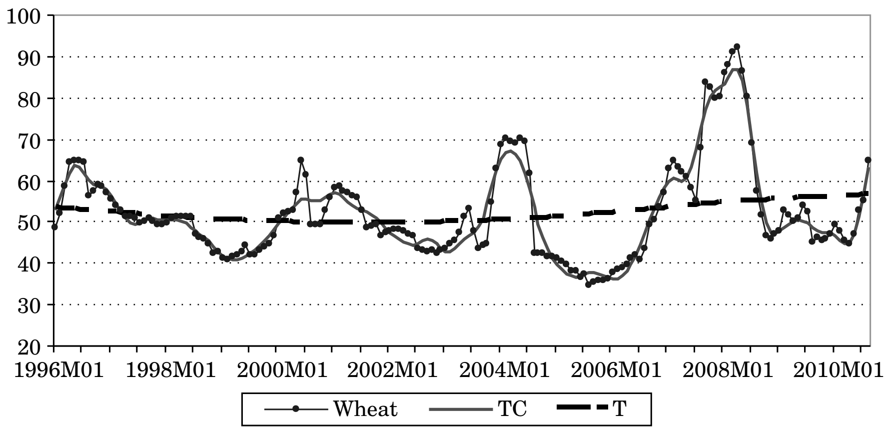

Fig. 1. Volatility of Polish monthly wheat procurement prices in the period from January 1996 to August 2010 (PLN/100 kg)
Source: own calculations based on the Polish Statistical Office (GUS) data.

When examining the depicted price variability we can notice that the most important part of it is connected to cyclical behavior. Variation of the cycle component of the wheat price series represents 84.4% of total variability. The length of cycles, as well as their amplitudes, are not constant over the analyzed period. The variance of the seasonal component, which is the most known type of variability in agricultural commodity markets, constitutes only 6.3% of total variance of the price series. Decomposition procedure applied allowed us to conclude that seasonality is also time varying. In 2009 the highest prices during a year were in February (seasonal index was 1.06) and the lowest from August to October (0.95–0.96). Trend and irregular variation are responsible for 3.5% and 2.8% of the total variance of series, respectively.

The basic statistics characterizing the analyzed price behavior are included in Table 1. There is no big difference between values of the mean and the median what may suggest that the distribution of series is close to the normal one. Other statistics indicate that the distribution is rather right-skewed. Wheat prices may be seen as highly volatile as the range between minimum and maximum is equal to 57.64 PLN, however during half of the analyzed period they fluctuated between 44.17 and 57.11 PLN. An average deviation from the mean is 11.48 PLN (22.05%).

Table 1

Values of the basic statistical measures of the nominal wheat procurement prices in Poland, their returns and stochastic component for the period from January 1996 to August 2010

Measure	Nominal prices	Log returns of prices	Stochastic component
Mean	52.0407	0.0017	0.0000
Median	49.5150	0.0035	-0.0037
Variance	131.7160	0.0045	0.0030
Standard deviation	11.4768	0.0669	0.0550
Minimum	34.5200	-0.3764	-0.2856
Maximum	92.1600	0.2102	0.2664
Range	57.6400	0.5865	0.5520
Lower quartile	44.1650	-0.0207	-0.0247
Upper quartile	57.1050	0.0238	0.0245
Interquartile	12.9400	0.0445	0.0491
Standardized skewness	7.5071	-4.5652	1.3968
Standarized kurtosis	5.6595	19.2221	20.8255
Coeff. of variation	22.0534	X	X

Source: own calculations based on the Polish Statistical Office (GUS) data.

Log return of wheat prices calculated according to the equation 3 are plotted in Figure 2. The mean of monthly returns is slightly positive. Returns of the wheat prices are not normally distributed. They behave as prices of the most of financial assets being left skewed and highly leptokurtic. The value of standard deviation amounts to 0.067 what indicates that unconditioned volatility is 6.7%. Applying equation 5 allows us to asses price risk in one year horizon. The estimated statistic is 0.23 what should be interpreted that during 12-month period the risk of a change of wheat prices is 23%.

The downside risk was estimated using equation 6. The calculated value is 0.049, which indicates 4.5% of risk connected with decrease in prices. The risk of decrease in wheat prices in 12-month horizon is 17%.

The values of the statistics presented so far can be overestimated because expectations of the market agents were ignored. In order to capture only this part of the analyzed price volatility which is unpredictable, equation 7 was employed to the log price returns series (Fig. 2). Parameters of the model estimated using the OLS method and backward selection procedure are the following:

$$r_t = 0.005 + 0.463r_{t-1} - 0.063D_7 - 0.042D_8 + 0.056D_9 + \varepsilon_t;\ R^2_{ADJ} = 30.75;\ DW = 1.82.$$

All coefficients, apart from the constant, are statistically significant. Model explains over 30% of the total variance of returns. It means that by such part of variation the previous estimates of the price risk were overvalued. In Figure 2 the estimated stochastic component with the log returns can be compared. Estimated standard deviation of ε_t is 0.055 (see Table 1). The risk in one year time perspective is now 19%, which is lower than 23% when the whole variation of price returns is taken. The distribution of stochastic component now seems to be symmetric, and not skewed as it was in case of the log price returns (see standardized skewness coefficients in Table 1). Stochastic component of the prices is also highly leptokurtic.

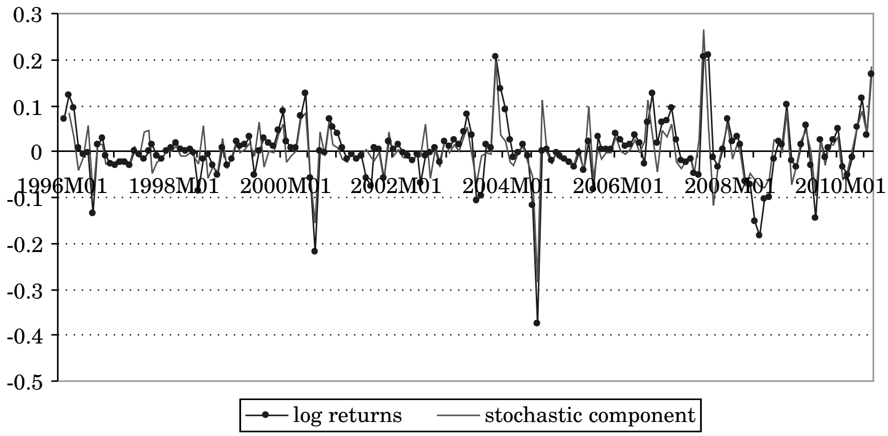

Fig. 2. Log returns and stochastic component (ε_t) of the analyzed prices
Source: own calculations based on the Polish Statistical Office (GUS) data.

Examining the unconditional price risk we have initially assumed that its level doesn't change from period to period. Numerous researches show that the prices form so called volatility clusters, which indicate that the concerned risk might be time varying. To estimate time varying risk we use the values of the stochastic component presented in Figure 2. The first estimation was made using EWMA model. In our empirical illustration two values of the smoothing constant were used: 0.94 and 0.98 (see Figure 3). When the variance of stochastic component and smoothed values are compared it appears that the model with lambda equal to 0.98 is better from the statistical standpoint (i.e. the errors are lower).

When analyzing estimated values of standard deviation calculated as the root of variance from the equation 8 (Fig. 3), we can suppose that wheat price risk may be time varying and furthermore it seems to be rising over time. So, it implies that integration with the EU market hasn't reduced the price risk in the Polish wheat market. This finding also asserts conclusions from our earlier conducted analysis (FIGIEL, HAMULCZUK 2008).

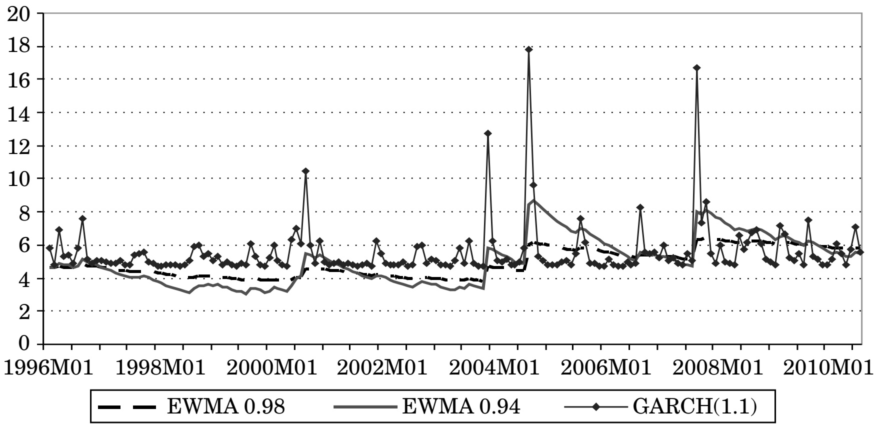

Figure 3. Conditional volatility of the analyzed prices (%)
Source: own calculations based on the Polish Statistical Office (GUS) data.

Before starting to estimate a GARCH(1.1) model we analyze an ARCH effect in the stochastic component of the price movements. Computed LMARCH statistics[1] (ENGLE 1982) for 12 and 24 lags are 9.91 ($p = 0.62$) and 13.86 ($p = 0.95$), respectively. These values do not allow us to reject H:0 hypothesis stating that ARCH effect doesn't exist. The obtained statistics suggest lack of volatility clustering. Non existence of conditional volatility was confirmed by the following results of estimation of the GARCH(1.1) model and respective t-values:

$$\begin{array}{lcccc} & \hat{\sigma}_t^2 = & 0.00207 & + \; 0.3598\, \varepsilon_{t-1}^2 & + \; 0.0813\, \sigma_{t-1}^2 \\ t \text{ value:} & & (1.97) & (0.36) & (0.43) \end{array}$$

Both past innovations and past variance are statistically insignificant what suggests that the simplest GARCH model doesn't describes properly conditional risk of the wheat prices. It should be emphasized that this is not a confirmation of the lack of conditional volatility at all. It simply means that GARCH(1.1) model doesn't properly describe it and there may exist another

[1] $LM_{ARCH} = T \cdot R^2$, where: T – number of observations, R^2 – determination coefficient.

models of the GARCH class which are more appropriate. We also have to bear in mind that the price series analyzed were monthly data whereas GARCH models are usually used to examine behavior of hourly or daily financial market price series. It's worth to mention that other authors have also not been able to provide evidence of unconditional volatility for the most monthly agricultural commodity prices in Poland (BORKOWSKI, KRAWIEC 2009). The long-run variance (long-run equilibrium) calculated according to equation 10 amounts to 0.0037, so unconditional standard deviation in percentage form is just 6.1%.

Conclusion

Price risk exposure is usually analyzed as related mainly to adverse movements in prices of financial assets. Behavior of the commodity prices is not much different as far as volatility is concerned, thus the need for proper identification and accurate measurement of price risk in the commodity markets is indispensable. The existing methodology offers a lot of solutions, however, due to lack of consensus about which methods of measuring price risk should be preferred, it seems reasonable to use various alternative approaches and compare obtained results to appropriately assess risk exposure.

Risk perception depends on knowledge about potential price movements and ability to forecast them by market agents. There is a strong economic evidence that market players are able to detect regular features of the price process. This suggests that price risk should be estimated using methods allowing the analysts to distinguish predictable and unpredictable components of the price series, otherwise, evaluation of real risk exposure could be easily overstated.

Analyzing monthly wheat procurement prices in Poland using parametric GARCH(1.1) we cannot confirm existence of the conditional volatility. On the other hand the results obtained from the EWMA model provide some evidence of changes in the volatility of the wheat prices over the analyzed period, especially appearance of a rising trend in it. This observation clearly suggests that after accession to the UE exposure to the price risk in Polish wheat market has increased what calls for a broader practical use of market risk management tools by participants of this market.

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