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EXPLAINING MAIZE PRICE IN NORTHERN REGION OF GHANA BY LINEAR REGRESSION MODEL

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Abstract: In this project, the price of maize from three northern regions (northern region,uppereast region and upperwest region) was investigated. Regression analysis was done to fit the price data with proper linear model.The linear model was identified through the cycle of autocorrealtion check, stepwise method and nomality check .Finally Logarithm tranforamtion of price data was chosen to make the linear regression residual normally distributed and stable.The linear regression results of logarithm transform showed positive correlation between the price of maize and price of rice in all three regions,which is different from expectation.It also shows that the price is correlated with the harvest season, however,which varies for different regions.

Introduction

Farming is a major source of income for many people in developing countries. In Ghana it represents 36 percent of the country's GDP and is hiring more than 50 percent of the population (Lisa Biederlackand Jonathan Rivers,2009). Agricultural production depends on a number of factors including economic, political, technological, as well as factors such as disease, fires, and certainly weather. As a consequence of climate change, agriculture in many parts of the world has become a riskier business activity. Given the dependence on agriculture in developing countries, this increased risk has a potentially dramatic effect on the lives of people throughout the developing world especially as it relates to their financial inclusion and sustainable access to capital. It's very important to develop some insurance products to protect crop producers from such risks.Price of crops is very important factor in farming industry and predicting price will help farmers reduce the loss from weather changes.

The agribusiness has become very complex in recent years, and hence the importance of agricultural planning has increased. Crop producers can often base their decisions for crop production and selling on yield and price forecasts. Prediction of future crop selling prices is another important aspect in decision planning. Accurate price predictions will help in planning what crops to be planted and when to sell them to optimize the overall profit. Consequently, a crop price forecasting model for predicting the upcoming prices in any specific location and at aggregation level (e.g. weekly) will help local farmers to optimize their crop selling strategy(Nantachai Kantanantha ,Nicoleta Serban,and Paul Griffin).

Predicting prices for food staples in poor regions is crucial for combating food insecurity, defined as the ability to purchase enough food to lead an active and healthy life. Food insecurity is most frequently caused by insufficient access to food instead of absolute lack of food availability. In Ghana, with its large population of poor who spend over half their income on food, the local price of food can be a significant source of food insecurity(Molly E. Brown ,Nathaniel Higgins , and Beat Hintermann,2009).

A number of models have been developed to forecast the cash prices. Kenyon and Lucas (1998) study the relationship between soybean season average prices and soybean ending stocks - the difference between supply and demand. They propose a simple price forecasting model using price historical data and the ending stocks based on linear regression. Many researchers studied the role of futures contract prices in agricultural price forecasting (Working, 1942; Tomek and Gray, 1970,Kenyon et al., 1993). Futures' price is often used as an indicator of the expected cash price (Hoffman, 2005). Eales et al. (1990) examine the difference between futures prices and the average cash prices surveyed from farmers and grain merchandisers in Illinois. In most cases, futures' price and cash price are not significantly different. Because the futures crop price is an indicator of the cash price behavior. Zulauf and Irwin conclude that marketing strategies offer little hope of increasing returns over simply selling at harvest. They suggest that, because futures are efficient, the futures market should be used as a source of information rather than as a trading medium. Kastens, Jones and Schroeder compared various simple-to-construct forecasting methods for cash prices and concluded that the deferred futures plus historical basis forecast method was the most accurate for most commodities considered. Brorsen and Irwin suggest that, rather than forecasting prices, extension economists should rely on the futures market to provide the price forecasts needed in outlook programs. Kastens and Dhuyvetter looked at incorporating deferred futures prices and historical localized basis to make grain storage decisions. However, positive returns to storage were not generally found, indicating that cash markets appear to be efficient.

Crop production flexibility today requires producers to make management decisions based on market conditions. Economically sound decisions are critical for producers to manage risk and take advantage of marketing opportunities. An integral factor in production and marketing plans is accurate forecasting of the local crop basis.

In the agribusiness literature, *commodity basis* is denoted as the difference between the local market cash price and the price of a futures contract for a specific time period. Being able to accurately predict basis is critical for making marketing and management decisions. Basis forecasts can be used along with futures prices to provide cash price projections(Mykel Taylor,Kevin C. Dhuyvetter,and Terry L. Kastens,2004).

Typically, basis forecasts are based on simple time series or naive models. That is, expected (future) basis is assumed to be historical basis. Nonetheless, especially complex models for forecasting basis are probably not relevant for producers, as producers must be able to constantly and quickly translate futures prices to cash price expectations for such information to be useful. Moreover, structural models requiring ancillary forecasts of explanatory variables are of little value to producers needing to make production decisions based on price forecasts with limited information available.

Many studies have examined factors affecting basis. Studies have shown basis forecasts based on simple historical averages compare favorably with more complex forecasting models.

A fundamental structural model incorporating storage cost, transportation cost, and regional supply and demand variables is developed to explain basis behavior(Bingrong Jiang and Marvin Hayenga).

Dhuyvetter and Kastens built upon previous work by Hauser, Garcia, and Tumblin by comparing practical methods of forecasting basis for wheat, corn, milo, and soybeans in Kansas. They found that a 4-year historical average was the optimal number of years to forecast basis. A longer-term average (5 to 7 years) was optimal for corn, milo, and soybeans. They looked at incorporating current market information into forecasts using futures price spreads and an historical average that is adjusted by current nearby basis information. The basis forecasts were slightly more accurate when incorporating price spreads between futures contracts than using current nearby basis information. However, neither of these methods was better than a simple historical average with time horizons greater than 8 to 12 weeks. This analysis did not recognize that the optimal amount of current information to incorporate, when adjusting an historical average, is likely a function of the time horizon. Incorporating current market information, such as current nearby basis deviation from an historical average, into a harvest basis forecast improves accuracy for only the 4 weeks ahead of harvest vantage point, but improves the accuracy of post-harvest basis forecasts (24 weeks after harvest) from nearly all vantage points considered (Scott W. Barnhart,1989).

Technological change has transformed agriculture in the US, Europe and large parts of Asia and South America, but it has largely bypassed West Africa. In this region, most farms are small, primarily cultivated with hand tools, planted with seeds with a low yield potential, using little or no chemical or organic fertilizer. The climate is arid or semi-arid, and there is inadequate infrastructure to provide water for irrigation. Consequently, most small farms are only able to attain yields which are less than one seventh of those regularly achieved in industrialized systems (Breman, 2003; Taylor et al., 2002).

Agriculture in northern Ghana remains particularly vulnerable. For example, the average range of district-level maize yields in the north from 1992 to 2005 was 35 percent higher than in the forest and 55 percent higher than at the coast. Higher rates of rural poverty are likely exacerbated by factors linked to fewer opportunities for intensifying and commercializing agriculture, such as poorer access to input and output markets as well as credit and advisory services. Concerns about food insecurity are likely to remain greater in the north, and such concerns may influence farmers to choose production strategies that minimize risk rather than maximize comparative advantages for market opportunities. Ghanaian agriculture is overwhelmingly dominated by smallholders; many commodities—including cocoa, maize, and cassava—are produced predominantly on small farms. More than 70 percent of Ghanaian farms are 3 hectares (ha) or smaller in size (Chamberlin 2007). The smallest average holdings are in the south (for example, 2.3 ha at the coast versus 4.0 ha in the northern savanna). Smaller farms tend to produce fewer commodities; for example, farms of 2 ha or smaller produce an average of 3.1 crops; whereas those of 4 ha or larger produce 4.7 crops, on average. Maize and cassava are particularly important crops for the smallest farms, reflecting the importance of these crops to food security strategies under poor or variable market conditions. (For the 12 percent of households that grew only these two crops, the median holding size was 0.8 ha.)

Smallholder market participation rates vary by holding size. Smaller farms produce fewer marketed crops and are less likely to sell the crops they do produce. Participation also varies with geography. The marketed share of farm products and the percentage of farmers who sell their produce tend to be lowest in northern Ghana Holding sizes increase from south to north, but this increase is accompanied by lower land productivity in the north. At the same time, land endowments are more important to farm livelihood strategies in the north, where larger holding sizes correspond to higher household incomes. This finding appears to indicate that efforts to increase farmer incomes should particularly emphasize land productivity in the north, where fewer off farm opportunities exist (Small holder agriculture in Ghana).

In Ghana, due to insufficient storage and drying facilities and lack of credit, a lot of farmers are obliged to sell their products at post harvest time when prices are low and re-buy during the lean season when prices are high. For example of the millet in the nearby area of Ghana, there is a widespread lack of storage facilities (Dembele and Staatz, 1999). Because they cannot store grains for an entire year, small farmers sell more than their surplus (defined by total output minus annual consumption) on the market after harvest and buy some grain back later in the year, often at higher prices. Because of the simultaneous influx of grain, prices drop to their base levels after harvest. As producers draw down their stocks, supply on the market decreases, whereas consumer demand remains unchanged, leading to a gradual increase of millet prices during spring. During the “hungry season” in summer, many farmers become net millet buyers because their own stocks are depleted, further boosting prices (Cekan, 1992). Annual prices peak just before harvest, the time of which differs across climate zones, which is the reason for the different price peaks in Niger on the one hand (July) and Burkina Faso and Mali on the other (August) (Molly E. Brown ,Nathaniel Higgins , and Beat Hintermann,2009).

The combination of limited income opportunities with high dependence on markets for food purchases, rural households’ purchasing power is stretched which in turn is likely to negatively impact on the quality and quantity of food they consume. Market centres for food are not well integrated into rural areas because of limited road access, poor road conditions, a one-way trade direction from traders to communities. This one-way trade direction compensates for the communities' limited access to markets but transaction costs tend to be high, which further constrains the already limited purchasing power of the rural population living in remote areas (Lisa Biederlack and Jonathan Rivers,2009).Knowing the trend of crop price is very important for the farmers to manage their productions and manage their income distributions. Northern regions of Ghana are the poorest parts of Ghana. Such crop price information will be of much more importance to the farmers in these regions.

Based on the reference papers and the actual data we got for Ghana, in this project, first we try to explain the maize price in these regions. Because farmers in northern region don't have many storage facilities and the trade of the crops are not far away from their hometown because of poor road system in northern region. The northern region, the trading is not affected much by the international markets. In Ghana's case, the time series linear regression model will be used to find the relationship among monthly maize price, monthly rice(food substitute for maize) price with consideration of seasonality(i.e. harvest season and non-harvest season) . The maize price lags are included in price forecasting models because there is a number of price drivers that are important but typically unobserved. In this case, these unobserved price drivers include income, distribution bottlenecks, local price-related policies, price expectations by farmers and consumers, and the quality of agricultural land. Some of these unobserved price determinants tend to move slowly over time. Lagged dependent variables on the right-hand side of a price equation capture these unobserved, autocorrelated price drivers. We control for the cyclical behavior of prices by introducing monthly dummy variables.

Objective

Crop Price is an important factor for developing crop-realted insurance products.In the project, first, I will try to explain maize price using linear model. The seasonality and maize substitute(rice) will be included as predictors.The model was shown as following. F() stands for some possible transformation of dependent time series variables.

$F(Mr_{t)}=\beta_0+\beta_1*rlr+\Sigma\alpha_i*month+\Sigma\gamma_i*f(Mr_{(t-i)})+\Sigma\delta_i*year$

Based on the model developed in the first step; try to do some forcasts of the price.

Hypothesis:The crop price is linear related with predictors shown above.

Based on this assumption, I did regression alalysis on these data.

Methodology

In order to determine the factors that influence maize price in these regions, since they are time series data sets, auto regression checks were done to test the autocorrelation between the lags of maize price. In SAS, the ARIMA procedure was used to get ACF and PACF charts.Based on the ACF and PACF, the order of autoregression was identified. By looking at the autocorrelation function (ACF) and partial autocorrelation (PACF) plots of the series, we can tentatively identify the numbers of AR and/or MA terms that are needed. ACF plot is a bar chart of the coefficients of correlation between a time series and lags of itself. The PACF plot is a plot of the partial correlation coefficients between the series and lags of itself. A partial autocorrelation is the amount of correlation between a variable and a lag of itself that is not explained by correlations at all lower-order-lags. The autocorrelation of a time series Y at lag 1 is the coefficient of correlation between Y(t) and Y(t-1), which is presumably also the correlation between Y(t-1) and Y(t-2). But if Y(t) is correlated with Y(t-1), and Y(t-1) is equally correlated with Y(t-2), then we should also expect to find correlation between Y(t) and Y(t-2). The partial autocorrelation at lag 2 is therefore the difference between the actual correlation at lag 2 and the expected correlation due to the propagation of correlation at lag 1. The partial autocorrelations at all lags can be computed by fitting a succession of autoregressive models with increasing numbers of lags. In particular, the partial autocorrelation at lag k is equal to the estimated AR(k) coefficient in an autoregressive model with k terms--i.e., a multiple regression model in which Y is regressed on LAG(Y,1), LAG(Y,2), etc., up to LAG(Y,k). Thus, by mere inspection of the PACF we can determine how many AR terms you need to use to explain the autocorrelation pattern in a time series: if the partial autocorrelation is significant at lag k and not significant at any higher order lags--i.e., if the PACF "cuts off" at lag k--then this suggests that you should try fitting an autoregressive model of order k .In the case of maize price of Ghana in three northern regions , the PACF plot has a significant spike only at lag 1, meaning that all the higher-order autocorrelations are effectively explained by the lag-1 autocorrelation. It has a very large spike at lag 1(showed in the following figure) and no other significant spikes, indicating that in the absence of differencing an AR(1) model should be used.

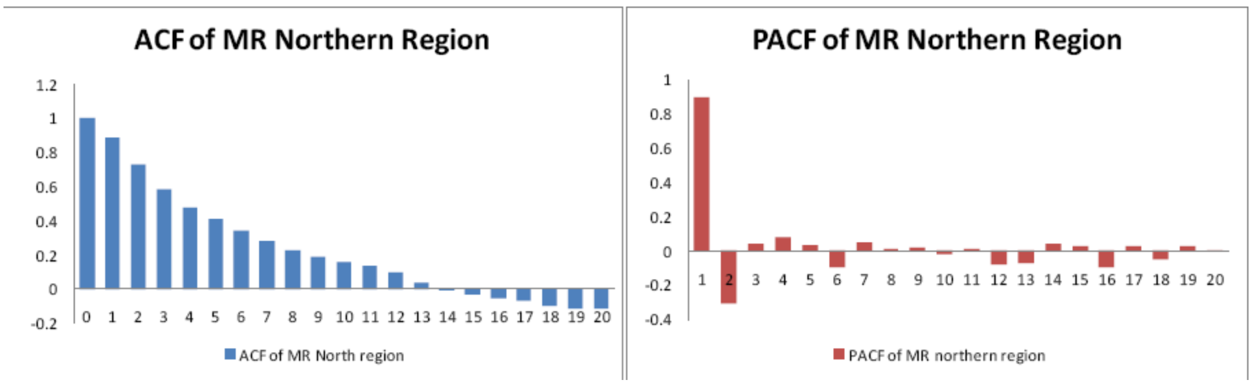


Figure1 ACF and PACF bart chart of maize price of northern region in Ghana.

Stepwise method was used to identify independent variables. The significance level of antry and stay of stepwise method was set at 10%.Based on the stepwise method, independent variables were chosed for the regression analysis.Auto regression procedure with maximum likelihood method was used to determine the linear regression model based on the variables identified in the previous steps. The residual was obtained through this step and the stationarity and normality of residue were checked using univariate procedure in SAS.If non-normally distributed data was observed based on the Kolmogorov-Smirnov test, certain transformations(including difference and logarithm) of dependent variable were done to make sure the residual was normally distributed, In this project, the natural logarithm transformation was used to improve the normality of the data.Then again back to the first step, the autorecorrealtion of the transformation was checked through ACF and PACF until the proper order of autoregression was applied(the ACF and PACF bart charts of logarithm transformation were shown below. The ACF and PACF charts still indicated the first order of autoregression.The ACF and PACF bar charts of first difference showed no significant autocorrelation.).

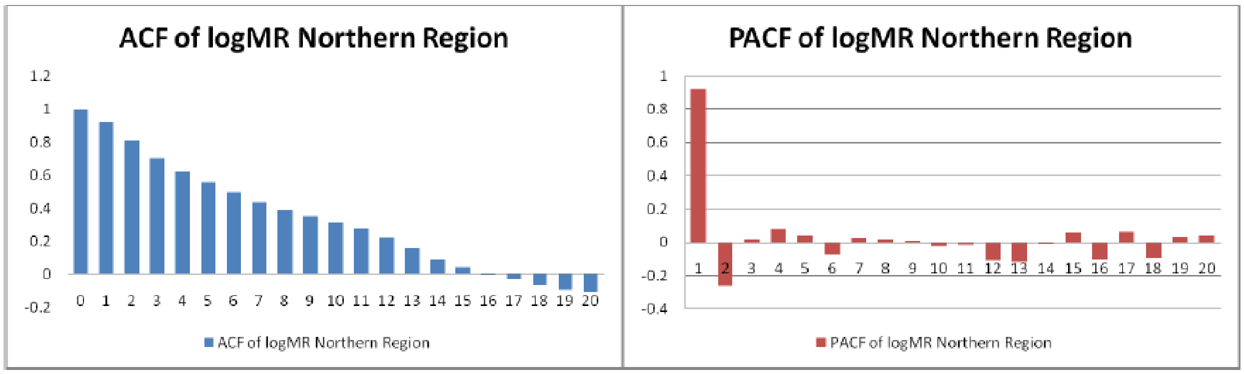
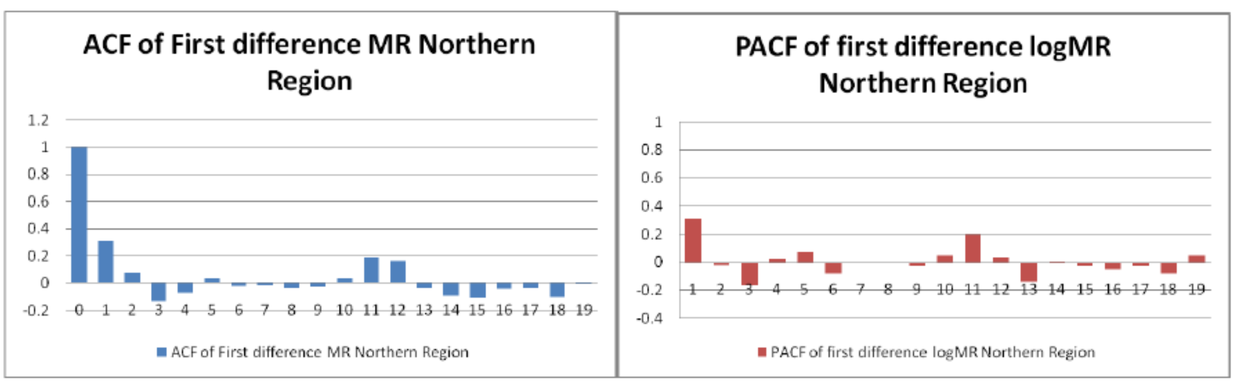


Figure2 ACF and PACF bar charts of logarithm transformation of maize price of northern region



Firgure3 ACF and PACF bar charts of first difference of maize price of northern region

Even though the first difference showed no significant autocorrelation, the logarithm transformation was applied .Because the logarithm transformation made the residual of regression model normally distributed and stable(especially for the maize price data of northern region and upper west region of Ghana),which is basic assumption the statistics test can be used to check the significance of coefficents of regression models.When the first lag of regression was included as a predictor in the regression model, the residual showed normality and showed no significant autocorrelation anymore.The logarithm transformation was finally chosen in the regression analysis.The logarithm form also gave the approximate quantity of percent change in depend variable (here, it is the percentage of change in price).

Results and Discussion

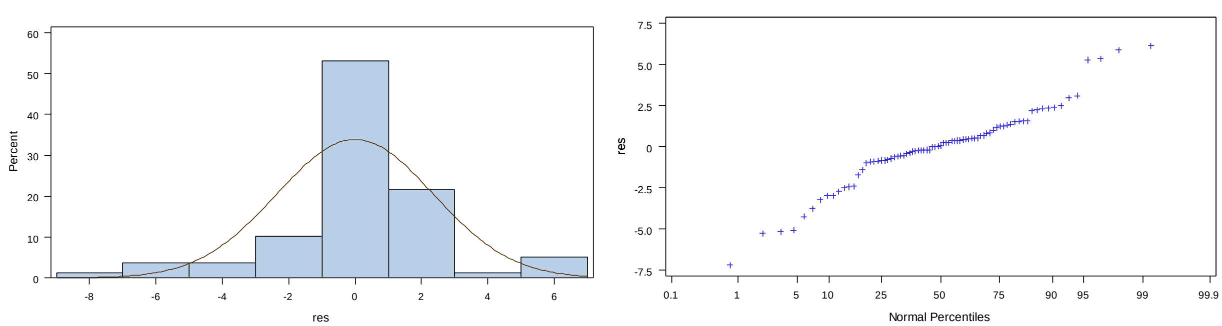
Northern region

The autocorrelation was checked in the orignial form of maize price data,first difference and natural logarithm form of price data.The ACF of original maize price showed strong but decreasing correaltion between different lags and PACF of it showed only one strong spike at lag1,which suggests a first order correlation. The linear regression was run through the autoregression procedure with first lag of maize price as one of the predictors in the model.The regression model with coeffiicents is as following:

MR_t=1.9436+0.6310$MR_{(t-1)}$+0.1072RLR+3.2306JUL-0.7345OCT-0.9213$Year_{2003}$+2.0241$year_{2005}$+7.1917$Year_{2008}$+Vt(R-square=0.8718)(1)

$V_t=-0.4481V_{(t-1)}+\varepsilon_t$

The normality of residual from this regression model was checked .The Histogram and Q-Q probability plot showed lack of enough normality.The P-value of Kolmogorov-Smirnov test is less than 0.01, which confirmed the lackness of normality.



Fuigure4 histogram and Q-Q plot of residual of model(1)

The results above showed the lackness of normality. So certain transformation of the maize price should be done to reduce this non-normality.The logarithm form of maize price was chosen to increase normality.The same routine was used to check the logarithm form.The ACF and PACF showed in figure2 suggests the first order autoregressin model.So the first lag of logrithm form was included in the model.The similar autoregression procedure was used to fit the data. The regression results showed as following:

$LOGMR_t$=0.6563+0.7086$LOGMR_{(t-1)}$+0.0048RLR-0.1844SEP-0.1453OCT-0.0496NOV-0.0503$Year_{2003}$+0.0813$year_{2005}$+0.1404$Year_{2008}$+Vt(R-square=0.8718)(R-sqr:0.9203)(2)

V_t=--0.3088$V_{(t-1)}$+ε_t

Variable	DF	Estimate	Error	t Value	Pr > |t|
Intercept	1	0.6563	0.2354	2.79	0.0069
lglogmr	1	0.7086	0.0998	7.10	<.0001
rlr	1	0.004808	0.001749	2.75	0.0076
Sep	1	-0.1844	0.0420	-4.39	<.0001
Oct	1	-0.1453	0.0451	-3.22	0.0019
Nov	1	-0.0496	0.0434	-1.14	0.2569
2008	1	0.1404	0.0704	1.99	0.0500
2005	1	0.0813	0.0509	1.60	0.1147
2003	1	-0.0503	0.0486	-1.04	0.3043
AR1	1	-0.3088	0.1744	-1.77	0.0810

The autocorrelation was checked for the residual from the model above.The ACF and PACF showed no significant autocorrelation.The bar chart of PACF showed no significant autocorrelation.

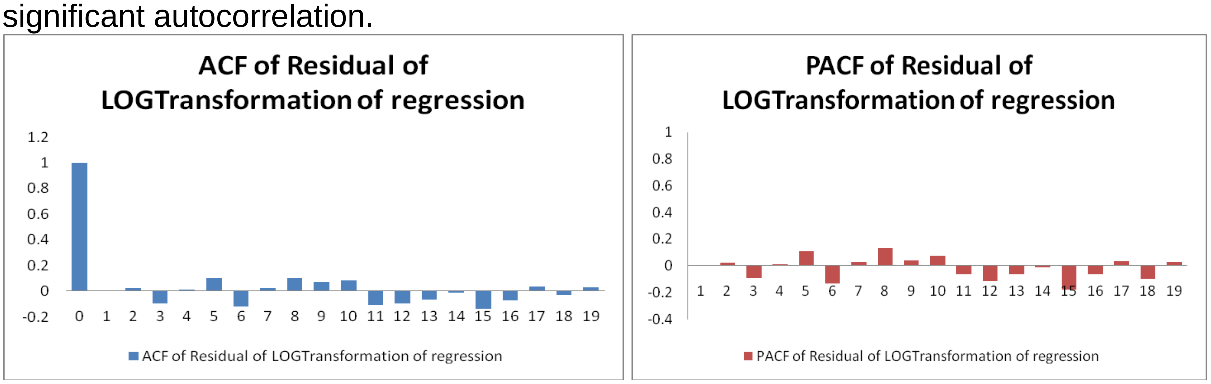
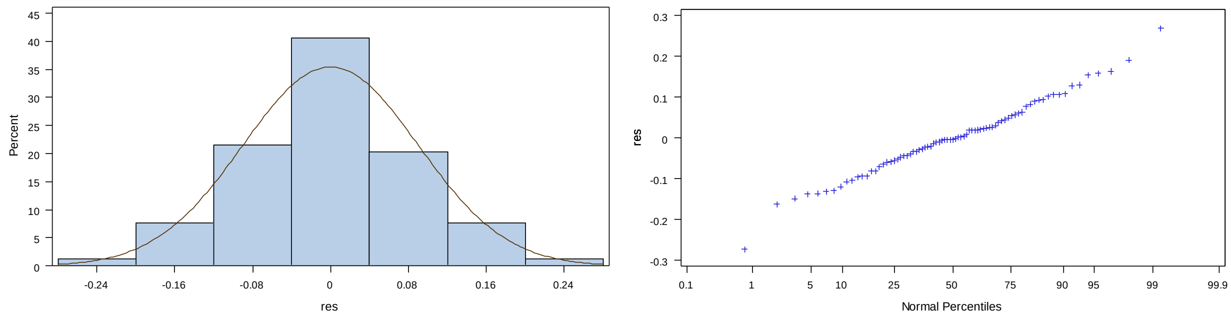


Figure4 ACF and PACF of residual of regression

The normality of the residual was checked through the univariate procedure in SAS.The histogram and the Q-Q probability plot showed the normality.This is confirmed by the Kolmogorov-Smirnov test (P-value=0.15).



Firgure5 Histogram and Q-Q plot of residual

All these checks indicated that the linear regression model of logarithm transformation was a good model for the price data.The significance of the coefficients of september and october dummy variables corresponded to low price in the harvest season of maize. The negative coefficients can be explained by the fact that after the harvest season the price will drop. The coeffient of september is less than that of october, which means the price in september dopped more than in october.The positive and significant relation with rice price means that the rice price and maize price will rise simutaneously however with different amount, which is not as expected. Because rice is a subsitute for maize, I expect negative relationship between these two prices.The positive relation might be from the lack of enough of supply of staples in the market.The significance of the first lag shows that the lag of price is a good expectation for the price of next duration.

Upper East region

The same procedure was done for the data from upper east region.Following was the result for linear regression .The R-square of the regression model is 0.8139.The ACF and PACf of the residual showed no significant auto correlation.The P-vale of Kolmogorov-Smirnov test is 0.065.The histogram and Q-Q plot of regression residual indicated that the transformation made the residual close to normally distribution.

Variable	DF	Estimate	Error	t Value	Pr > |t|
Intercept	1	0.7479	0.3371	2.22	0.0296
lglogmu	1	0.6797	0.1311	5.19	<.0001
rlu	1	0.003633	0.001577	2.30	0.0241
Jul	1	0.0700	0.0250	2.81	0.0064
2005	1	0.0526	0.0527	1.00	0.3215
2008	1	0.1536	0.0745	2.06	0.0427
AR1	1	-0.6627	0.1731	-3.83	0.0003

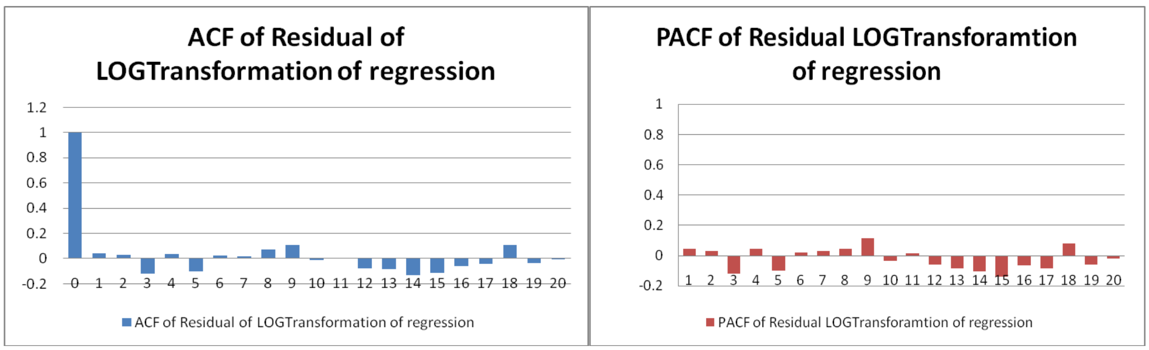


Figure6 ACF and PACF chart for residual of logarithm transformation regression.

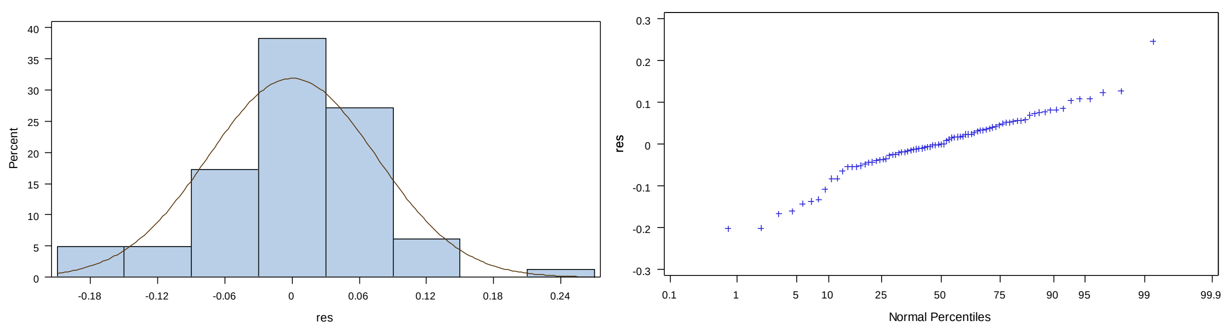


Figure 7Histogram and Q-Q plot of regression residual.

The significance of month July with positive coefficient corresponded to higher the pre-harvest price than other season.The significant positive relation between maize price and rice price can be explained by the same reason for the northern region,i.e. lack of enough supply of staples in this region.

Upper West region

For upper west region, the same procedure as previous two was used to fit the price data. It turned out that the logarithm transformation worked for this data set,too.The regression results are shown below in the table.The Normality was confirmed by both histogram,QQ-plot and Kolmogorov-Smirnov test with P-value 0.101.There is no significant auto correlation after this transformation ,which is confirmed by the ACF and PACF bar chart.The R-square of the linear regression is 0.8919.

Variable	DF	Estimate	Error	t Value	Pr > |t|
Intercept	1	0.7038	0.2512	2.80	0.0065
lglogmr	1	0.7145	0.0969	7.37	<.0001
rlr	1	0.003717	0.002064	1.80	0.0760
Oct	1	-0.1955	0.0579	-3.38	0.0012
Nov	1	-0.1269	0.0611	-2.08	0.0413
inf1	1	-0.004018	0.003650	-1.10	0.2747
2005	1	0.1243	0.0651	1.91	0.0604
2008	1	0.0889	0.0890	1.00	0.3213
AR1	1	-0.1094	0.1593	-0.69	0.4946

The significant positive relation between rice price and maize price still exits in this region.The significant negative coefficient of months of october and november corresponded to the low price after harvest.

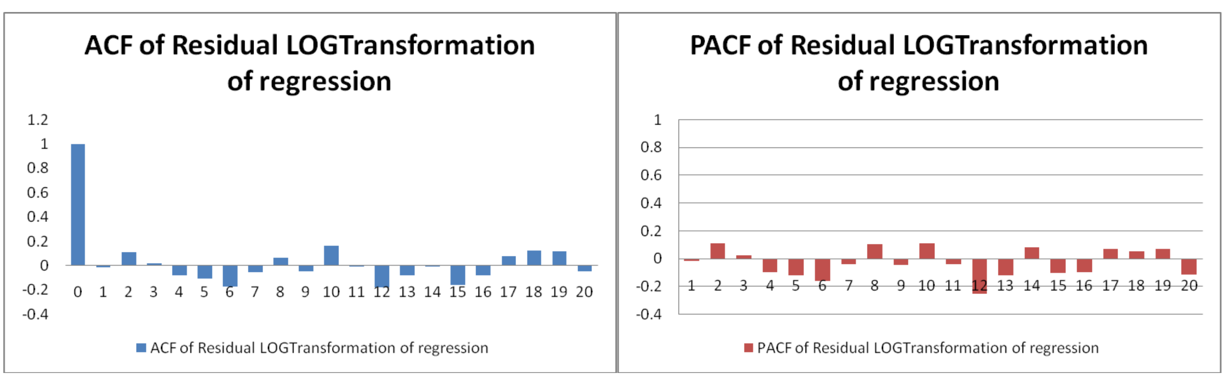


Figure 8 ACF and PACF chart of residual of logarithm transformation regression

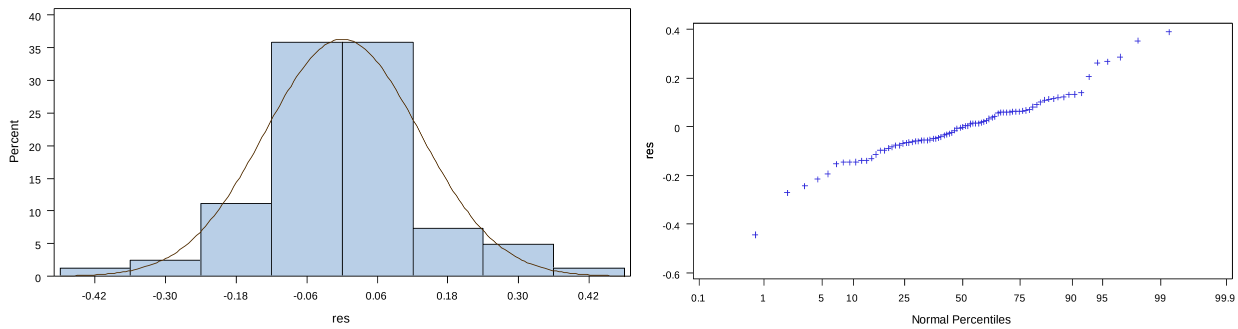


Figure 9 Histogram and Q-Q plot of residual

Conclusion

The regression analysis of three regions has similar results, the harvest season effect showed in all three linear regression models, even if the effect showed significant in different months.They have positive effect before harvest season and negative effect after harvest season.The positive relationship between rice price and maize price showed in all three models. This might be explained by the lack of supply of both of them.

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Appendix

Variable lists

MR-maize price rural monthly

LOGMR: logarithm of maize price

LGLOGMR: first lag of logmr

MU:maize price urban monthly

RLR:local ricew rural monthly

RLU:local rice urban

(All the price data was converted to new Ghana cedi.)

IINF1:inflaion rate*100

FEB-DEC:month dummy variables with value 0 and 1.

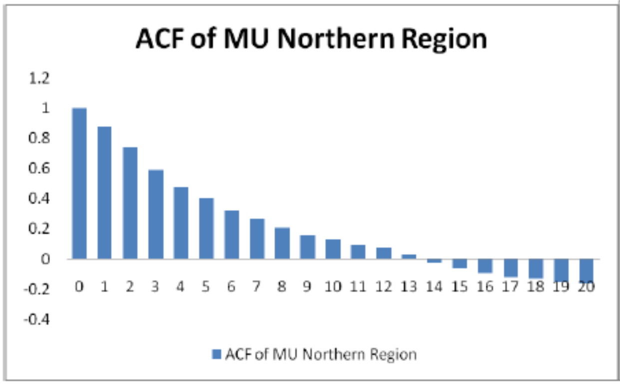
2002-2008-year dummy variables with value 0 and 1

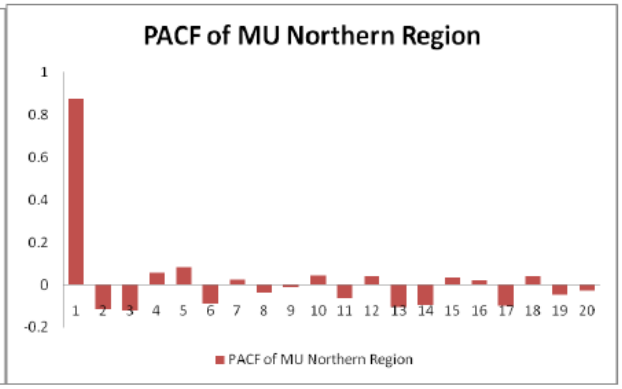
UW,UE,NR-area dummy variables with value 0 and 1 .UW-upper west,UE-upper east,North region

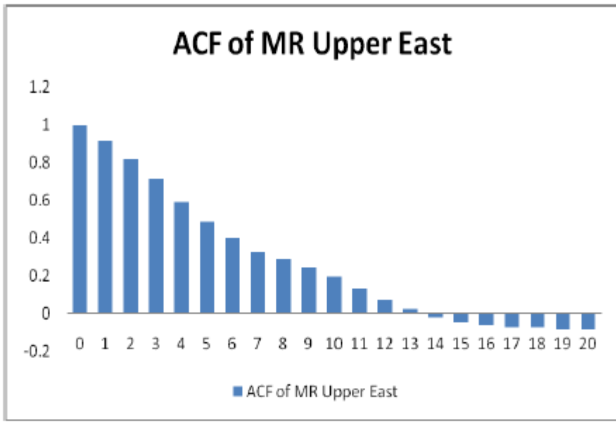
AR1:autoregression with order 1

Data was collected from year 2002 to 2008.All the price data was provided by department of Statistics in Ghana.

Charts of ACF and PACF for different regions



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0.4
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-0.2
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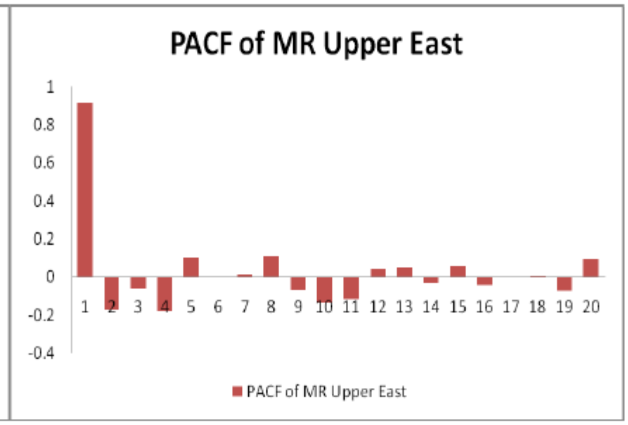
ACF of MR Upper East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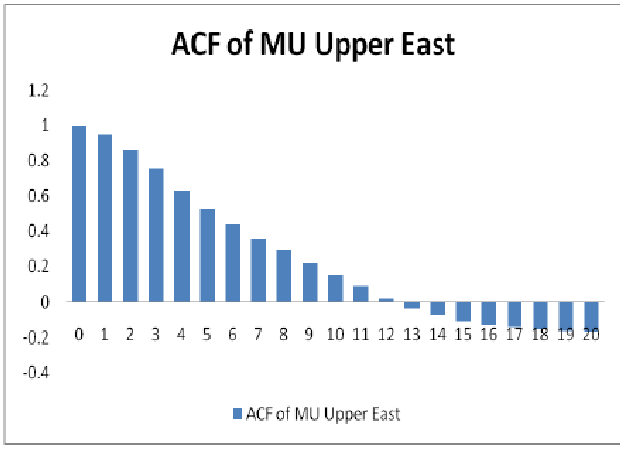
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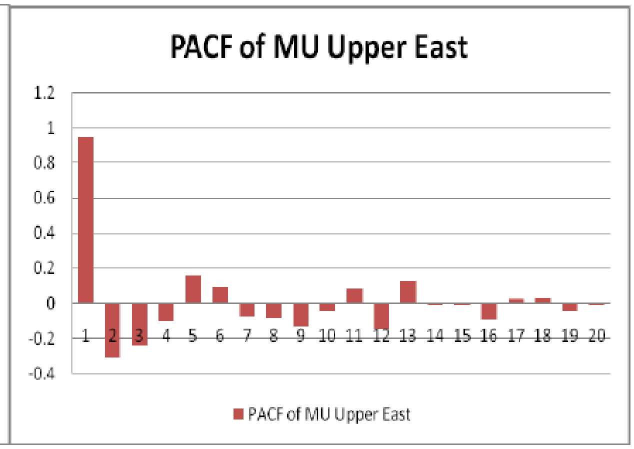
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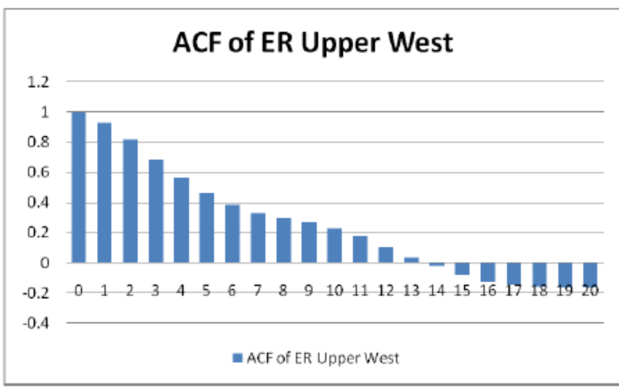
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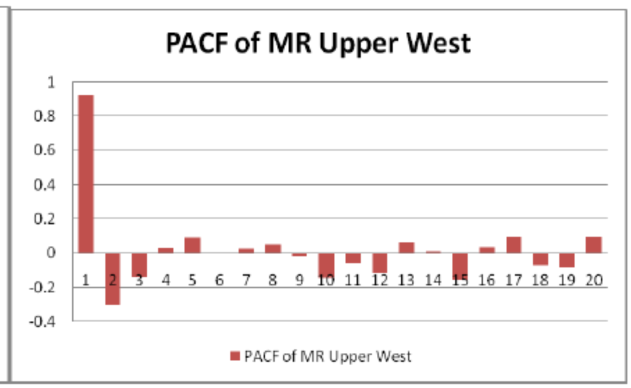
ACF of ER Upper West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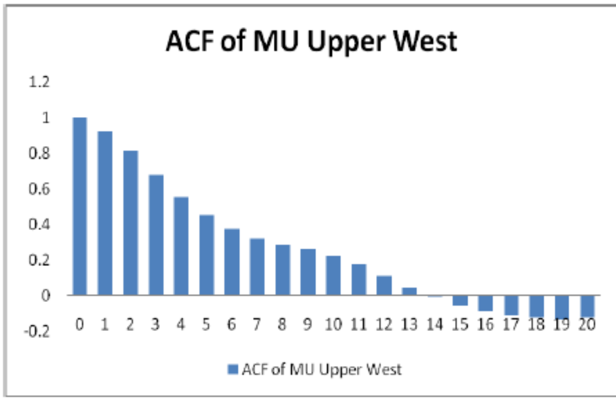
PACF of MR Upper West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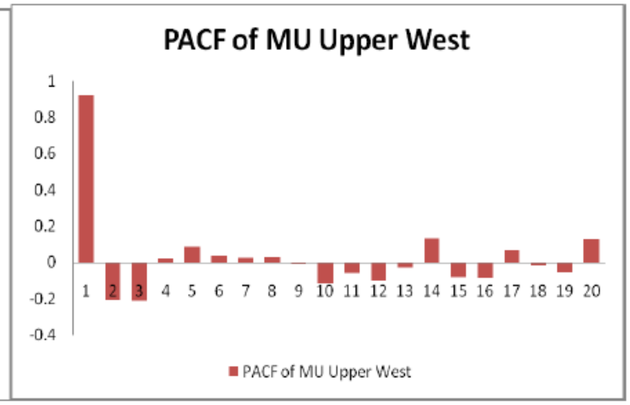
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PACF of MU Upper West