Jurnal Sosial Ekonomi Pertanian (J-SEP) Vol. 17 No. 2 Juli 2024: 181-190
https://jurnal.unej.ac.id/index.php/JSEP
ISSN: 1978-5437 (Print), 2356-2382 (Online)
Published by the University of Jember, Indonesia
DOI: 10.19184/jsep.v17i2.48312

Jurnal Sosial Ekonomi Pertanian
(J-SEP)
(*Journal of Social and Agricultural Economics*)

CORN PRICE VOLATILITY IN THE WORLD MARKET

VOLATILITAS HARGA JAGUNG DI PASAR DUNIA

Prasmita Dian Wijayati*, Aditya Arief Rachmadhan, Noor Rizkiyah
[1]*Universitas Pembangunan Nasional "Veteran" Jawa Timur, Surabaya, Jawa Timur, Indonesia*
* *Corresponding author's email: prasmita.dian.agribis@upnjatim.ac.id*

Submitted: 30/05/2024 Revised: 22/06/2024 Accepted: 31/07/2024

ABSTRACT
Corn is one of the food commodities traded globally as food, feed and biofuel commodities. Global demand for corn will tend to increase from year to year considering the multifunctional uses of corn. Climate change also take part in decreasing global production. Producer countries, namely China, America, and Brazil, suffered severe drought in 2020. It had impact in global corn market since the low of production. Globally, corn is used as food, but Indonesia imports corn as feed. Therefore, the price of corn in the global market is of concern to the Indonesian government. Fluctuations alone are not enough to describe the movement of corn prices, it is necessary to do a volatility analysis to find out how much uncertainty corn prices are in the global market. This study aims to determine the volatility of corn prices in the world market. The data used is secondary data obtained from the World Bank's Pink Sheet Data from 1960 to 2020. This study uses the econometric method using the ARIMA (Autoregressive Integrated Moving Average) and ARCH GARCH (Autoregressive Conditional Heteroscedasticity-Generalized Autoregressive Conditional Heteroscedasticity) model. The results showed that corn prices were volatile most of the year from 1960 to 2020.

***Keywords**:, corn commodity, price-volatility, world market*

ABSTRAK
Jagung merupakan salah satu komoditas pangan yang diperdagangkan secara global sebagai komoditas pangan, pakan dan *biofuel*. Permintaan jagung global akan cenderung meningkat dari tahun ke tahun, mengingat kegunaan jagung yang multifungsi. Perubahan iklim juga berperan dalam penurunan produksi global. Negara-negara produsen yaitu Tiongkok, Amerika, dan Brazil mengalami kekeringan parah pada tahun 2020. Hal ini berdampak pada pasar jagung global karena rendahnya produksi. Secara global, jagung digunakan sebagai pangan, namun Indonesia mengimpor jagung sebagai pakan. Oleh karena itu, harga jagung di pasar global menjadi perhatian pemerintah Indonesia. Fluktuasi saja tidak cukup untuk menggambarkan pergerakan harga jagung, perlu dilakukan analisis volatilitas untuk mengetahui seberapa besar ketidakpastian harga jagung di pasar global. Penelitian ini bertujuan untuk mengetahui volatilitas harga jagung di pasar dunia. Data yang digunakan merupakan data sekunder yang diperoleh dari Pink Sheet Data Bank Dunia pada tahun 1960 hingga tahun 2020. Penelitian ini menggunakan metode ekonometrika dengan menggunakan model ARIMA (*Autoregressive Integrated Moving Average*) dan ARCH GARCH (*Autoregressive Conditional Heteroscedasticity-Generalized Autoregressive Conditional Heteroscedasticity*). Hasil penelitian menunjukkan bahwa harga jagung mengalami volatilitas hampir sepanjang tahun dari tahun 1960 hingga 2020.

Kata kunci: ARCH GARCH, harga, jagung, volatilitas

How to Cite: Wijayati, P., Rachmadhan, A.A., Rizkiyah, N. (2024). Corn Price Volatility in the World Market. *JSEP: Jurnal Sosial Ekonomi Pertanian (J-SEP)*, 17(2): 181-190.

INTRODUCTION

Researchers nowadays have analyzed historical price fluctuations along with climate data to determine how that has affected inflation. Climate change has already pushed up food prices and inflation over all. Meanwhile, continued global warming is projected to increase food prices in the future. SDGs no hunger become more challenging as this issue arises (Erdogan et al., 2024; Kotz et al., 2024; Rizkiyah & Shofiyah, 2021).

Global warming affects crops in several ways. Yields of corn fall dramatically after the increasing temperature (Dhaliwal & Williams, 2022). Poor countries feel the effects of high prices more, but all nations will be affected by climate-fueled inflation. It’s entirely usual for food prices to fluctuate alongside the season, but the exceptionally hot and dry summer being experienced across the globe has caused poor harvest and many crops to fail (Chaudhry et al., 2021).

Across the world, food prices rose sharply in 2020. The monthly changes of prices tracked in international prices. Volatile climatic conditions have been responsible for reduced production which is impacting the volatility of food prices (Birgani et al., 2022). Global food system makes production in one location impact the price and availability of food in another location in the world. Many countries are highly dependent on food imports. It is important to recognize this as a form of climate vulnerability, as climate change impacts in producing countries are likely to exacerbate global food price shocks (Chernova & Noha, 2019; Rozi et al., 2023; Ruccy et al., 2022; Wijayati et al., 2019).

In a changing climate, agricultural production is expected to become more variable, with higher risks of crop failures because of drought, floods, and extreme heat (Meng & Qian, 2024; Qian et al., 2023). That, in turn, could increase the volatility of food price on global markets, with particularly serious implications for countries that import a large share of their food. Global trade creates global food system, even though it has many benefits for both buyers and sellers, but it can also be source of risk. Through trade, adverse events in one part of the world can affect other countries as well (Adamchick & Perez, 2020; Ji et al., 2024).

Global climate change affects corn production globally. Corn producers in the world suffered severe drought in the last decade. Although corn yields have increased from 1995 to 2012, the sensitivity of maize yields to drought stress associated with high vapor pressure deficit has increased. It implies if there is no agronomic changes to improve drought tolerance of plants, yields would decrease (Lobell et al., 2014; Malau et al., 2023; Rachmadhan et al., 2020).

Prices of agricultural products experienced high fluctuations in the middle of 2007. Prices of maize recorded its highest levels in early 2008 and then fell drastically in mid-2008. Furthermore, food commodity prices also increased in mid-2010 and peaked prices occurred in 2011. USDA recorded the price of yellow corn in August 2011 was $7.30 per bushel (one bushel is equivalent to 27 kg). Previously in June 2008 the price of yellow corn was recorded at $6.55 per bushel and fell drastically in September 2009 to $3.10 (USDA, 2011).

In 2008 the United States began to develop biofuels with the main raw material being corn. This development occurred after the Renewable Fuels Standard (RFS) policy in 2007. This policy resulted in an increase in the annual target for biofuels production, thus requiring more corn raw materials. One-third of the world's corn production comes from the United States. In addition, the United States is also an exporter of two-thirds of the world's corn. However, as much as 37.9 percent of the total supply of corn in the United States is used as raw material for biofuels (USDA, 2018).

The United States is the world's largest supplier and exporter of corn, causing the US domestic biofuels policy to affect world corn prices. Corn prices rose to record highs and set to climb further as torrential rains threatened to reduce further US crop prospects in a market already facing tight supplies and surging demand. The World Bank itself uses corn prices in the US as a reference price because the US is the country that has the most influence on supply and plays a crucial role in world corn trade (Kocak et al., 2022).

The world food crisis occurred in 2008, corn was one of those affected by the food crisis. The development of biofuels in the US accounts for a 23 percent increase in world corn prices (Klein & Luna, 2022). This factor, along with heavy rain across US corn acreage and combined with tight global grain supplies, resulted in record prices for corn. In 2012, the development of biofuels accounted for 40 percent of the corn price spike (Lee & Durmaz, 2016).

World prices for corn commodities have experienced several shocks due to production shortages, policy changes, and world economic crisis. Whereas corn is a very strategic commodity that can be used as food, feed, and fuel. Price shocks in the market can be reflected through price volatility. The standard deviation of prices from corn commodities in several periods can be seen through this volatility analysis.

This analysis of world corn price volatility can be used as a reference to determine the period when corn prices experience shocks. The novelty of this research is used 1960 to 2020 data; so the research is considering two economic crises in 1973 and 2008. This analysis is particularly useful in countries that have a very high import dependence on maize (eg China, Mexico, Japan, Vietnam, and South Korea). Indonesia also imports corn which is used as feed. Imports will be carried out when domestic production cannot meet domestic demand. Therefore, this analysis is also useful for the Indonesian government in anticipating the volatility of corn prices in the world market.

METHODS

Data Collection

The data used is the monthly time series of corn commodity actual prices from January 1960 to December 2020 (732 data) obtained from the World Bank's Pink Sheet Data (World Bank, 2022). Corn price data refers to prices in the United States.

Data Analysis

Volatility analysis in this study uses the ARCH GARCH model. ARCH GARCH analysis uses the concepts of variance and standard deviation with the aim of knowing how fast the data changes. The phenomenon of volatility is characterized by symptoms of heteroscedasticity (variance that changes erratically from time to time). The stages in the ARCH GARCH analysis are as follows:

1. Identification of ARCH Effects

   The corn price data will be tested whether it contains heteroscedasticity as a sign of the ARCH effect. The tests were carried out using the correlogram test. If the value of the Autocorrelation Function (ACF) is not close to zero, then the data is not stationary and contains heteroscedasticity (Widarjono, 2018).

2. Model Estimation

   Before estimating the ARCH GARCH model, the Box Jenkins method was used to find the best ARIMA model. The stages in the ARIMA model estimation are as follows.

Data Stationarity Test

Stationarity test was carried out with the Augmented Dickey Fuller test. If the ADF test value is less than the critical value, then the data is stationary. If not, differencing will be carried out until it is stationary.

Determination of the best ARIMA model

The best ARIMA model is selected tentatively by determining the order of AR (p), MA (q), and d obtained from how much differencing is done. In the end, the ARIMA model (p,d,q) will be formed. The best model was selected with the following criteria: the smallest Akaike Info Criterion (AIC) value, the smallest Schwartz Criterion (SC) value, the smallest Sum Square Resid (SSE), and the largest adjusted R-square value.

After the best ARIMA model is known, the next step is to estimate the best ARCH GARCH model. The best ARIMA model that has been formed is tested whether there is an ARCH effect using the ARCH LM test. Data containing ARCH effect can be used to estimate the best ARCH GARCH model. The criterion is if the probability value of F statistic is less than 0.05, then the corn data used contains the ARCH effect. Furthermore, similar to the formation of the ARIMA model, the ARCH GARCH model is also determined tentatively with the criteria of having the lowest AIC value, significant coefficient, the number of coefficient values is not more than one and is not negative, and has the largest SSE value and log likelihood value (Firdaus, 2011).

1. Model Evaluation

   The model needs to be evaluated to prove that the model built is adequate. This study evaluates the effect of ARCH with the ARCH LM test. If the p-value > 0.05, then the model built has no ARCH effect, which means that the model built is adequate.

2. Calculation of Price Variance Value

   After the model is adequate, forecasting can be done using the ARCH GARCH model. This last stage is done by entering the parameters in the obtained equation.

3. Model Identification

   Corn data needs to be tested first whether it contains heteroscedasticity or not. The main requirement in the ARCH GARCH model is the existence of heteroscedasticity. This study uses the Correlogram test. The value of Autocorrelation Function (ACF) was observed in the first 15 lags. The presence of heteroscedasticity is indicated by the ACF value which is not close to zero in the first 15 lags. A kurtosis value that is more than three also indicates a heteroscedasticity problem because it is more pointed than the normal curve.

Table 1. Identification of Heteroscedasticity

ACF Value	Lag Probability 1-15	Curtosis Value	Heteroscedasticity Symptomp
Not close to zero	Significant	5,233	Yes

Based on the Correlogram and kurtosis test in Table 1, the price of maize is heteroscedasticity. This indicates that the data can be analyzed further to determine its volatility.

Model Estimation

1. The best ARIMA estimate

   Stationarity test is the first step for the best ARIMA estimation. Stationarity was tested using the Augmented Dickey Fuller test (ADF test). If the t value of the ADF test statistic is greater than the critical value, then the data is stationary. The data can also be said to be stationary if the probability value is less than the 5 percent significance level. Differencing will be carried out until the data is stationary.

Table 2. ADF test results on corn data

ADF Test level	ADF Test First Differencing
T-statistic	T-statistic
-2.493	-11.779***

Note: *** significant at 1%

   Based on the ADF test, it can be seen that the corn price has not been stationary at the level but has reached stationary at the first difference. Data that has been stationary can then be forwarded to find out the best ARIMA. The best ARIMA model is determined in a tentative way based on the following criteria: parsimonious, significant coefficient, invertibility and stationary, convergent, has the smallest AIC and SC values, has the smallest standard of regression and sum square residual values, has the largest Aadjusted R square value, and has the biggest F statistic. The best ARIMA model based on these criteria is ARIMA (3, 1, 4).

2. The best ARCH GARCH estimate

   The estimation of the ARCH GARCH model begins with the ARCH test. If the probability value of F statistic is less than the 5 percent nay level, then the data contains the ARCH effect. The following shows the results of the ARCH test.

Table 3. ARCH effect test results

The best ARIMA model	F statistic
ARIMA (3, 1, 4)	713.266***

Note: *** significant at 1%

The corn price data that will be used contains the ARCH effect so that it can be continued for the estimation of the ARCH GARCH model. The estimation of the ARCH GARCH model is carried out in a tentative way like the previous ARIMA model. The best ARCH GARCH model is determined by the following criteria: has a significant coefficient, has the lowest AIC value, the total coefficient value is not negative and not more than one, has the smallest sum square resid value and the largest log likelihood value. In accordance with these criteria, the best ARCH GARCH model chosen is ARCH (1, 0).

Model Evaluation

Evaluation needs to be done to find out whether the selected ARCH GARCH model is adequate. The evaluation of the model in this study is the ARCH LM test to identify whether there is still an ARCH effect on the data. A good model is a model that does not contain the ARCH effect. The model is said to be free from the ARCH effect if the probability value of the ARCH LM test is greater than the 5 percent significance level. The ARCH LM test produces a probability value of 0.9051 (> 0.05), which means that the selected ARCH GARCH model is free from the ARCH effect and the ARCH model (1, 0) is considered adequate to be used.

RESULT AND DISCUSSION

Equation of Variance and Volatility Behavior

Based on the model that has been selected, namely ARCH (1, 0), then the variance equation formed for corn commodity prices on the world market is as follows:

$$\sigma^2_t = 46.2215035217 + 0.992120746995\ e^2_{t-1} \qquad (1)$$

Based on this model, it can be seen that the corn commodity price variance is influenced by the volatility of corn prices in the previous period. The coefficient of the ARCH rate of 0.992 (close to 1) indicates that the volatility of corn prices in the global market tends to be high. The model can be described in the following graph of volatility behavior.

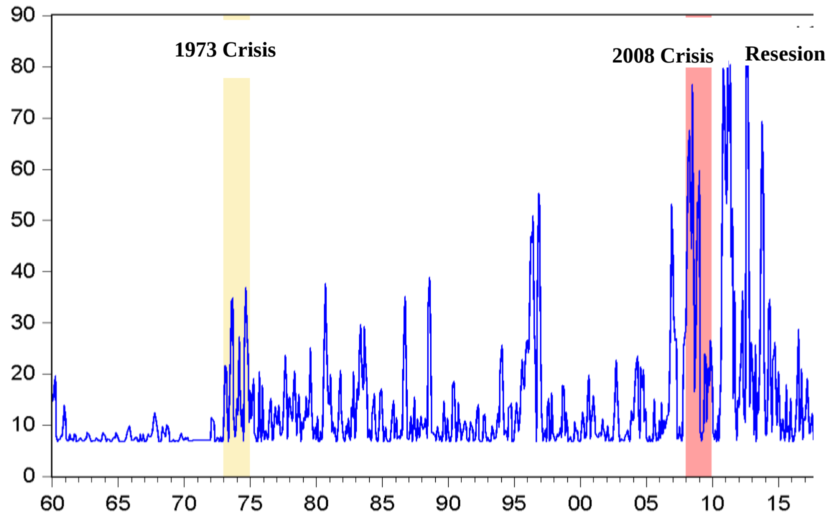

Figure 1. Corn price volatility behaviour

Figure 1 is a graph of the conditional standard deviation of corn prices in the global market from January 1960 to December 2020. The behavior of volatility can be seen through the graph of the conditional standard deviation. High chart peaks indicate that there has been high volatility in the price.

During the period from January 1960 to December 2020, the world has experienced several crises and recessions. Food crises were recorded to have occurred in 1973 and 2008. Furthermore, the world faced a global recession due to the Covid-19 pandemic at the end of 2019 to 2020. Based on the graph, it can be seen that the crisis was indeed one of the causes of price volatility. Corn commodity experienced a price spike in the 1973-1975 crisis. Corn prices were also volatile during the 2008 crisis. However, there are differences between the two crises. The volatility of corn prices in the 1973 crisis was only seen during the crisis. After the crisis in 1976, prices fell again. Meanwhile, in the 2008 crisis, price volatility still occurred even though the crisis was over. Previous researchs also show that corn price volatility was higher in the 2008 crisis than the 1973 crisis (Osei et al., 2024; Sholihah & Kusnadi, 2019; Wijayati et al., 2022).

The global food crisis of 2007-2008 brought food price volatility into sharp focus for many goverments around the world. The crisis resulted from complex interactions of multiple factors, such as higher oil prices, depreciation of the US dollar, biofuel policies, changing food demand patterns, unusual weather, structural features of international commodity markets and world agricultural trade, as well as trade dynamics and government' trade policy responses. Global food price volatility is still not widely recognize as a climate-related risk. But, in fact, it has to do with climate change (Haile et al., 2016; Osei et al., 2024; Taghizadeh-Hesary et al., 2019).

Price volatility in food staples, like corn, can effectively reduce household income. In developing countries, it is common for people to spend as much as half their money on food. So, small changes in price can make a large impact. Developing countries that depend on food imports are keenly aware of their vulnerability to global food price shocks (Chernova & Noha, 2019). The 2007-2008 crisis highlighted the importance of protecting domestic food markets from those shocks. Having seen the price of maize double between 2007 and 2008, many import-dependent countries are now determined to become self-sufficient in this staple food (Chernova & Noha, 2019). For example, Indonesia. Indonesia was largely unnafected by the 2007-2008 price surge.

The volatility of corn commodity prices in the world market can disrupt countries that have a high dependence on imports and countries that use corn as a staple food. Corn is a staple food for the population of eastern Africa and southern Africa. Corn accounts mostly of low-income household expenditures in Africa. About one-third of the caloric intake of people in Sub-Saharan Africa comes from maize. Africa imports more than a quarters of its required maize grain from countries outside the continent as most of the maize production in Africa is done under rain-fed conditions (Ekpa et al., 2019).

Irregular rainfall can trigger shortages during occasional droughts. So that when the world experiences a food crisis, it is indicated that these countries are experiencing famine because they are unable to access basic food economically. The Intergovernmental Panel on Climate Change (IPCC) on its Fifth Assesment Report, summarizes existing evidence on how climate change will affect food security and food production systems. Climate change has the potential to affect all aspects of food security, including food access and price stability. Climate change will increase inter-annual variability and will negatively affect production of major crops such as maize in most temperate and tropical regions (Meng & Qian, 2024).

Empirically, the volatility of corn prices was caused by three general factors, including global demand, speculation, and energy prices or energy policies related to biofuels. Volatile prices after the 2008 food crisis are also indicated by the United States' biofuel development policy. Development of biofuels in the United States is using yellow corn. China is also developing biofuels using the same type of corn as the United States (Evalia et al., 2022; Haile et al., 2016; Kocak et al., 2022).

Increased demand for animal protein commodities, such as beef or chicken, can indirectly increase the demand for corn as feed. Corn prices after the 2008 crisis were volatile which was also caused by high demand as a raw material for biofuels. There is widespread price speculation starting from the crude oil and metals market to the agricultural commodity market. Prices go back down when the speculation is over. Meanwhile, the global recession that occurred in 2020 did not cause volatile corn prices as in the 1973 crisis and 2008 crisis (Al-Maadid et al., 2017; Dybowski & Bugala, 2016; Osei et al., 2024).

CONCLUSION AND RECCOMENDATION

Based on the analysis of corn price volatility, it shows that corn has a volatile price at the global level. The 2008 crisis had a large volatility impact even after the crisis was over. The volatility of corn prices is indicated due to the policy of developing biofuels in the United States, increasing global demand, speculation, and energy prices, or energy policies related to biofuels, as well as global climate change.

Many countries are highly dependent on corn imports. This is important to recognize as a form of climate vulnerability, as climate change impacts in producing countries are likely to exacerbate global corn price shocks. Diversification can help countries reduce their food systems' vulnerability to climate change. Balancing food imports, particularly of staples such as corn, with domestic production, and maintaining a diverse array of domestically grown crops to provide alternative food sources in the event of a staple crop failure. Restricting corn exports during food crises, may exacerbate risks at the global level.

REFERENCES

[USDA] US Department of Agriculture. (2011). *Feed Grains Database*. Feed Grains Database. https://www.ers.usda.gov/Data/FeedGrains/

[USDA] US Department of Agriculture. (2018). *Corn, Disappearance, and Share of Total Corn Used for Ethanol*. Corn, Disappearance, and Share of Total Corn Used for Ethanol. www.ers.usda.gov

Adamchick, J., & Perez, A. M. (2020). Choosing Awareness Over Fear: Risk Analysis and Free Trade Support Global Food Security. *Global Food Security, 26*(September), 100445. https://doi.org/10.1016/j.gfs.2020.100445

Al-Maadid, A., Caporale, G. M., Spagnolo, F., & Spagnolo, N. (2017). Spillover Between Food and Energy Prices and Structural Breaks. *International Economics*, *150,* 1–18. https://doi.org/10.1016/j.inteco.2016.06.005

Birgani, R. A., Kianirad, A., Shab-Bidar, S., Djazayeri, A., Pouraram, H., & Takian, A. (2022). Climate Change and Food Price: A Systematic Review and Meta-Analysis of Observational Studies, 1990-2021. *American Journal of Climate Change*, *11*(02), 103–132. https://doi.org/10.4236/ajcc.2022.112006

Chaudhry, I., Suleman, R., Bhatti, A., & Ullah, I. (2021). Review: Food price Fluctuations and Its Influence on Global Food Market. *Annals of Social Sciences and Perspective*, *2*(1), 21–33. https://doi.org/10.52700/assap.v2i1.33

Chernova, V. Y., & Noha, V. I. (2019). A Study of the Characteristics of Food Import Dependence of The Countries. *Amazonia Investiga*, *8*(24), 484–492.

Dhaliwal, D. S., & Williams, M. M. (2022). Evidence of Sweet Corn Yield Losses from Rising Temperatures. *Scientific Reports*, *12*(1), 1–6. https://doi.org/10.1038/s41598-022-23237-2

Dybowski, G., & Bugala, A. (2016). Global Food Market - New Factors Influencing Development. *AGROFOR International Journal*, *1*(2), 13–19. https://doi.org/10.7251/AGRENG1602013D

Ekpa, O., Palacios-Rojas, N., Fogliano, Kruseman, G., Fogliano, V., & Linnemann, A. R. (2019). Sub-Saharan African Maize-Based Foods - Processing Practices, Challenges and Opportunities. *Food Reviews International*, *35*(7), 609–639. https://doi.org/10.1080/87559129.2019.1588290

Erdogan, S., Kartal, M. T., & Pata, U. K. (2024). Does Climate Change Cause an Upsurge in Food Prices? *Foods*, *13*(1), 1–20. https://doi.org/10.3390/foods13010154

Evalia, N. A., Harianto, H., Nurmalina, R., & Hakim, D. B. (2022). Price Transmission Between Input and Output Markets: The Covid-19 Effect on Laying Hens' Industry in Indonesia. *Jurnal Manajemen Dan Agribisnis*, *19*(3), 418–427. https://doi.org/10.17358/jma.19.3.418

Firdaus, M. (2011). *Aplikasi Ekonometrika untuk Data Panel dan Time Series*. IPB Press.

Haile, M. G., Kalkuhl, M., & Von Braun, J. (2016). Worldwide Acreage and Yield Response to International Price Change and Volatility: A Dynamic Panel Data Analysis for Wheat, Rice, Corn, and Soybeans. *American Journal of Agricultural Economics*, *98*(1), 172–190. https://doi.org/10.1093/ajae/aav013

Ji, G., Zhong, H., Feukam Nzudie, H. L., Wang, P., & Tian, P. (2024). The Structure, Dynamics, and Vulnerability of the Global Food Trade Network. *Journal of Cleaner Production*, *434*, 140439. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.140439

Klein, H. S., & Luna, F. V. (2022). The Impact of the Rise of Modern Maize Production in Brazil and Argentina. *Historia Agraria*, *86*, 1–38. https://doi.org/10.26882/histagrar.086e09k

Kocak, E., Bilgili, F., Bulut, U., & Kuskaya, S. (2022). Is ethanol production responsible for the increase in corn prices? *Renewable Energy*, *199*, 689–696. https://doi.org/https://doi.org/10.1016/j.renene.2022.08.146

Kotz, M., Kuik, F., Lis, E., & Nickel, C. (2024). Global Warming and Heat Extremes to Enhance Inflationary Pressures. *Communications Earth and Environment*, *5*(1), 1–13. https://doi.org/10.1038/s43247-023-01173-x

Lee, J., & Durmaz, N. (2016). Impact of climate change on corn production in the U.S.: Evidence from panel study. *Applied Econometrics and International Development*, *16*(1), 93–104.

Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., & Hammer, G. L. (2014). Greater Sensitivity to Drought Accompanies Maize Yield Increase in the U.S. Midwest. *Science*, *344*(6183), 516–519. https://doi.org/10.1126/science.1251423

Malau, L. R. E., Rambe, K. R., Ulya, N. A., & Purba, A. G. (2023). The Impact Of Climate Change On Food Crop Production In Indonesia: *Jurnal Penelitian Pertanian Terapan*, *23*(1), 34–46. https://doi.org/10.25181/jppt.v23i1.2418

Meng, H., & Qian, L. (2024). Performances of Different Yield-Detrending Methods in Assessing the Impacts of Agricultural Drought and Flooding: A Case Study in The Middle-and-Lower Reach of the Yangtze River, China. *Agricultural Water Management*, *296*(July 2023), 108812. https://doi.org/10.1016/j.agwat.2024.108812

Osei, A.-A. A., Etuah, S., Nimoh, F., Owusu Asante, B., Abunyuwah, I., & Mensah, N. O. (2024). Does Fuel Price Volatility Induce Price Instability in the Agricultural Commodity Supply Chain? Empirical Evidence From Ghana. *Journal of Agriculture and Food Research*, *17*(May), 101216. https://doi.org/10.1016/j.jafr.2024.101216

Qian, L., Meng, H., Chen, X., & Tang, R. (2023). Evaluating Agricultural Drought And Flood Abrupt Alternation: A Case Study Of Cotton In The Middle-And-Lower Yangtze River, China. *Agricultural Water Management*, *283*(April), 108313. https://doi.org/10.1016/j.agwat.2023.108313

Rachmadhan, A. A., Kusnadi, N., & Adhi, A. K. (2020). Pengaruh Kebijakan Subsidi Pupuk terhadap Produksi Gula Kristal Putih Indonesia. *Jurnal Agro Industri Perkebunan*, *8*(1), 9–19. https://doi.org/https://doi.org/10.25181/jaip.v8i1.1266

Rizkiyah, N., & Shofiyah, S. (2021). Strategi Pengembangan Ekonomi Lokal melalui Kawasan Desa Wisata Berbasis Komoditas Unggulan Kopi Liberika (Kba) di Desa Kumpai Batu Atas Kecamatan Arut Selatan Kabupaten Kotawaringin Barat. *Mimbar Agribisnis*, *7*(2), 1572–1584. https://doi.org/10.25157/ma.v7i2.5513

Rozi, F., Santoso, A. B., Mahendri, I. G. A. P., Hutapea, R. T. P., Wamaer, D., Siagian, V., Elisabeth, D. A. A., Sugiono, S., Handoko, H., Subagio, H., & Syam, A. (2023). Indonesian Market Demand Patterns for Food Commodity Sources of Carbohydrates in Facing the Global Food Crisis. *Heliyon*, *9*(6), e16809. https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e16809

Ruccy, M. V., Suharno, S., & Asmarantaka, R. W. (2022). Analisis Tingkat Ketergantungan Impor pada Industri Susu Indonesia. *Jurnal Agribisnis Indonesia*, *10*(1), 101–112. https://doi.org/10.29244/jai.2022.10.1.101-112

Sholihah, F., & Kusnadi, N. (2019). Dampak Pengembangan Biofuels Terhadap Volatilitas Harga Beberapa Komoditas Pangan di Pasar Dunia. *Jurnal Agro Ekonomi*, *37*(2), 157–170. https://doi.org/http://dx.doi.org/10.21082/jae.v37n2.2019.157-170

Taghizadeh-Hesary, F., Rasoulinezhad, E., & Yoshino, N. (2019). Energy and Food Security: Linkages through Price Volatility. *Energy Policy*, *128*, 796–806. https://doi.org/10.1016/j.enpol.2018.12.043

Widarjono, A. (2018). *Ekonometrika: Pengantar dan Aplikasinya, Disertai Panduan EViews*. UPP STIM YKPN.

Wijayati, P. D., Harianto, & Suryana, A. (2019). Permintaan Pangan Sumber Karbohidrat di Indonesia. *Analisis Kebijakan Pertanian*, *17*(1), 13–26. https://doi.org/10.21082/akp.v17n1.2019.13-26

Wijayati, P. D., Laily, D., & Atasa, D. (2022). Volatilitas Harga Pangan pokok di Pasar Global Sebagai Dampak Pandemi COVID-19 dan Resesi Ekonomi Dunia. *AGROMIX*, *13*(1), 89–103. https://doi.org/10.35891/agx.v13i1.2874

World Bank. (2022). *World Bank Commodity Price Data (The Pink Sheet)*. https://www.worldbank.org/en/research/commodity-markets