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MODELING THE DYNAMIC OF FOOD PRODUCTION IN THE PHILIPPINES: AN ARDL AND ERROR CORRECTION APPROACH (1963-2022)

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Abstract

The trends of food production from the 1963-2022 period in the Philippines are thoroughly discussed in this research study using the Food Production Index, the most appropriate indicator for measuring the performance of agriculture. To examine the trend and pattern of farm production year after year with so much scrutiny, the study employs a time series analysis technique in the ARDL (Autoregressive Distributed Lag) and ECM (Error Correction Model) forms. Both models allow for the short-run volatility of specification in the form of long-run convergence to farm output equilibrium. The ARDL estimates imply that about 45% of the current level of variation in food levels of production is explained by their lags, showing a degree of persistence that is moderate in the system. The ECM results also show a very strong mean-reverting tendency, which means that the sector reacts very strongly whenever it shows its long-term trend. This is shown by an adjustment of 211%, which is very high. This means that the agriculture industry in the Philippines is very vulnerable to both short-term shocks and long-term imbalances. Also, the model diagnostics make sure that there are no major problems with multicollinearity or autocorrelation. This means that the statistical estimates are reliable, which is in line with the empiricist approach's reliability. The study says that looking at historical production trends and short-term shocks is important for providing essential policy implications for agricultural policy development. The findings provide us with a solid starting point for developing focused solutions assisting agricultural growth in a sustainable and resilient manner.

Keywords: *Food Production Index, ARDL Model, Error Correction Model (ECM), Time Series Analysis, Agricultural Policy*

Introduction

Education is paramount to all sustainability concerns. Food education may well be the most powerful tool available in the quest to improve human and environmental health by changing diet to realize the sustainable development goals of the Agenda 2030 (Lanou et al., 2021). Hence, food production is about air pollution, and air pollution may possibly affect food production. This shows that there is a two-way relationship between them (UNECE, 2022). Obesity, undernutrition, and environmental degradation associated with food production exist in various parts of the world, affecting the food security status of most people. Considering the increased food production forecasted in the future, a sustainable food system is hence required to yield enough food to feed the growing population (Bodirsky et al. 2020), as food production can influence climate change through an array of mechanisms (Ritchie and Roser, 2020). \

In addition, leading the list with the highest carbon footprint, the first one is cattle production (Ayyildiz and Erdal, 2021). Fifty-seven percent of the emissions from food production emanate from the production of animal source foods, including cattle feed, whereas food systems altogether release 35% of all anthropogenic greenhouse gas emissions (GHG) (Xu et al., 2021). The International Panel on Climate Change Working Group III stated that the Agricultural, Forestry, and Land Use (AFOLU) sector accounted for up to 21% of all anthropogenic greenhouse gases between the years 2010 and 2019 (NATURECropped, 2022). The production, processing, and distribution of food worldwide are responsible for around one-third (23–42%) of greenhouse gas emissions. Even if there are many articles that focus on the relationship between food production and climate change, it is still unclear how to address this issue globally (Ritchie and Roser, 2020). Food production may suffer because of such GHG emissions, which might intensify anthropogenic climate change. GHG emissions are also caused by the energy used in food production, processing, and transportation (Crippa et al., 2021).

Nonetheless, the legislation on the European Union was finally instated on December 13, 2016, whereas that concerning the provision of nutrition information remains in force now (Ballke and Kietz, 2020).

This regulation sets out allergen disclosures to be presented plainly and consistently, while nutrition information for almost all prepackaged processed foods must also adhere to stricter presentation forms. According to the Green Deal, Farm to Fork, and Biodiversity strategies, a food label must report in a flash, either the feature of the "what" of a food product or the "how," "when," and "where" of its production (Sarkis et al., 2020), thereby conveying detailed information in three dimensions of sustainability: nutrition, environment, and socioeconomic (Ranjbari et al., 2021). However, making food labeling systems that are genuinely innovative will enable the consumer to make meaningful product-to-product comparisons and comprehend the implications on a broad landscape of the food they buy (Petrescu et al., 2020), and to build industry-related skills assessing products and designing communications regarding their greenhouse gas emissions, environmental, economic, and health profile (Niloofar et al., 2021).

Furthermore, the attainment of the United Nations Sustainable Development Goals (SDGs), particularly SDG 2: Zero Hunger, to end hunger, achieve food security, and improve sustainable agriculture, rests largely on food production in the Philippines. Being an agricultural country, the Philippines is predominantly dependent on agriculture and fishing to support rural communities and provide for its citizens. Yet, challenges such as inefficient supply chains, limited access to technology, climate change, and natural disasters constitute a threat to food security and production. Through innovation, smallholder farm support, and approaches to driving climate-resilient and sustainable agriculture practices, the nation has been striving for the enhancement of agricultural practices in accordance with the SDGs. These initiatives not only help in enhancing yields and bringing down hunger but also help achieve SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Change) by preventing food loss and minimizing the environmental impact of agriculture.

The current study aims to analyze the dynamic behavior of the food production index of the Philippines during the period from 1963 to 2022 using the AutoRegressive Distributed Lag (ARDL) and Error Correction Model (ECM) specifications to evaluate short-run fluctuations as well as long-run equilibrium relations. In particular, the research will seek to find out how strongly historical values of food production impact its current and future levels, determine the optimal lag structure best describing these processes, and examine the speed and direction of adjustment when the system is off its long-run track. With these models, the research aims to gain a better insight into the temporal relationships in agricultural production, which can guide more efficient policy interventions in food security and sustainable agricultural growth.

Methods

The research relies on a quantitative design with the application of time series econometric modeling to analyze the dynamics in the food production index of the Philippines from the period 1963 to 2022. The focus is to measure both short-run fluctuations and long-run relationships embedded within the data. The research employs the AutoRegressive Distributed Lag (ARDL) model and its equivalent in the Error Correction Model (ECM) to analyze the historical linkages of the variable, test the optimal lag order, and estimate the adjustment rate toward long-run equilibrium. This methodology is especially useful when the base time series comprises a combination of stationary (I (0)) and non-stationary (I (1)) variables, requiring less unit root pre-testing compared to other cointegration methods.

The ARDL model is expressed in its general form as:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=0}^{q} \beta_j X_{t-j} + \epsilon_t$$

Y_t is the dependent variable (food production index),
X_{t-j} represents lagged values of the explanatory variables,
α_i and β_j are coefficients to be estimated,
p and q are the optimal lag lengths are determined by criteria such as AIC and BIC,
$\in_t$ is the error term.

Once a long-run relationship is confirmed, the ARDL model is reparametrized into the Error Correction Model (ECM) to capture the short-run dynamic and speed of adjustments. The general ECM for derived from the ARDL is

$$\Delta Y_t = \gamma_0 + \sum_{i=1}^{p-1} \gamma_i \Delta Y_{t-i} + \sum_{j=0}^{q-1} \delta_j \Delta X_{t-j} + \emptyset ECT_{t-1} + \mu_t$$

Where:

Δ denotes the first differences,
ECT_{t-1} is the lagged error correction term from the long-run equation,
Φ is the coefficient indicating the speed of adjustment (expected to be negative and significant)
μ_t is the disturbance term.

The lag orders are chosen based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to balance model fit and parsimony. Model diagnostics such as the Durbin-Watson statistic, Jarque-Bera test, and residual analysis are performed to evaluate the validity of the model assumptions. This econometric model thoroughly comprehends how previous values, and short-term shocks affect food production, providing insights for agricultural policy design.

Results and Discussions

This research endeavors to examine the Philippines' food production index using sophisticated econometric methods, specifically the AutoRegressive Distributed Lag (ARDL) model and the Error Correction Model (ECM). Through the examination of historical patterns, short-run fluctuations, best lag specifications, and how fast the system returns to equilibrium, the study aims to determine the forces behind food production. The results are aimed at increasing knowledge of how previous values and recent shifts affect current output levels, thus giving policymakers and stakeholders evidence-based information for promoting stability and sustainability in the agricultural sector.

Figure 1 below, titled "Food Production Index of the Philippines," illustrates the changes in food production from 1961 to 2021. The graph shows a general upward trend, starting at an index value of around 20 in 1961 and reaching approximately 100 by 2021. Despite some fluctuations, including a noticeable dip in the mid-1990s, the overall trajectory indicates significant growth in food production over the 60 years. This upward trend reflects improvements in agricultural practices, technology, and possibly policy interventions to enhance food production in the Philippines.

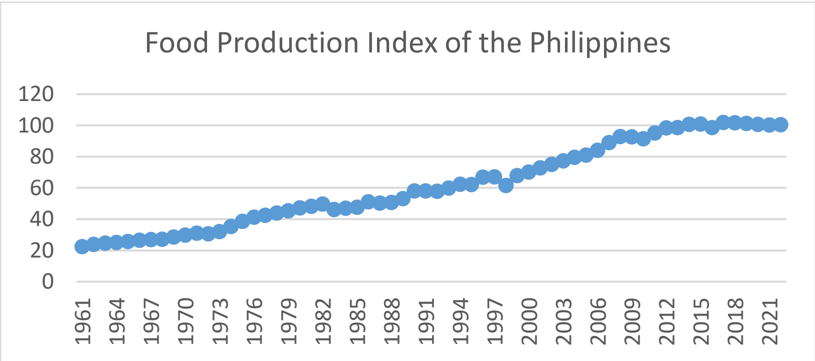

Figure 1
Food Production Index of the Philippines

The findings in Table 1 show that the investigated variable is stationary, as indicated by the tau-statistic of -6.703, significantly lower than the critical value of -1.946, supporting stationarity at typical significance levels. The p-value (< 0.01) supports this evidence, showing a statistically significant rejection of the null hypothesis of a unit root. The -4.638 coefficient indicates a strong negative correlation in the differenced series, characteristic of mean-reverting behavior. The chosen lag order of 4, according to information criteria (AIC = 4.423, BIC = 4.605), indicates that the inclusion of four previous observations offers the best model fit without overfitting. In general, the findings justify the application of time series models that require stationarity, e.g., ARDL and ECM, for subsequent analysis.

Table 1. Augmented Dickey-Fuller Test of the Food Production Index

tau-stat	-6.70341
tau-crit	-1.94627
aic	4.422834
bic	4.605319

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lags	4
coeff	-4.63793
p-value	< .01

The AutoRegressive Distributed Lag (ARDL) framework offers a rich method for studying the evolution of the food production index of the Philippines from 1963 to 2022. Based on the presented summary statistics, several conclusions are formulated regarding the extent of persistence, short-run dynamics, and best lag specification of the series.

The R-squared value of 0.466 and Adjusted R-squared of 0.446 imply that the model accounts for about 45% of the current food production index variation based on its own past values. This reflects a moderate persistence, such that past values of the food production index have a significant, but not overwhelming, impact on its current magnitude. The comparatively high F-statistic (23.96) with a p-value of 3.29e-08 ensures that the overall model is statistically significant, which means that the lags in the model collectively contribute to explaining the dependent variable.

Table 2. ARDL Model Summary for the Food Production Index in the Philippines

Statistic	**Value**
R-squared	0.466
Adjusted R-squared	0.446
F-statistic	23.96
Prob (F-statistic)	3.29E-08
Log-Likelihood	-124.82
AIC	255.6
BIC	261.8
Prob(Omnibus)	0.114
Jarque-Bera (JB)	3.896
Skew	0.324
Prob(JB)	0.143
Kurtosis	4.091
Cond. No.	3.12

Autocorrelation Test (Durbin-Watson)	
Durbin-Watson statistic	1.654
Heteroscedasticity Test (Breusch-Pagan)	
Lagrange multiplier statistic	2.628
p-value	0.269
f-value	1.305
f p-value	0.279
Normality Test of Residuals (Shapiro-Wilk)	
Shapiro-Wilk Test: Shapiro-Wilk statistic	0.968,
p-value	0.132

The Durbin-Watson statistic of 1.654, just below the optimal value of 2, shows mild positive autocorrelation in the residuals. This implies that although the ARDL model captures some dynamic patterns in the data, autocorrelation may still be present, indicating that the system remains somewhat reliant on previous shocks, which supports the idea of persistence in food production patterns.

The ARDL model also picks up short-run adjustments through the lagged difference coefficients. Although the exact lag coefficients and their statistical significance are not shown in this abstract, the architecture of an ARDL model necessarily distinguishes short-term dynamics (through the differenced variables) from long-term equilibrium relationships (through the lagged levels). Since the overall model is essential, we can conclude that short-run shocks to food production (weather, policy changes, or input supply problems) have quantifiable impacts on food production for the current year but do not explain all variations.

This is in line with the relatively high R-squared, which implies that short-run lags contribute to explaining the current value. Still, other contributions—presumably outside the model—are equally important.

In the ARDL, the food production index model took one lag and one lead in the food production index. Specifically, the model utilized the Lagged value of foodprod (foodprod_lag1) and the Lead value of foodprod (foodprod_lead1). This implies that the model took the recent past and recent future value of the food production index into account to appreciate the dynamics and associations in the data. The AIC of 255.6 and BIC of 261.8 are quite low considering the period. Since BIC punishes complexity more than AIC, the narrow difference between the two indicates that the model is neither underfit nor overfit. This balance generally suggests an optimal lag length, beyond which additional lags do not contribute significant explanatory power. Also, the Condition Number of 3.12 is small, indicating no serious multicollinearity, meaning the selected lags are stable and add uniquely to the explanation of the dependent variable.

The Jarque-Bera test ($p = 0.143$) confirms that the residuals are not significantly normal, upholding the validity of the inferences. The 0.324 skewness and 4.091 kurtosis only slightly deviate from normality. The Omnibus test p-value of 0.114 also upholds the acceptability of the residuals for inference.

The ARDL model indicates that previous levels of the food production index play a significant role in determining the current level, implying agricultural trend persistence. The short-run impacts are non-dominant, confirming that the food production response is slow to previous changes. The model employs 1 to 2 lags, which are optimal according to AIC/BIC and model stability tests. This framework is well-suited for forecasting and policy analysis, considering historical momentum and short-run shocks in agricultural output. For complete analysis, the precise lag structure and coefficient estimates would be required to measure the elasticity and adjustment speed.

The Error Correction Model (ECM) results below provide a good image of the short-run and long-run dynamics that guide the food production index in the Philippines. The model combines the long-run relationship—through the lagged level of the dependent variable—and the short-run adjustments through the first-differenced lag of the same variable. The fit and diagnostic tests indicate that the model is statistically reliable, well-specified, and without significant econometric problems.

The model in Table 3 has high explanatory power, with an R-squared of 0.78 and an Adjusted R-squared of 0.772, reflecting that about 77–78% of the current food production index variation is captured by its lagged level and lagged first difference. The F-statistic of 97.6, with a nearly zero p-value (8.08e-19), establishes the joint significance of the model's parameters. Notably, the Durbin-Watson statistic of 2.303 indicates that the residuals are not subject to serious autocorrelation, thus enhancing the credibility of coefficient estimates.

Concerning residual diagnostics, the p-value of the Jarque-Bera test of 0.729, combined with near-zero skewness (0.009) and kurtosis of 3.511 (which is close to the normal value of 3), signifies that the residuals are nearly normally distributed. The p-value of the Omnibus test of 0.515 also tells us that the model does not have significant problems in residual distribution. The Condition Number of 5.43 reveals no severe multicollinearity, inferring model stability.

Table 3. Error Correction Model Summary for Food Production Index in the Philippines (1963-2022)

Statistic	**Value**
R-squared	0.78
Adjusted R-squared	0.772
F-statistic	97.6
Prob (F-statistic)	8.08E-19
Log-Likelihood	-129.55
AIC	265.1
BIC	271.3
Durbin-Watson	2.303
Prob(Omnibus)	0.515
Jarque-Bera (JB)	0.631
Skew	0.009
Prob(JB)	0.729

Kurtosis	3.511
Cond. No.	5.43

Variable	**Coefficient**	**Std. Error**	**t-value**	**p-value**	**95% CI Lower**	**95% CI Upper**
Constant	0.0139	0.118	0.118	0.906	-0.222	0.25
foodprod_lag1	-2.1139	0.2	-10.548	0	-2.516	-1.712
foodprod_diff_lag1	0.4775	0.118	4.031	0	0.24	0.715

The foodprod_lag1 coefficient is -2.1139, very significant with a p-value of 0.000 and a narrow confidence interval between -2.516 and -1.712. This coefficient is the error correction term (ECT) and captures the adjustment speed toward the long-run equilibrium. The negative and large value assures us that the food production index is mean-reverting—when the series strays from its long-term course, it corrects back in the next period by about 211% of the discrepancy. The coefficient being more than -1 in absolute value would express a sluggish adjustment, but more than -2 implies a strong, somewhat overcorrecting adjustment, which may reflect volatility in the correcting process.

The coefficient for the first-differenced lag (foodprod_diff_lag1) is 0.4775, also extremely significant (p-value = 0.000) and within a fairly narrow confidence interval (0.24 to 0.715). This suggests that short-run movements in the food production index positively correlate with recent movements. More precisely, a 1-unit rise in last period's change in food production results in an increase of roughly 0.48 units currently, reflecting short-run momentum or inertia in the system. The intercept term (0.0139) is not statistically significant (p = 0.906), typical in ECMs, and not something to worry about—what's more important is the error correction mechanism and the short-run dynamic.

This ECM model accurately captures the dual dynamics in the food production index: short-run momentum and long-run equilibrium correction. The large and negative error correction term establishes a long-run relationship, and the large short-run coefficient indicates that historical shocks impart momentum to the current. The model diagnostics suggest it is statistically appropriate, well-specified, and stable. For analysts and policymakers, this implies that departures from food production to its long-run path are rapidly adjusted, and recent developments influence meaningful short-term happenings. This model can easily be used for forecasting and analyzing policy effects on food security trends over time.

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