Optimal Grain Marketing Revisited: A German and Polish Perspective

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ABSTRACT

Increasing grain price volatility over the last year has revived the discussion on optimal marketing strategies. Various models of optimal grain marketing have been proposed and simulated in the literature. In this study an overview on these models is presented and critical aspects are discussed. Optimal strategies are then applied to the wheat market in Germany and Poland. Results indicate that gains from optimal marketing are rather small and uncertain in the real world, indicating that scientific assistance might be of limited importance. However, an understanding of optimization and price generating processes is likely to improve farmers' decisions, e.g. if farmers have additional (private) information to improve price forecasts.

1   INTRODUCTION

Post harvest grain marketing decisions have regained significant attention of producers, consultants and other experts in the EU as a result of the rapid price changes over the marketing year 2007/08. After decades of highly predictable prices, producers in the EU are facing the challenge of adjusting the production structure and the marketing of products to dynamically changing and uncertain market conditions. The new Eastern European member states, such as Poland, are additionally facing a backlog in the institutional development regarding the establishment of commodity exchanges, advisory and extension services, and public institutions providing access to information. In Poland, smallholders in particular have restricted access to markets and information. Therefore, reliable price forecasts and applicable marketing strategies are in high demand by grain producers.

However, the scientific literature on grain marketing and/or forecasting issues focusing on European agricultural markets is rather limited. In Europe and elsewhere, the scientific research in this field tends to mainly focus on futures markets; however, statistical evidence indicates only a low involvement of farmers in futures markets worldwide. According to Schroeder and Goodwin (1993), in the US less than 3 % of the grain volume produced is traded by futures contracts; forward contracts account for about 11 % and options traded account for another 4 %. The futures exchange in Hanover, Northern Germany (RMX, Risk Market Exchange), does not even come close to a one percentage share with respect to pro-

duction volumes. In Poland, future contracts are still an emerging issue. Despite the fact that the Polish commodity exchange in Warsaw has formally introduced futures contracts on bread wheat and feed wheat since 1997, no respective turnover can be observed over the last ten years. The lack of appropriate legislative acts governing the futures transactions and the restricted access of small volume traders are most likely the most important factors hindering the development of the future exchange in Poland.

In addition to the fact that research has not primarily focused on grain marketing and/or forecasting issues, Brorsen and Irwin (1996: 68) claim that the "agricultural economists' research on forecasting and marketing strategies is of limited relevance to real world applications." They attribute this to low rankings of university extension services, which ranked twelfth out of nineteen information sources, behind farm magazines, commercial newsletters, etc. (Smith 1989). This is due to a lack of incentives for researchers who aim at peer-reviewed journals employing secondary data instead of conducting empirical research that solves real world problems using primary data. With respect to optimal grain marketing decisions, the assessment seems to be fitting for the whole EU (i.e. Germany and Poland).

Our paper aims to fill and explain the above-mentioned gap in the literature by whether economic research can significantly improve farmers' decisions in optimal grain marketing. Therefore, in the second section we review selected approaches to derive optimal marketing strategies. Afterward we apply the models using recent data for the German and the Polish wheat markets. The theoretical and empirical results identify and discuss the opportunities and constraints regarding the support of optimal post harvest grain marketing decisions.

2 THEORY OF OPTIMAL GRAIN MARKETING

The models described in this section represent the decision problem faced by a typical grain farmer with storage facilities. Farmers must decide how much of the stored grain to sell - and when to sell it - in the planning horizon, which is defined in this study as the time span between harvests. Under price uncertainty a stochastic dynamic optimization algorithm is developed to solve the problem according to the respective target function. Farmers usually aim to maximize expected profits and minimize risk and/or instability. Loy and Mueller (2004) interviewed forty-four grain farmers in Germany with grain storage facilities. Their answers clearly indicate that profit maximization is of highest importance to farmers. Stability of cash flows and profit certainty are second-ranked goals. Additionally, three Polish experts were asked for their analytic expertise regarding the main objectives of a typical Polish grain pro-

ducer. They indicated that the profit maximization assumption holds, particularly for specialized commercial farms. Furthermore, minimizing risk and stabilizing income are top goals for all producers. In the following considerations, however, we assume the maximization of expected profits to be the sole target function.

2.1 Model Assumptions and Solution Algorithms

In our model, a competitive risk-neutral farmer with storage capacities is assumed to face a fluctuating demand under risk. The farm level output price is a stochastic variable; its density functions are identical and independent (iid) for each decision period (i.e. week) over the marketing season. Farmers' marketing strategies do not affect the distribution of current or future prices. Farmers have a fixed quantity of grain stored after harvest, which can be sold immediately at harvest or in portions during the planning horizon (marketing season). The marketing decision is irreversible, which means that stocks cannot be refilled after selling. Other marketing alternatives such as forward, future contracts or options are not considered. Furthermore, we assume that marginal storage costs are deterministic and increasing over time and cover inventory losses, interests, commercial storage costs, etc.

Berg (1987) was the first to address the decision problem under the above-mentioned assumptions. He discusses two solution algorithms, open-loop and closed-loop. The first describes a fixed sequence of actions over the planning horizon, while the second relies on additional information on current price developments. In the open loop algorithm, the period for which the difference between expected price and respective storage costs is maximized is determined. The grain is always sold in that period. This strategy will be called sER (simple Expected Revenue).

The sER strategy can be improved by a simple updating procedure. If the decision rule is rechecked in every period through the marketing season, then we call it the ER strategy. The ER algorithm is superior compared to the sER, because it allows more flexible planning. However, its performance still falls behind the closed-loop algorithm developed by Berg (1987).

The closed loop algorithm by Berg (1987) also uses the incoming price information. Let P_t be the current market price in decision period t. We assume that there is a threshold price, P_t^*, at time t, at which the farmer is indifferent between selling and holding the stock. In each period, a risk-neutral farmer compares the revenue of selling at price P_t, (R_t) with the expected

revenue by applying certain threshold prices in remaining periods ($E[R_{t+1}]$).[1] Selling the stock in decision period t occurs as long as $R_t >= E[R_{t+1}]$. We will denote $R_t^* = E[R_{t+1}]$ as the optimal cutoff revenue (OCR). For instance, at the end of the planning horizon (i.e. t=T) the only feasible option for farmers is selling at any price (R_T^*=0); thus, the expected profit ($E[R_T]$) is the expected price for that period minus the respective storage costs. One period earlier (T-1) farmers sell the stock for a price that provides a revenue higher than (or equal to) $E[R_T]$. Thus, the OCR (threshold revenue) in decision period T-1 is $R_{T-1}^* = E[R_T]$. Following up this decision rule, the expected revenue for T-2 is calculated as follows:

$$E\left[R_{T-2}\right] = \int_{R_{T-1}^*}^{\infty} R_{T-1} f\left(R_{T-1}\right) dR \left(\int_{R_{T-1}^*}^{\infty} f\left(R_{T-1}\right) dR \right) + \int_0^{\infty} R_T f\left(R_T\right) dR \left(1 - \int_{R_{T-1}^*}^{\infty} R_{T-1} f\left(R_{T-1}\right) dR \right) \qquad (1)$$

with

R_{T-i} :   Revenue at time $T-i$

$f(R_{T-i})$:   Probability of R_{T-i}

R_{T-i}^* :   Cutoff Revenue at time T-i

Hence, determining an optimal marketing strategy involves finding a unique vector of threshold prices or revenues R_t^*, t= 0, 1,…, T-1. To switch from cutoff revenues to threshold prices, we simply add the cumulative storage costs from the harvest up to that time. The decision problem can be solved by backward recursion in a dynamic programming framework. In the case of risk-neutral farmers, the strategies discussed (ER, sER, OCR) lead to either a sell or hold-all strategy. Another simple reference system is the ES (equal share) strategy for which farmers sell an equal share of the stored grain in each period during the marketing season.

2.2   Model Extensions

So far we have kept the model simple by considering the problem in terms of a risk-neutral decision maker or ignoring the dependence of prices along time periods. In the following discussion we address some possible extensions regarding these issues.

Assuming risk aversion, one must maximize the expected utility (i.e. the certainty equivalent of the revenue) instead of the expected revenue. In this case the optimal marketing strategy

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[1]   In the respective period the storage costs up to that period are considered to be sunk costs. However, to simplify equation (1) and to ensure the comparability of revenues over time, current prices and expected future revenues are denominated by storage costs of the past periods. By doing so, we denominate profits to the time at the beginning of the storage season.

might lead to multiple selling dates with varying quantities sold because income certainty decreases *ceteris paribus* with the amount in storage, as does the certainty equivalent income per unit of future sales. Thus, by selling in the current period, the absolute deviation of future income decreases.[2]

Updating prices and price density functions at each point in time can improve the marketing strategy outcome because real world cash prices often show significant autocorrelations and time-dependent probability distributions. One of the first models to consider autocorrelations of prices is presented by Blakeslee and Lone (1995). Fackler and Livingston (2002) present a continuous-time stochastic dynamic programming approach based on Ito diffusion processes for cash prices by which also the time dependency of prices is modeled. Though these models have a significant impact in the case of risk averse farmers, the effect of autocorrelated cash prices on expected storage revenues or gross margins declines rapidly with the level of auto-correlation. For the border case that revenues are following a random walk (without drift), the volatility of future revenues cannot be exploited at all. For stationary autoregressive or mean reverting cash prices or similar continuous processes, the algorithms by Blakeslee and Lone (1992) and Fackler and Livingston (2002) are superior to Berg's approach. However, the economic significance of the advantage in terms of expected additional profits compared with other marketing strategies is rather small for risk-neutral actors.

3 EMPIRICAL IMPLEMENTATION

3.1 Data and Statistics

Our empirical application deals with German and Polish wheat markets. We use weekly wheat prices to determine optimal grain marketing strategies for both markets. Data on German wheat prices are collected from several sources: Farm prices are provided by a public extension service (the Landwirtschaftskammer in Schleswig-Holstein), whereas wholesale prices are collected by a market information agency (ZMP in Bonn). The German data cover

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[2] Even though the implementation of risk awareness in these models is made straightforward by implementing a utility function, one might question whether producers are really concerned about risk within a marketing season. Annual risks and variations of gross margins are more likely to be relevant for producers. However, these risks are not modeled in the proposed solution algorithms. As sales are often split to multiple periods, the law of large numbers accounts for some reduction in the variance of annual gross margins, at least in the case of stationary stochastic price processes.

the period from 1993 to 2008.[3] Polish data are provided by the Polish Ministry of Agriculture; the available set contains weekly farm prices from 2003 to 2008. All prices are nominal and converted in Euros. The official exchange rate of 1.9588 German Marks per Euro is used for German prices prior to 2002. The Zloty/Euro daily rate is taken from the Oanda web page; the daily rates have been aggregated by equal weights to weekly rates. We run the simulations using farm prices for both markets. However, as farm prices are often missing in weeks just before the harvest and data for Poland are available for a short period of time (2003 to 2008), unit root tests are applied to the German wholesale prices only. Figures 3 and 5 show the development of the average farm prices and wholesale prices in Germany and Poland. The results for the unit root tests can be projected to the farm prices in Germany and Poland because the respective series indicate a very strong co-movement.[4] Graphical inspection indicates that prices show significant autocorrelations, a downward trend, and some seasonal regularity, which has been considered in the testing procedures.

Figure 3:   Farm and wholesale prices of bread wheat in Germany in Euro/t
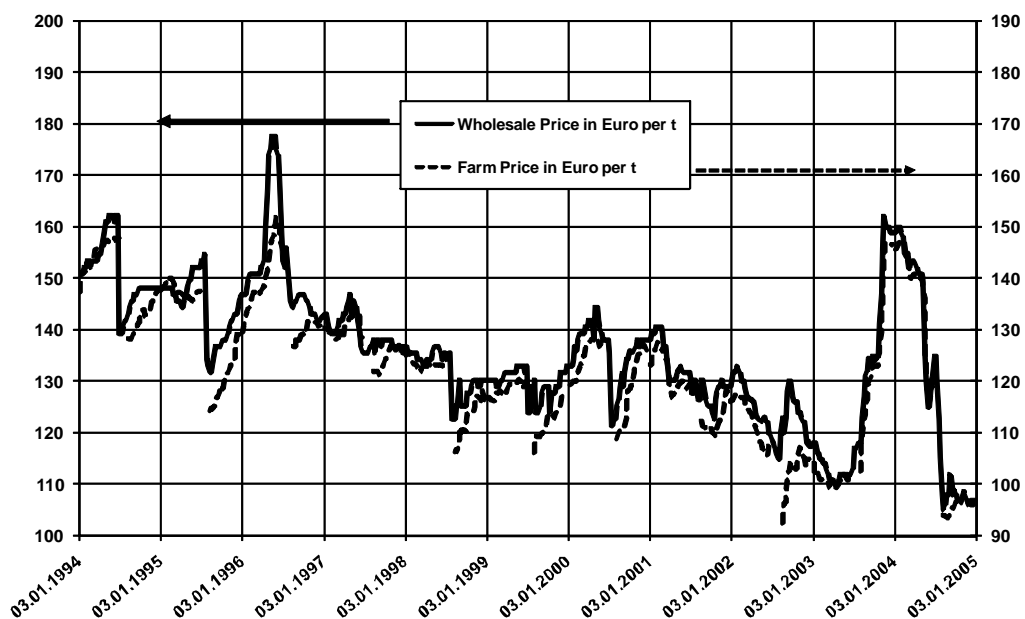
Source: LWK (2008), ZMP (2008).

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[3]   The data represent current price quotations for Schleswig-Holstein and Hamburg, a state and city in northern Germany, respectively. Because grain markets in Germany are highly integrated, we assume in the following that these price quotations sufficiently represent the German market.

[4]   Alternatively, panel estimation and testing techniques could be applied to the farm prices.

When marginal storage costs are deterministic or constant and linear or nonlinear with respect to time, price level, or stock volume, the data generating process of cash prices determines the adequacy of the optimization algorithm and the potential gains of the chosen marketing strategy. Because random walks do not leave any opportunity for making profits by marketing strategies, unit root tests need to be applied at first.

Table 2 reports the results of the unit root tests for the wholesale wheat prices in Germany. The ADF and the Schmidt-Philips tests reject the unit root hypothesis. However, the KPSS test rejects the Null-hypothesis of trend-stationarity for the nominal price series.[5]

Table 2: **Unit root test results for wholesale wheat prices**

Wheat prices	Test statistic	CV	d-Lag	Trend
ADF	-3.64*	-3.41	2	X
SP Z(Rho)	-18.05	-18.10	2	--
SP Z(Tau)	-3.021*	-3.02	2	--
KPSS	0.45**	0.15	2	X
Wheat prices*	Test statistic	CV	d-Lag	Trend
ADF	-5.79**	-2.86	1	0
SP Z(Rho)	-63.95**	-18.10	1	--
SP Z(Tau)	-5.81**	-3.02	1	--
KPSS	0.12	0.46	1	0

Notes: ADF: Augmented Dickey-Fuller Test; SP Z(): Schmidt-Phillips Z() Statistics (Schmidt and Phillips, 1992); H1: No Unit Root; KPSS: Kwiatkowski et al. (1992); Ho: No Unit Root; CV: Critical value; d-Lag: Number of difference lags; Wheat prices*: Residuals from a static time series model with annual and seasonal dummies.
Source: Own calculations using JMulti Version 4 (Krätzig, 2000-2007).

After filtering out the trend (annual shifts) and seasonal dummies by a simple OLS estimation, the obtained residuals are unambiguously stationary (see wheat prices* in Table 2).[6] The residuals still indicate some significant autocorrelations. While the initial trend filtered prices follow an AR(3) process with a cumulative AR(1)-component of 0.9648, the residuals from the deterministic time series model with seasonal and annual shift dummies indicate a slightly

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[5] The dynamic order of the process is determined by information criteria (Krätzig et al., 2000-2007).

[6] Instead of using a simple trend to cover systematic changes over time, we introduced annual dummies which can also reflect supply changes due to varying weather conditions, etc. Annual shifts much better reflect the variation in nominal prices, and the approach matches our theoretical models.

less significant AR-lag with a coefficient of 0.89. Most of the annual and seasonal dummies are significant and the deterministic components explain about three-fourths of the variation in nominal prices.[7] In conclusion, there is significant evidence that the data generating process behind the wholesale and farm wheat prices in Germany is not purely random but indicates deterministic features such as annual and seasonal shifts.

The model selection between the deterministic and random components is not unambiguous here. *Ex post* forecasts based on simple autoregressive models of higher order with or without a trend component are almost as good as predictions from using the annual and seasonal dummies including an AR(1)-component. The economic significance of the deterministic components, however, differs considerably between model specifications and estimation approaches. Though still statistically significant, the economic impact of deterministic components (trend, annual shifts, and seasonal pattern) largely erodes when deterministic and random components are estimated simultaneously instead of iteratively.[8]

3.2 Results of models optimization

We apply the algorithms presented in the second 2.1 to farm prices for bread wheat in Germany and Poland. Storage costs are estimated using data obtained from a farm survey conducted in Germany in 2004 (Loy and Mueller, 2004). Marginal storage costs are about 1 Euro per month per t of wheat.[9] The decision on whether or not to put wheat into storage at all is not modeled here. Therefore, all prices are denominated by storage costs and by the average price in August, which is generally the harvest period in both countries investigated. The marketing period (planning horizon) starts in September and ends in May; no carry-over stocks are considered. Prices for June and July are dropped from the sample. Figure 4 shows the development of weekly average gross margins from storing bread wheat in Germany. These data are used to estimate the seasonal pattern of gross margins (revenues) employing a simple dummy variable approach.

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[7]   The data generating processes have been identified by standard procedures applying Akaike Information, Schwartz and Hanan/Quinn criteria (see Hannan and Rissanen, 1982).

[8]   We rely on the model specification that estimates the deterministic components in a first step. We thereby maximize the economic impact of these factors, which can explain 76% of the total variation in cash prices. The AR-component adds another 20% to the coefficient of determination.

Figure 4: **Average seasonal pattern of storage gross margins in Germany's wheat market from 1994 to 2004**
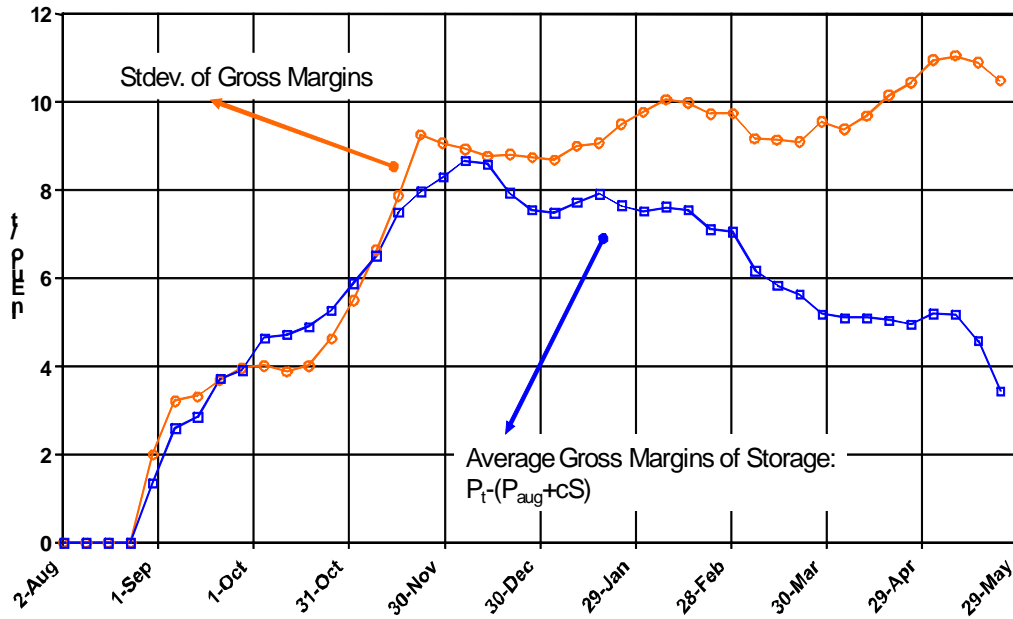
Notes: Symbols as defined above. Years refer to the period from August (previous year) to May (actual year).

Source: Own calculations based on data from a farm survey conducted by Loy and Mueller (2004) and bread wheat prices from LWK (2008).

For the estimated error term we calculated the variance to generate a truncated standard normal distribution which is then added to the estimated deterministic pattern of denominated seasonal gross margins or storage revenues. The last two values enter the backward optimization algorithm to calculate the optimal cutoff revenues (OCR).[10] The OCRs are transformed back to threshold prices and applied to current nominal prices to simulate the optimal grain marketing decision. The results for the simulation of the OCR strategies are summarized in Table 3. We also report simulation results regarding the alternative approaches discussed earlier (ER, sER and ES) to compare the economic impact of different strategies. All simulations were repeated 10,000 times.

Table 3 reports the respective mean storage revenues ($R_t = P_t - c_t S$) as well as the corresponding standard deviations and the coefficients of variation of the storage revenue over all runs,

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[9]   Interests to cover capital costs of the stored grain are not modeled explicitly and cash flows in the season are not denominated. Both are considered to be of minor importance due to the short time horizon of thirty-nine weeks for every annual marketing season.

[10]   Even though the residuals differ statistically from a normal distribution, economically the match is sufficient. More detailed results on that issue can be provided by the authors upon request.

which can be interpreted as estimators for the expected values. In each simulation the stock is sold in a particular period, except for the ES strategy.[11] The last column contains the optimal selling time (week).[12] We split the analysis with regard to two periods.

Table 3:   Simulations for bread wheat prices in Germany and Poland

	Germany			
Analyzed period 1994 - 2004	Revenue			Mean selling time
	Mean (€/t)	Standard deviation (€/t)	Coefficient of variation (%)	
OCR	117.2	9.9	8.49	18.27
sER	121.9	8.9	7.32	15.00
ER	115.5	7.5	6.49	18.00
ES	118.4	6.8	5.73	19.50
Analyzed period 2005-2008	Revenue			Mean selling time
	Mean (€/t)	Standard deviation (€/t)	Coefficient of variation (%)	
OCR	149.4	10.2	6.85	10.33
sER	147.5	11.8	8.04	15.00
ER	148.3	11.9	8.06	6.33
ES	149.7	12.0	8.04	19.50
	Poland			
Analyzed period 2005-2008	Revenue			Mean selling time
	Mean €/t	Standard deviation (€/t)	Coefficient of variation (%)	
OCR	142.1	9.6	6.76	9.00
sER	153.6	23.4	15.25	15.00
ER	140.4	12.3	8.76	6.00
ES	152.6	22.1	14.51	19.50

Notes: OCR: optimal cutoff (price) revenue; sER: simple expected revenue (without updating); ER: expected revenue (with updating); ES: equal (selling) shares. Years refer to the period from August (previous year) to May (actual year).

Source: Own calculations.

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[11] The mean selling time for the ES strategy is just the mean over the periods in which grain is sold weighted by the shares of the volume that is sold in the respective period.

[12] Gross margins (GM) and revenues (R) deviate by the price level in August (GMt=Pt-Paug-cS; Rt=Pt-cS).

Considering the German market in the period 1994-2004 we found that the OCR strategy wins over the expected revenue approach with simple updating (ER), whereas the sER and the ES strategies, are superior with respect to the mean revenue. Additionally, ES strategies leads to the lowest absolute and relative variations of storage revenues (risk reduction). The simulations presented so far are based on *ex post* but not *ex ante* forecasts. The outcome might change because the simulated strategies rely on a different level of information. The sER strategy, for instance, uses the most *ex post* information on storage revenues. Additionally, the empirical simulation is based on a fairly small sample (n = 11); thus, chance might matter.

We now apply the algorithms to the period from 2005 to 2008 without adjusting the estimated coefficients in the simulations to account for the problem of *ex post* forecasts. The results are reported in the middle of Table 3: The findings show a change in the ranking in favor of the OCR strategy, which is now ranked second in the German case. The OCR mean revenue exhibits similar values to the ES strategy, which is now ranked as the superior one. The OCR outperforms the ER and sER strategies by 1 or 2 Euros per ton, respectively. Moreover, the OCR strategy provides the lowest revenue variance, indicating that this strategy is less risky compared to others. Considering that the sER strategy relies most on *ex post* information, the considerable decline to the last rank in the *ex ante* simulation is consistent.

The *ex ante* simulation for Poland using the same set of coefficients only supports the favorite ranking of the OCR compared to the ER strategy as far as the mean revenues are considered. The ES and sER strategies are again ranked first, which is caused by the deviations between Polish and German prices. In particular, in the 2006-2007 marketing season Polish wheat prices show significant increases, while German prices are nearly constant from October 2006 on (see Figure 5). This price development favors the ES and sER strategies. However, the sample size of the *ex ante* simulation (n = 4) is even more critical compared to the initial *ex post* simulation with eleven seasons. Additionally, we use the estimators generated from German prices. Because market integration seems to be imperfect, the estimators for the Polish prices might differ as well.[13] Nevertheless, the OCR strategy also provides low revenue risk in the Polish case, as indicated by the standards deviation and the coefficient of variation.

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[13] Due to a lack of data this hypothesis cannot be tested here.

Figure 5:   **Farm prices in Germany and Poland from 2003/04 to 2007/08**
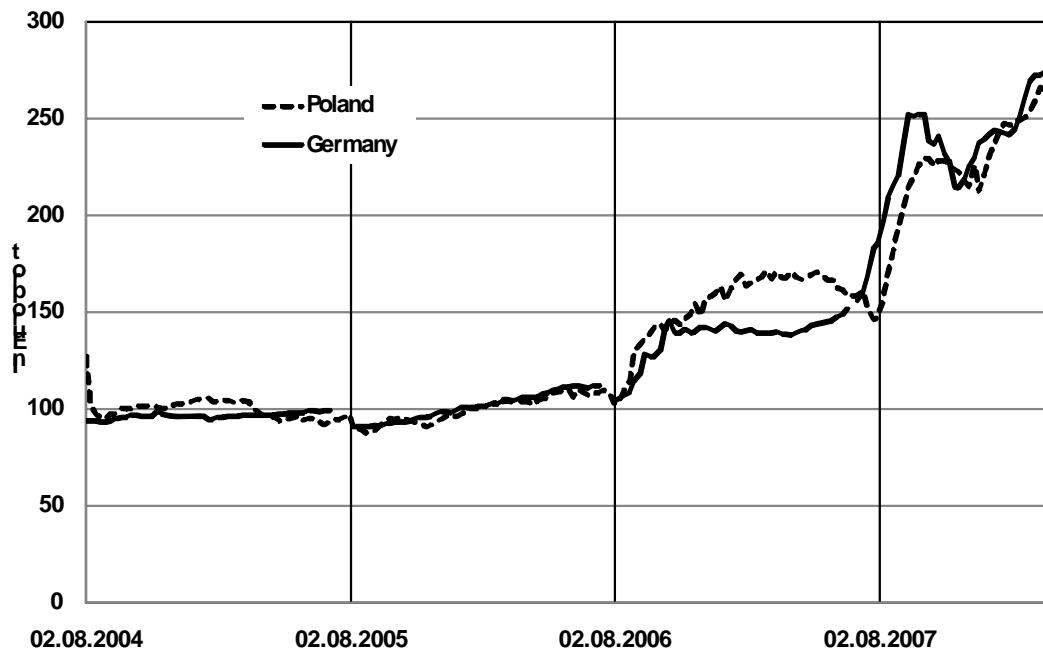
Source: LWK (2008), MAP (2008), and Oanda (2008) for exchange rates between Zloty and Euro.

4   CONCLUSIONS AND OUTLOOK

Our intention was to examine different revenue maximizing marketing strategies of grain producers. The optimal cutoff revenue algorithm promises significant gains from marketing grain within the storage season, claiming that price volatility might be a chance rather than a burden for risk-neutral farmers. This hypothesis strongly depends on the properties of the data generating price process and thereby the respective price forecasting model. If forecast errors are highly correlated in time, the impact of optimal grain marketing strategies might be rather small. From the above results, the following issues seem to be of critical importance:

(1)   The data generating process of revenues (prices) determines the choice of the optimal solution algorithm. Because this decision often is empirically ambiguous, there is significant subjective leeway in the choice of the optimal solution algorithm, and hence the marketing strategy. Thus, to a considerable extent practitioners have to rely upon certain assumptions or the chosen strategy. Empirical justification is limited.

(2)   If marketing strategies are followed by a majority of farmers, prices in the real world are likely to react accordingly and thereby model assumptions might become (invalid) endogenous and therefore the optimal marketing strategy.

(3)   Price predictions using data generating processes commonly indicate low levels of forecasting efficiency. Expectations about future price distributions are often conditional with respect to the forecast horizon. Thus, some, or even the majority, of price variations in future periods are vanishing over time (the forecast horizon). This part of volatile prices cannot be exploited by any marketing strategy.

(4)   Though grain markets between old and new EU member countries do not seem to be fully integrated, the conclusions with respect to the optimal marketing strategy are the same. The contribution of scientific research is rather limited as long as price forecasts and market information cannot be improved.

(5)   Nonetheless, an understanding of the above might at least prevent farmers from following unreasonable marketing strategies and inadequately evaluating them by looking back, e.g. at *ex post* best prices.

(6)   We assumed risk neutrality in our considerations. Berg shows that an increasing degree of risk aversion results in an increasing amount sold at the beginning of the planning horizon. However, the measurement of risk is of critical importance to this result. So far, only risk within the season is modelled, but producers might be more concerned about annual risks because short-term risks in general do not lead to farm bankruptcies. Short-term risks can be covered by hedging on futures markets.

What can be done? What should be done? Improved forecasts are required and therefore more information needs to be gathered. "Future prices can efficiently reflect a complex set of factors but still provide poor forecasts. ... Empirical models provide as poor, if not poorer, forecast." (Tomek, 1987: 23). Thus, futures prices are likely to be the best publicly available forecasts and should be used in deriving the optimal marketing strategies. However, there is plenty of room for improvements in price forecasting models and instruments, even with employing futures contract prices.

Last but not least, models, methods, and concepts need to be simplified and transformed to be understood and applied in the real world. To begin, researchers might focus on economically relevant strategies and separate them from purely statistically significant ones.

REFERENCES

BERG, E. (1987). A Sequential Decision Model to Determine Optimal Farm-Level Grain Marketing Policies. *European Review of Agricultural Economics* 14, 91-116.

BLAKESLEE, L., LONE, T. A. (1995): Modelling grain-marketing decisions when prices are generated autoregressively. *European Review of Agricultural Economics*: 87-99.

BRORSEN, B.W., IRWIN, S.H. (1996): Improving the Relevance of Research on Price Forecasting and Marketing Strategies. *Agricultural and Resource Economics Review* 25(1): 68-75.

FACKLER, P.L., LIVINGSTON, M.J. (2002): Optimal Storage by Crop Producers. *American Journal of Agricultural Economics* 84: 645-659.

HANNAN, E. J., RISSANEN, J. (1982): Recursive Estimation of Mixed Autoregressive-Moving Average Order, *Biometrika* 69: 81-94.

KRÄTZIG, M. (2000-2007): JMulti Version 4, Analyzing Multiple Time Series.

KWIATKOWSKI, D., PHILLIPS, P.C.P., SCHMIDT, P., SHIN, Y. (1992): Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54: 159-178.

LOY, J.-P., MÜLLER, C. (2004): Farm Survey on Grain Storage in Germany, Kiel.

LWK (2008): Data from the ZMP-Program to collect farm prices in Schleswig-Holstein, Landwirtschaftskammer (LWK), Schleswig-Holstein.

MAP (2008): Data for wheat farm prices in Poland 2003-2008, Ministry of Agriculture Poland Warsaw.

Oanda (2008): http://www.oanda.com/.

SCHMIDT, P., PHILLIPS, P.C.B. (1992): LM tests for a unit root in the presence of deterministic trends, Oxford Bulletin of Economics and Statistics 54: 257-287.

SCHROEDER, T., GOODWIN, B. (1993): Analysis of Producer Pricing Methods. In NCR-134 Conference: Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Iowa State University.

SMITH, R.D. (1989): National Assessment of Producer Marketing Alternatives: Practices and Attitudes, Texas A&M University.

TOMEK, W.G. (1987): Commodity Futures Prices as Forecasts. *Review of Agricultural Economics* 19: 23-44.

ZMP (2008): Wholesale Wheat Prices, Zentrale Markt- und Preisberichtstelle (ZMP), Bonn.