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Causal Relationship Between Climate Pressures and Agricultural Producer Prices in Türkiye; the Toda Yamamoto Approach

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Abstract

Increases in greenhouse gas emissions, a key indicator of climate change, pose significant risks and uncertainties for the agricultural industry. From a theoretical supply-side perspective, greenhouse gas emissions may be associated with agricultural productivity losses and, consequently, with potential upward risks for producer prices. However, the Toda-Yamamoto framework used in this study tests predictive Granger causality rather than the magnitude or sign of a structural price effect. This study examines the predictive Granger-causality relationship between total greenhouse gas emissions (CO_2, CH_4, N_2O) and the agricultural producer price index (UFE), which represents the agriculture, forestry, and fishing sectors in Türkiye, using data for 1983 to 2024. The analysis first applies the standard Toda-Yamamoto and Bootstrap Toda-Yamamoto causality tests without dummy variables. These tests are then re-estimated by incorporating structural-break dummy variables to assess the sensitivity of the findings to major break periods. The clearest statistical evidence of predictive causality was obtained from the standard Toda-Yamamoto test without dummy variables; however, this evidence should be interpreted with caution. The Bootstrap Toda-Yamamoto result is only marginally significant at the 0.10 level, and the dummy-augmented specifications do not support a statistically significant causal relationship. This suggests that climate policies must not be viewed in isolation from agricultural and price stability policies.

Concurrently, it highlights the significant role of measures designed to mitigate greenhouse gas emissions.

Keywords
Climate change; greenhouse gas emissions; agricultural PPI; time series analysis; causality analysis

1. Introduction

Carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) are among the most important greenhouse gases associated with climate change. Although CH_4 and N_2O are emitted into the atmosphere in smaller amounts than carbon dioxide, their adverse effects on global warming are greater than those of carbon dioxide [1]. The emission of these gases has significantly increased since the Industrial Revolution, leading to their accumulation in the atmosphere and intensifying the greenhouse effect, contributing to a rise in global temperatures.

Agriculture can both contribute to and mitigate climate change [2]. Agricultural production has been demonstrated to have a substantial impact on greenhouse gas emissions. As the Intergovernmental Panel on Climate Change (IPCC) asserts, methane (CH_4) and nitrous oxide (N_2O) emissions are primarily attributable to agricultural and animal production activities [3]. It has been determined that approximately 10-14% of greenhouse gas emissions (GHG), including 50-60% of methane (CH_4) and nitrous oxide (N_2O), which are two significant GHGs, can be linked to agricultural practices and the production of both natural and synthetic fertilizers [4, 5]. Exhaust emissions from tractors and other agricultural machinery used in the sector also contribute to total emissions as a secondary source. In addition, the excessive or improper use of chemical fertilizers and pesticides significantly contributes to increased carbon emissions. Fertilizer used in agriculture is broken down by microorganisms in the soil and converted into N_2O, a potent greenhouse gas. Although this gas accounts for only a small share of global greenhouse gas emissions, it has a 300 times greater warming effect per unit than carbon dioxide [6]. In addition, the size of agricultural enterprises is another factor. Large-scale agricultural production can vary significantly in terms of emissions, production methods, and energy use [7]. The diversity of agricultural production also plays a key role in determining greenhouse gas emissions. In particular, crops that require large amounts of water tend to have a greater impact than others. For example, paddy rice accounts for 9-11% of greenhouse gas emissions [8].

Soil-related emissions contribute significantly to climate change and are particularly important for assessing global warming potential (GWP). Basheer et al. report gas-specific estimates showing that soil-related emissions account for approximately 21% of nitric oxide (NO), a reactive nitrogen species, as well as 53% of nitrous oxide (N_2O), 35% of carbon dioxide (CO_2), and 47% of methane (CH_4) fluxes [9]. These percentages are not additive shares of total GWP; rather, they indicate separate gas-specific contributions, whose climate relevance depends on each gas's atmospheric lifetime, radiative efficiency, accounting boundary, land-use category, and estimation method.

Research indicates that carbon dioxide emissions from the agricultural sector significantly contribute to climate change; however, some perspectives suggest that agriculture can also be a vital part of the solution to this issue. Follett asserts that it is feasible to mitigate the effects of elevated atmospheric CO_2 levels by sequestering CO_2 in agricultural soils [10]. This can be accomplished by implementing sustainable agricultural practices, enhancing efficiency, reducing meat consumption, sequestering CO_2 in carbon pools, utilizing animal manures effectively, and engaging in afforestation. Smith et al. and Sauerbeck hold similar views and argue that agriculture can reduce carbon dioxide emissions by reducing fossil fuel use in agricultural practices, substituting fossil fuels with biofuels, stopping the conversion of forest land into agriculture, and improving soil fertility with the addition of humus rather than with synthetic fertilizers [11, 12].

In 2023, greenhouse gas emissions from the agriculture sector of Türkiye tested 71.8 million tons of CO_2 equivalent [13]. While countries have been prioritizing industrialization in their growth models, the COVID-19 pandemic-which broke out on the world stage in 2020-demonstrated the importance of the agricultural sector in an economy, not least for food supply security.

Food inflation in Türkiye is driven by several factors, including rising input costs, higher fuel prices, increased transportation costs, long marketing chains, high intermediary commissions, and external shocks such as terrorism or war [14]. Population remains a strong driving force behind crop prices, although its impact is limited by the slowdown in its growth rate [15].

In addition to the anticipated increases in the Agricultural Producer Price Index resulting from climate change, other deleterious effects may also emerge. Rising agricultural prices may reduce consumers' purchasing power and alter demand patterns, particularly for lower-income households. They may also generate broader macroeconomic pressures through food inflation, production costs, and input-output linkages with other sectors. Since agricultural commodities serve both as essential consumption goods and as raw materials for several industries, climate-related disruptions in agricultural production may have wider implications for inflation, employment, trade balances, and food security.

The growing global population and increased demand for food will cause agriculture-related emissions to grow more rapidly in the coming years. To mitigate the impact of climate change on crop production, two strategies can be employed. The first strategy is to reduce greenhouse gas emissions and adapt agricultural production practices to lower emissions. The other strategy involves introducing social, economic, and agronomic adaptations and investments to enhance resilience to the damaging impacts of climate change, thereby improving the sustainability and reliability of food production.

In this study, total greenhouse gas emissions are used not as a direct measure of the short-run meteorological conditions experienced by the agricultural sector, but as a macro-level indicator of cumulative environmental pressure associated with climate change. Carbon dioxide, methane, and nitrous oxide are among the principal anthropogenic drivers of global warming, and their accumulation in the atmosphere is linked to long-term changes in temperature patterns, precipitation regimes, drought risks, and broader uncertainty in agricultural production conditions. Accordingly, total greenhouse gas emissions are interpreted as an indirect, long-term proxy for climate-related pressure rather than as a direct measure of weather conditions or local agro-climatic stress.

This choice, however, entails an important limitation. National aggregate greenhouse gas emissions do not directly capture the climatic conditions that farmers experience in specific regions and production seasons, such as temperature anomalies, rainfall variability, drought intensity, frost events, or extreme weather shocks. Therefore, the emissions variable used in this study should not be regarded as a full substitute for direct climate indicators. The empirical analysis should instead be interpreted as a macro-level time-series investigation of whether aggregate emissions contain predictive information for agricultural producer prices, rather than as a structural assessment of the direct climate-price transmission mechanism.

Three main motivations drive this study. First, the existing literature on the relationship between greenhouse gas (GHG) emissions and agriculture has predominantly focused on the effects of agricultural production on emissions. In contrast, studies examining whether emissions contain predictive information for agricultural outcomes remain limited. In particular, empirical studies directly examining the causal link between greenhouse gas emissions and agricultural producer prices in Türkiye are scarce. Second, determining whether greenhouse gas emissions have predictive content for agricultural producer prices is important for understanding agricultural price dynamics. However, such evidence should not be interpreted as identifying a structural transmission mechanism. Third, the literature on Türkiye remains limited. Özbay, which is the closest prior study in terms of country context and environmental focus, examines the relationships among industrialization, economic growth, CO_2 emissions, and the FAO-reported agricultural production index using the ARDL approach [16]. Therefore, it differs from the present study in both the dependent variable and the econometric framework. In this respect, the present study contributes to the literature by focusing on agricultural PPI rather than agricultural output and by employing the Toda-Yamamoto and Bootstrap Toda-Yamamoto causality frameworks.

1.1 Literature Review

Several studies have examined the relationship between carbon emissions and agricultural production using causality or time-series frameworks. Asumadu-Sarkodie and Owusu analyse the relationship between carbon dioxide emissions and agricultural production in Ghana [17], while Ben Jebli and Ben Youssef investigate the link between CO_2 emissions and agricultural value added in Tunisia [18]. Ben Jebli and Ben Youssef extend this analysis to five North African countries [19]. Rehman et al., Nasrullah et al., and Ahmed Dar et al. examine the effects of emissions on maize or rice production in Pakistan, South Korea, and Cuba, respectively [20-22]. In the case of Türkiye, Özbay reports a positive but limited effect of CO_2 emissions on the agricultural production index [16]. By contrast, Chandio et al. find a negative effect of carbon emissions on wheat yield in Türkiye, while Sibanda and Ndlela report no significant effect of agricultural production on carbon emissions in South Africa [23, 24].

Another area of research examines the relationship between climate change and agricultural production, considering factors such as productivity, output, temperature, drought, and precipitation. Haile et al. suggest that climate change could reduce global crop production by 9 percent in the 2030s and by 23 percent in the 2050s, and could increase annual fluctuations in global crop production by 1-3 percent over the next forty years [25]. They have argued that this significant decline in agricultral supply could trigger supply shocks, leading to a sharp rise in agricultural prices. Gupta et al. calculated that, in the absence of climate change and ozone pollution in India, agricultural productivity would be 5.7 percent higher [26]. Based on this finding, they determined that yield losses caused by climate change significantly reduce economic welfare by driving up food prices. Odongo et al. discovered that in Eastern and Southern Africa, fluctuations in supply driven by variations in precipitation are the primary factor influencing food inflation [27]. Nguyen et al. used a set of terms consisting of "factors affecting crop prices" and "the impact of climate change on crop prices" and stated that the factors identified by these terms play a determining role, at a rate of 55%, in the impact on agricultural product prices [15]. Yusifzada examined the cointegration and causal relationships between the Climate Conditions Index (CCI) and agricultural inflation across 153 countries [28]. The author found that the median Granger causality p-value across the 153 countries was 0.036 and identified a Granger causal relationship between the CCI and the agricultural producer price index at a 90 percent confidence interval. Based on these results, the author noted that climate change significantly affects agricultural prices across countries. Li and Chen examined the effects of carbon emissions on the producer price index and found that they have no discernible impact in the short run, negative effects in the medium term, and volatile effects in the long run [29]. Satapathy et al. found that climate shocks are one of the main structural drivers of price volatility in agricultural markets [30]. Paija et al. found that a 1% increase in carbon emissions in Nepal reduces agricultural productivity by 0.45% [31].

A review of the literature shows that existing studies have largely focused on agricultural production, agricultural output, or specific crop indicators in relation to carbon emissions. By contrast, studies examining the predictive Granger-causality link between aggregate greenhouse gas emissions and agricultural producer prices remain limited, particularly for Türkiye. Therefore, this study aims to contribute to this relatively underexplored area by focusing on agricultural PPI and by considering CO_2, CH_4, and N_2O emissions jointly.

2. Method

The Toda-Yamamoto causality test was first developed by Toda and Yamamoto in 1995 [32]. The method tests for Granger causality by estimating an augmented VAR model in levels, with additional lags equal to the maximum order of integration of the variables. In contrast to the Granger causality test, which requires the variables to be integrated of the same order and to have a cointegrated relationship [33], the Toda-Yamamoto causality test can be applied when the series are of mixed integrated orders and no cointegration is present. This approach avoids the potential loss of long-run information that may arise from differencing the variables. Subsequently, in 2006, Hacker and Hatemi-J enhanced this methodology by incorporating bootstrap critical values into the test [34].

Augmented Dickey-Fuller (ADF), a traditional unit root test developed by Dickey and Fuller [35, 36], the Phillips-Perron (PP) test developed by Phillips and Perron [37], and the KPSS test developed by Kwiatkowski, Phillips, Schmidt, and Shin do not take structural breaks into account [38]. The multiple linear regression model with *m* breaks is defined as follows by Bai and Perron [39]:

$$y_t = x_t\beta + z_t\delta_j + \mu_t \quad t = T_{j-1} + 1, \dots, T_j \text{ and } j = 1, \dots, m + 1 \tag{1}$$

In Model 1, y_t is the dependent variable observed at time t; x_t and z_t are covariance vectors with dimensions (p × 1) and (q × 1), respectively; β and δ_j, $j = 1, 2, \dots, m + 1$, are the respective coefficient vectors; and μ_t is the error term at time t.

A bivariate Vector Autoregressive (VAR) model was estimated to examine the dynamic predictive relationship between agricultural PPI and greenhouse gas emissions over the period

1983-2024. The lag length was set to one period based on the information criteria and diagnostic tests. In the model, dummy variables for 1991, 2001, and 2018 (d91, d01, d18) were added as exogenous variables to capture structural breaks. This made it possible to systematically assess both the variables' internal dynamics and the potential effects of certain turning points.

The VAR (1) model used in the study is presented in equation (2).

$$Y_t = \alpha + \sum_{i=1}^{p+d_{max}} A_i Y_{t-i} + \Gamma D_t + \varepsilon_t \tag{2}$$

where Y_t = [$lufe_t$, $lsera_t$]' denotes the vector of endogenous variables, D_t = [$d91_t$, $d01_t$, $d18_t$]' represents the vector of dummy variables, α is the intercept vector, A_i denotes the coefficient matrix, Γ is the coefficient matrix of dummy variables, and ε_t is the error term.

Given the annual sample of 42 observations, the inclusion of lagged endogenous variables, a constant term, and three structural-break dummies considerably reduces the effective degrees of freedom. In the baseline Toda-Yamamoto specification with $p + d_{max} = 2$, using 2 tags resulting in the loss of two initial observations, leaving 40 effective observations for estimation. Each equation includes four lagged endogenous regressors and a constant term, yielding five estimated coefficients. When the three structural-break dummies are included, the number of regressors per equation increases to eight, leaving approximately 32 residual degrees of freedom per equation. In the bootstrap implementation with $p + d_{max} = 3$, the effective sample is further reduced to 39 observations. With 6 lagged endogenous regressors, one constant and three dummy variables, each equation contains ten estimated coefficients, leaving approximately 29 residual degrees of freedom per equation. Therefore, the findings should be interpreted as finite-sample evidence rather than as strong large-sample inference, and the potential over-parameterisation should be kept in mind when evaluating the Wald statistics.

The structural-break dummies were included as exogenous control variables rather than as restricted variables in the Wald causality test, because they capture one-off regime-shift periods rather than dynamic endogenous processes. Including these dummies in the Wald restriction would test the direct effects of break episodes, rather than Granger causality between emissions and agricultural producer prices.

3. Analysis and Findings

As the time series included in the analysis consisted of level values, they were analyzed after taking their natural logarithms. The variables and their sources are shown in Table 1.

Table 1 Variables and their sources.

Variables	Explanation	Sources
lufe	Dependent variable. Agricultural producer price index, in natural logarithms, consisting of the total for the agriculture, forestry, and fishing sectors, series code TFUE-GK378599484, base year 2020 = 100	TUIK (Turkish Statistical Institute) https://biruni.tuik.gov.tr/medas/?kn=159&locale=tr
lsera	Independent variable. Total greenhouse gas emissions, in natural logarithms, consisting of CO_2, CH_4, and N_2O gases, expressed in Mt CO_2eq/year	EDGAR (Emissions Database for Global Atmospheric Research) https://edgar.jrc.ec.europa.eu/
d91	Dummy variable for the 1991 structural break date	
d01	Dummy variable for the 2001 structural break date	
d18	Dummy variable for the 2018 structural break date	

The independent variable, total greenhouse gas emissions, combines CO_2, CH_4, and N_2O emissions and is measured in Mt CO_2 equivalent per year. In the present study, this variable is employed as an indirect macro-level proxy for climate-related pressure. This choice is motivated by the central role of greenhouse gas emissions as anthropogenic drivers of climate change and by their relevance to long-term environmental risks that may affect agricultural production conditions. Nevertheless, the emissions series does not measure the direct climatic conditions experienced by the agricultural sector, such as temperature, precipitation, drought, or extreme weather events. Consequently, the empirical findings should not be interpreted as estimates of the effects of direct meteorological climate variables. Rather, they should be read as limited time-series evidence on whether aggregate emissions carry predictive content for agricultural producer price dynamics.

The stationarity properties of the variables were examined using the ADF, PP, and KPSS tests. The results reported in Table 2 reveal a mixed but partially reinforcing pattern of evidence regarding the integration orders of the series. For lufe, the ADF and PP tests indicate a unit root in levels, whereas the series becomes stationary after first differencing. The KPSS test provides only limited support for level stationarity. Taken together, these findings are broadly consistent with an I(1) characterization, although the evidence is not fully decisive.

Table 2 ADF, PP and KPSS unit root tests.

		ADF		
Variables	Level	Prob	First Difference	Prob
lufe	-1.4414 (-4.2050)	0.8328	-4.2197* (-4.2050)	0.0096
lsera	-3.309221*** (-3.192902)	0.0790		
		PP		
lufe	-1.0776 (-4.1985)	0.9206	-4.2856* (-4.2050)	0.0081
lsera	-3.3547*** (-3.1929)	0.0719		
		KPSS		
	Level	Critic Values		
lufe	0.1961**	0.1460		
lsera	0.0671*	0.2160		

*, **, and *** represent significance levels of 0.01, 0.05, and 0.10, respectively. The values in parentheses are the critical values of the tests. The test was performed with a constant and a time trend.

The results for lsera exhibit a similarly mixed profile. The ADF and PP tests suggest level stationarity at the 0.10 significance level, and the KPSS test also supports stationarity. However, when the evidence across tests is considered jointly, the integration order of lsera remains somewhat ambiguous. Accordingly, a conservative specification was adopted, with the maximum order of integration was set at d_{max} = 1. This choice is consistent with the logic of the Toda-Yamamoto approach, which is designed to accommodate uncertainty regarding the integration properties of the variables without requiring pretests to deliver a definitive common order of integration. The subsequent causality analysis was therefore conducted within an augmented level VAR framework, with lag length expanded by the maximal integration order.

Traditional unit root tests do not account for structural breaks in their findings. Nonetheless, structural breaks may exist that could influence the variables throughout the analysis period. Bai and Perron's Global L breaks, a method for testing multiple structural breaks, identifies both number and locations of breakpoints within a defined maximum break range, rather than establishing a singular break point. This ensures that the break dates are correctly positioned within the model throughout the analysis period. The test results are presented in Table 3.

Table 3 Bai-Perron multiple structural break test.

Break 1	Break 2	Break 3
246.5099 (11.47) [1991]	216.6141 (9.75) [2001]	196.0629 (8.36) [2018]
UD Max Statistic 246.5099 (11.70) WD Max Statistic 269.0002 (12.81)		

The values in parentheses are the test critical values at the 0.05 significance level, and the values in square brackets are the break dates. The UDMax and WDMax statistical values were analyzed at the 0.05 significance level according to the UDMax and WDMax critical values based on Bai-Perron (Economic Journal, 2003) critical values.

The Bai-Perron test for structural breaks can examine up to 5 breaks. However, in analyses based on yearly data with a small sample size, choosing a large number of breaks canrapidly consume the degrees of freedom for the regressors. Therefore, to allow for a more balanced choice, a total of 3 break dates were included in the regression as dummy variables.

The first of the break dates, 1991, is the year in which the United States carried out a military intervention in Iraq, Türkiye's close neighbour. This war, which took place right near Türkiye, was a period when costs increased due to rising prices of fuels and fertilizers used in agricultural production. In the same year, following the dissolution of the Soviet Union, uncertainty in this region-an important grain-producing area-increased, disrupting the balance between supply and demand and, in turn, leading to greater price volatility.

The second break date, February 2001, corresponds to a period of economic crisis in Türkiye. The currency shock during the crisis led to sharp increases in the prices of fuel, fertilizers, feed, and agricultural pesticides, which in turn drove up agricultural PPI. In 2001, the Marrakech Accords (COP7) were also adopted, introducing more detailed arrangements for implementing the provisions of the Kyoto Protocol (1997). These arrangements clarified rules for measurement, reporting, and verification, as well as inventory procedures. Türkiye was removed from the category of countries that provide financial support while remaining in Annex I (at COP7). The reflection of these arrangements on the agricultural sector is that the methodology for collecting and measuring agricultural emissions was defined, and the issue of reducing greenhouse gas emissions was placed on the policy agenda.

The final break date-summer and autumn of 2018-corresponds to a period marked by an exchange rate shock and high inflation. The exchange rate increases led to substantial rises in the prices of imported input items. To be able to intervene in these developments, policymakers used measures such as tax regulations that facilitate imports, regulatory changes, and product-based public procurement.

The first stage of the Toda-Yamamoto causality is to determine the VAR model and select the appropriate lag length. The result of the tests carried out for this purpose is given in Table 4.

Table 4 Appropriate lag duration.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-68.1619	NA	3.24e-05	3.8506	4.0661	3.9272
1	161.6267	387.0126*	6.84e-10*	-6.9277*	-5.6348*	-6.4677*
2	174.3303	18.0525	1.40e-09	-6.2805	-3.9103	-5.4372
3	196.0679	25.1697	2.02e-09	-6.1088	-2.6612	-4.8822
4	226.0726	26.8463	2.36e-09	-6.3722	-1.8473	-4.7623

The lag length was determined by the model that minimized the information criteria (AIC/SC/HQ). This selection is intended to enhance model fit while also mitigating the risk of over-parameterization. In certain econometric analyses, it is not possible to conduct calculations for the initial observations due to the model's starting values or the selected lag length. Consequently, the EViews software indicates this by placing the text “NA” in the corresponding row. The abbreviation “NA” stands for “Not Available”. In this context, the selection of lags was determined based on computable criterion values. The asterisk (*) displayed in the table serves to enhance the visibility of the relevant lag length. The maximum order of integration of the series was determined as d_{max} = 1, and the information criteria suggested a lag length of p = 1; therefore, a VAR($p + d_{max}$) = VAR(2) model was estimated.

Table 5 reports the results for the VAR(2) model estimation. From the Lufe equation, the coefficient of the one-period lag on the agricultural producer price index is 0.9951 and is significant. This indicates that the agricultural producer price index exhibits strong persistence, meaning that current producer price dynamics are largely shaped by their own past values. On the other hand, although the coefficient of the one-period lag of GHG emissions is negative, it is not statistically significant. Therefore, in this context, it seems that a short-run direct effect of lagged emissions on agricultural production cannot be detected.

Table 5 VAR(2) results.

Variables	Coefficient	Prob
lufe (-1)	0.9951	0.0564
lsera (-1)	-0.1208	0.4344
R^2: 0.9947	Adj. R^2: 0.9939	

The R^2 and adjusted R^2 values for both models were around 0.99, indicating that the models fit the sample very well. But coefficient estimates show that in the short term, the dynamics of agricultural producer prices and greenhouse gas emissions are driven more by their own past values than by that of the other. Taken together with the structural-break and causality results reported below, these findings suggest that the emissions-price relationship may be influenced by persistence, long-run trends, and regime shifts rather than by a strong short-run direct effect.

The stability of the constructed VAR model is an important factor in the model's reliability. Therefore, the VAR model was subjected to a stationarity test, and the obtained polynomial distribution is depicted in Figure 1.

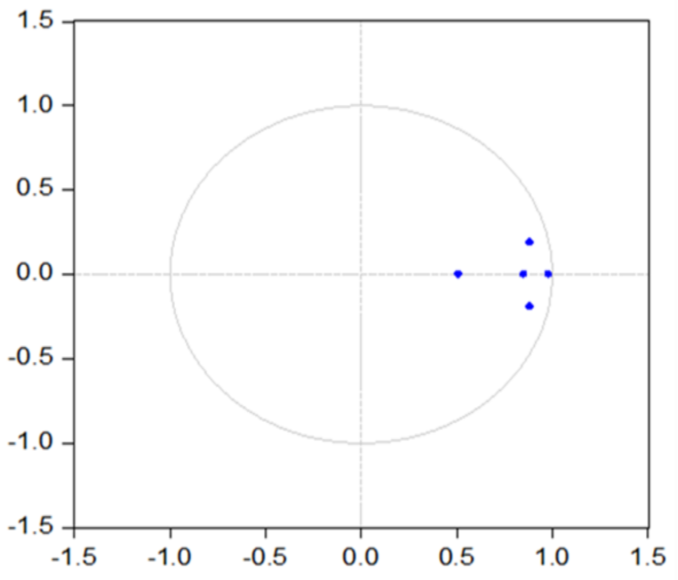

Figure 1 Polynomial distribution.

Since the points representing the variables lie within the unit circle, the VAR model with 1 lag be stationary.

Before applying the Toda-Yamamoto causality test, several diagnostic tests are conducted in order to assess the reliability and robustness of the estimated model. These tests and their results are presented in Table 6.

Table 6 Structural tests.

Tests	Results	Prob.
Autocorrelation LM Test	4.583475	0.3329
Normality Test	1.754198	0.4160
White Heteroskedasticity	52.1260	0.0750

As illustrated in Table 6, the estimated model does not exhibit issues related to autocorrelation, normality, or heteroskedasticity. These results provide no evidence of major violations of the standard VAR diagnostic assumptions. Based on these findings, the Toda-Yamamoto causality test was conducted. The results are detailed in Table 7.

Table 7 Toda Yamamoto causality test.

Direction of Causality	Value	df	Null Hypothesis: Value	Null Hypothesis: Std Error	Prob
lsera → lufe	4.5137	1	H_0: C(3) = 0 -2.3948	H_0: C(3) = 0 1.1272	0.0336**
lufe → lsera	1.4414	1	H_0: C(10) = 0 -0.0239	H_0: C(10) = 0 0.019931	0.2299

** indicates the 0.05 significance level.

Table 7 reports the Toda-Yamamoto test results for predictive Granger causality between greenhouse gas emissions and agricultural PPI. For the direction from lsera to lufe, the Wald statistic is 4.5137 with a p-value of 0.0336, indicating evidence of predictive Granger causality at the 0.05 significance level. However, this result should not be interpreted as evidence of a structural economic mechanism. The Toda-Yamamoto test indicates whether lagged values of one variable improve the prediction of another; it does not identify the magnitude, sign, or transmission channel of an economic effect. Accordingly, the predictive causality detected in the baseline specification should not be interpreted as evidence that greenhouse gas emissions directly determine agricultural producer prices. Agricultural producer prices are shaped by a wide range of economic and environmental factors, including temperature anomalies, precipitation and drought conditions, agricultural yields, exchange rate movements, fertilizer costs, energy and fuel prices, transportation costs, trade regulations, and agricultural support policies. Some of these factors may simultaneously affect both emission dynamics and agricultural price formation. Therefore, excluding these common determinants from the bivariate framework implies that the observed predictive relationship may partly reflect omitted variables or shared macroeconomic and environmental shocks rather than a direct emissions-to-price transmission mechanism.

Upon examining the null hypothesis value, a coefficient exhibiting a negative sign is noted. From an econometric standpoint, it would be erroneous to interpret this negative coefficient as suggesting that an increase in the lsera variable would result in a decrease in the lufe variable. The Toda-Yamamoto causality test is limited to indicating predictive Granger causality, or statistical precedence, between variables; it does not identify the magnitude, sign, or structural transmission mechanism of an economic effect. When the null hypothesis value is divided by the standard error using absolute values, the resulting t-statistic is greater than twice the standard error (≈-2.12). This finding reinforces the coefficient's statistical significance. Furthermore, the p-value from the Wald test (0.0336) corroborates this finding.

The second causal relationship was examined as running from the dependent variable lufe to the independent variable lsera. According to the Wald test findings, the Wald statistic is 1.4414 and the p-value is 0.2299; there is no evidence of a Granger causal relationship running from the dependent variable lufe to the independent variable lsera. Upon examining the null hypothesis, a negative coefficient is observed. This interpretation aligns with the conclusions drawn from the previous Wald test results. In addition, since the p-value of the null hypothesis is not statistically significant, it is not possible to provide an econometric interpretation. When the null hypothesis value is divided by the standard error, the resulting t-statistic is ≈-1.20, which is below the commonly accepted absolute critical value of 1.96 at the 0.05 significance level. This supports the conclusion that the coefficient is not statistically significant.

Our earlier findings suggest that long-run trends and potential regime shifts may shape the relationship between greenhouse gas emissions and the agricultural producer price index. For this reason, restricting the causality analysis to the standard Toda-Yamamoto framework may not fully capture the possible effects of structural breaks. Whether structural breaks affect the model results is an important question that needs to be answered. Therefore, the study includes Toda-Yamamoto and Bootstrap Toda-Yamamoto tests with dummy variables. Through these tests, the sensitivity of the causality results to the break periods will be revealed. In other words, these additional analyses were conducted to assess whether the predictive Granger-causality evidence remains robust after accounting for structural breaks.

For this purpose, the results of the dummy-augmented Toda-Yamamoto causality test are reported in Table 8.

Table 8 Dummy-augmented Toda-Yamamoto causality test.

Direction of Causality	Value	df	Null Hypothesis: Value	Null Hypothesis: Std Error	Prob	Result
lsera → lufe	2.5553	1	H_0: C(3) = 0 -1.5683	H_0: C(3) = 0 0.9811	0.1099	Not rejected
lsera → lufe	2.9948	1	H_0: C(4) = 0 1.7176	H_0: C(4) = 0 0.9925	0.0835	Marginally significant at the 0.10 level
d91 → lufe	1.0668	1	H_0: C(6) = 0 0.1912	H_0: C(6) = 0 0.185148	0.3016	Not rejected
d01 → lufe	0.5596	1	H_0: C(7) = 0 -0.1473	H_0: C(7) = 0 0.1969	0.4544	Not rejected
d18 → lufe	0.0147	1	H_0: C(8) = 0 0.0211	H_0: C(8) = 0 0.1737	0.9032	Not rejected

Note: d91, d01 and d18 are exogenous dummy variables representing structural breaks in 1991, 2001, and 2018, respectively. The dummies were included as exogenous regressors, while the Wald restrictions were imposed only on the lagged endogenous coefficients. The results should be interpreted with caution in light of the relatively small sample size and the potential presence of structural breaks.

Table 8 reports the Toda-Yamamoto causality results for the lufe equation after incorporating structural break dummies. The Wald tests on the lagged coefficients of lsera do not provide strong evidence of Granger causality from lsera → lufe at the 0.05 significance level. However, the p-value for the second lag suggests a borderline association at the 0.10 level. The coefficients of the structural break dummies are individually insignificant, indicating that the corresponding break dates do not exert a direct and independent effect on the lufe equation.

The Toda-Yamamoto causality test allows the examination of causal relationships through an augmented VAR model without being sensitive to the variables' degrees of stationarity. However, since the Wald statistic used in this test is based on an asymptotic chi-square distribution, the test's reliability may be questionable, especially in small samples and when the error terms deviate from the classical assumptions. In order to prevent misinterpretation of the analysis results arising from these controversial aspects of the Toda-Yamamoto test, the Bootstrap Toda-Yamamoto causality test was also applied. The Bootstrap method uses resampling to obtain the empirical distribution of the Wald statistic, thereby reducing its dependence on asymptotic critical values. In this context, the Bootstrap Toda-Yamamoto test strengthens the econometric validity of the causality findings by providing more reliable critical values and p-values, particularly under finite-sample conditions.

While formulating the Bootstrap Toda-Yamamoto causality test, the R program established the optimal lag length to be 6 lags as per the AIC criterion, 5 lags following the HQ criterion, and 3 lags as indicated by the SC criterion. Due to the small number of observations, using too many lags may degrade estimation quality; therefore, a lag length of 3 was selected as the appropriate choice. In the R program, the VAR model was estimated with 3 lags in total. However, in the Toda-Yamamoto approach, the last lag was included as an additional augmented lag, and the causality test was conducted using only the coefficients of the first 2 lags. Therefore, the test degrees of freedom were reported as df = 2.

In this bootstrap specification estimated with three lags in total, including the additional augmented lag required by the Toda-Yamamoto procedure, the number of lagged endogenous regressors increases further, thereby reducing the residual degrees of freedom and raising the risk of over-parameterization. For this reason, the bootstrap results are treated as a sensitivity exercise rather than as a simple confirmation of the baseline model.

The Wald test hypothesis is shown in Equation 3:

$$H_0: x.\mathrm{l}1 = 0 \; and \; x.\mathrm{l}2 = 0 \tag{3}$$

In this equation, x represents the independent variable lsera. The null hypothesis can be stated as follows: these lags of x have no effect on y, where y is the dependent variable lufe.

The dependent variable lufe is defined as y in the R program. Accordingly, in the Bootstrap Toda-Yamamoto causality test, the equation used in this regard is shown in equation 4, reflecting the direction from the dependent variable to the independent variable, y → x.

$$H_0: y.\mathrm{l}1 = 0 \; and \; y.\mathrm{l}2 = 0 \tag{4}$$

As shown in Table 9, according to the obtained p-value (p = 0.0501), there is evidence of Granger-predictive causality running from greenhouse gas emissions to agricultural producer prices. When compared with the results of the Toda-Yamamoto test, the results provide evidence of predictive Granger causality from the independent variable (lsera) to the dependent variable (lufe). However, the significance levels of the relationship differ. The Wald test, as part of the Bootstrap Toda-Yamamoto causality assessment from y to x, was constructed with the null hypothesis that the lagged y variables do not affect x (i.e., their effect is equal to zero). The test statistic yielded a bootstrap p-value of 0.8896, well above conventional significance levels. Therefore, the H_0 hypothesis cannot be rejected, and no statistically significant predictive Granger causality is found between the lagged values of the y variable and x. In other words, within the Bootstrap Toda-Yamamoto framework, it is concluded that there is no y → x causal relationship.

Table 9 Bootstrap Toda-Yamamoto causality test.

Direction of Causality	Test Value	df	Prob
lsera → lufe	5.9845	2	0.0501***
lufe → lsera	1.1295	2	0.8896

*** represent significance levels of 0.10, respectively.

Based on the rationale presented in the Toda-Yamamoto test with dummy variables, dummies were also included in the Bootstrap Toda-Yamamoto test to reveal the sensitivity of the causality results to the break periods.

The results reported in Table 10 indicate that no statistically significant causal relationship is detected in the dummy-augmented Toda-Yamamoto causality tests. The separate coefficient tests for d91, d01, and d18 indicate that their direct effects are statistically insignificant. However, after controlling for these structural-break dummies, the previously observed causality from emissions to agricultural PPI is no longer statistically significant. This suggests that the causality finding is sensitive to the treatment of structural breaks and should therefore be interpreted with caution.

Table 10 Dummy-augmented Bootstrap Toda-Yamamoto causality test.

Direction of Causality/ Dummy Variable	Value	df	Null Hypothesis	Prob	Result
lsera → lufe	2.7906	2	No causality from lsera to lufe	0.6470	Not rejected
lufe → lsera	0.0567	2	No causality from lufe to lsera	0.9710	Not rejected
d91 → lufe	-3802	-	d91 does not affect lufe	0.9125	Not rejected
d01 → lufe	-3557	-	d01 does not affect lufe	0.9453	Not rejected
d18 → lufe	-2743	-	d18 does not affect lufe	0.6082	Not rejected

Note: Structural-break dummies are included as exogenous controls and are excluded from the Wald causality restrictions.

This finding indicates that the causality result obtained from the standard Toda-Yamamoto specification should not be interpreted as a robust and invariant relationship across all model variants. In particular, the loss of statistical significance after incorporating structural-break dummies and applying bootstrap-based finite-sample inference suggests that the emissions-price nexus is sensitive to model specification. Therefore, the results should be understood not as strong evidence of a stable structural relationship between greenhouse gas emissions and agricultural producer prices, but rather as limited and conditional evidence of predictive Granger causality that emerges under specific econometric assumptions.

The difference between the conventional dummy-augmented Toda-Yamamoto test and the bootstrap version should not be interpreted as an inconsistency. The former relies on asymptotic Wald inference, whereas the latter derives p-values from repeated resampling and may therefore produce more conservative results in finite samples. The df column is left blank for the dummy-variable rows because these rows refer to single-coefficient tests for exogenous controls rather than lag-restriction-based causality tests.

3.1 Sensitivity Analysis: Toda-Yamamoto and Bootstrap Toda-Yamamoto Causality Tests under d_{max} = 0

Although the baseline Toda-Yamamoto analyses were conducted under the $d_{max} = 1$ assumption, the models were re-estimated under the $d_{max} = 0$ specification as an alternative validation exercise to assess the sensitivity of the findings to the assumed integration order. This additional analysis allows us to assess whether the predictive causality results are sensitive to the assumed order of integration and model specification. In particular, sensitivity checks based on alternative d_{max} assumptions serve as an important complementary tool in time-series applications with small samples and structural breaks, thereby enhancing the reliability and interpretability of the empirical evidence.

Within this framework, the re-estimated Toda-Yamamoto and Bootstrap Toda-Yamamoto test results under the $d_{max} = 0$ specification are reported in the table below (Table 11).

Table 11 Causality Test Statistics and Bootstrap Inference under the d_{max} = 0 specification.

Model Specification	Direction of Causality	Test Statistic	p-value	Inference
Unrestricted TY	x → y	2.1719	0.1487	No causality
	y → x	0.7265	0.3994	No causality
Dummy-Augmented TY	x → y	0.2767	0.6022	No causality
	y → x	0.3366	0.5655	No causality
Unrestricted Bootstrap TY	x → y	2.1729	0.6530	No causality
	y → x	0.7265	0.5580	No causality
Dummy-Augmented Bootstrap TY	x → y	0.2767	0.7230	No causality
	y → x	0.3366	0.6280	No causality

The reported Wald statistics pertain to the conventional Toda-Yamamoto specifications, whereas the associated p-values for the bootstrap-based models are obtained from 1,000 replications. All estimations are conducted under the d_{max} = 0 specification. In the dummy-augmented models, structural break dummies for 1991, 2001, and 2018 are included. Statistical inference is based on the 0.05 significance level.

The findings indicate that, even under the d_{max} = 0 specification, there is no statistically significant causal relationship between x and y. Neither the conventional Toda-Yamamoto tests nor the bootstrap-based resampling results provide evidence of significance in either causal direction. This suggests that neither the inclusion of structural break dummies nor the bootstrap correction is sufficient to render the relationship between the variables statistically meaningful. Accordingly, the results imply that the predictive causality evidence in the sample is, at best, weak and specification-sensitive.

The sensitivity analysis further reinforces the specification-dependent nature of the empirical findings. Under the alternative d_{max} = 0 specification, neither the conventional Toda-Yamamoto tests nor the bootstrap-based tests provide statistically significant evidence of causality in either direction. This implies that the baseline causality result is not robust to alternative assumptions about the maximum intergration order. Accordingly, the empirical evidence should not be interpreted as confirming a strong, stable, and specification-invariant relationship between emissions and price. Rather, the findings point to a limited, conditional, and model-dependent form of predictive causality, whose statistical significance varies with lag selection, integration-order assumptions, bootstrap inference, and the treatment of structural breaks.

These findings should also be evaluated in light of the limited bivariate structure of the empirical model. Since the model does not include potential transmission channels such as temperature, drought, agricultural yields, exchange rates, fertilizer costs, or energy prices, the predictive causality result cannot be interpreted as identifying a direct economic mechanism. Moreover, some of these omitted variables may act as common drivers of both aggregate greenhouse gas emissions and agricultural producer prices. Hence, the estimated relationship may be partly attributable to unobserved common factors rather than to a stable causal pathway from emissions to prices.

The findings can be compared with previous studies that examine emissions, agricultural production, and price-related outcomes. Chandio et al. identify a Granger-causality relationship between carbon dioxide emissions and cereal production in Türkiye, while Rehman et al. report a relationship between emissions and maize production in Pakistan [20, 23]. Ben Jebli and Ben Youssef also provide evidence of causal interactions between CO_2 emissions and agricultural value added or agricultural activity [18, 19]. In this context, the baseline results of the present study are broadly consistent with the view that climate-related variables may contain predictive information for agricultural outcomes. However, because the present analysis does not include channel variables such as temperature, drought, yields, exchange rates, or input costs, the findings should be interpreted as predictive Granger-causality evidence rather than as confirmation of a specific economic transmission mechanism.

4. Conclusion and Recommendations

This study examined the predictive Granger-causality relationship between greenhouse gas emissions and the agricultural Producer Price Index in Türkiye using the Toda-Yamamoto and Bootstrap Toda-Yamamoto approaches, both with and without structural-break dummy variables. The findings suggest that greenhouse gas emissions contain predictive information for agricultural producer price dynamics only under certain model specifications. Specifically, the standard Toda-Yamamoto test provides statistically significant evidence of predictive causality from emissions to agricultural producer prices. In contrast, the bootstrap-based result is only marginally significant, and the dummy-augmented specifications do not support a statistically significant causal relationship. Moreover, the additional d_{max} = 0 sensitivity analysis indicates that the causality inference is not preserved under alternative assumptions regarding the maximum order of integration. Therefore, the results should not be interpreted as strong confirmation of a stable relationship between emissions and prices. Rather, they provide limited, conditional, and specification-sensitive evidence of predictive Granger causality.

A further limitation concerns the interpretation of the emissions variable itself. Total greenhouse gas emissions are used as an indirect, macro-level indicator of climate-related pressure, but they are not equivalent to direct agro-climatic stress indicators. The variable does not capture temperature anomalies, rainfall patterns, drought severity, frost events, or other extreme weather conditions that directly affect agricultural producers. For this reason, the findings should not be interpreted as structural evidence on the direct effect of climatic shocks on agricultural producer prices. Rather, they provide indirect and limited evidence on whether national aggregate emissions contain predictive information for agricultural price dynamics.

This limitation is particularly important because multiple economic, environmental, and institutional factors beyond aggregate emissions influence agricultural producer prices. Temperature anomalies, rainfall variability, drought indicators, agricultural yields, exchange rate movements, fertilizer and feed costs, energy and fuel prices, transportation costs, trade policies, and agricultural support mechanisms are among the key determinants of agricultural price dynamics. Some of these variables may affect both greenhouse gas emissions and agricultural producer prices, meaning that the predictive relationship observed in the bivariate model may partly reflect omitted common drivers. Consequently, the results should not be interpreted as evidence of a direct, identifiable economic transmission mechanism from emissions to prices. Rather, they should be viewed as a limited and conditional Granger-predictive association that may be sensitive to omitted shared determinants.

Since agriculture depends heavily on weather conditions and serves as both a source of and a potential sink for greenhouse gas emissions during production, these emissions may be a risk factor for agricultural producer price dynamics.

From an econometric perspective, the unit root tests indicate mixed integration properties across the series, while the Bai-Perron test detects significant structural breaks in 1991, 2001 and 2018. This situation provides a methodological justification for using the Toda-Yamamoto procedure that overcomes the limitations of the usual cointegration and standard Granger causality procedure. The diagnostic tests do not indicate major violations of the classical VAR assumptions. Due to the potential unreliability of test results in the standard Toda-Yamamoto test when applied to small samples and when error terms deviate from classical assumptions, a Bootstrap Toda-Yamamoto causality test was performed. Bootstrap testing revealed a Granger-causal relationship from the lsera variable, which denotes greenhouse gas emissions, to the lufe variable, representing agricultural PPI, at the 0.10 significance level. The standard Toda-Yamamoto and Bootstrap Toda-Yamamoto tests point in the same direction, but the strength of the evidence differs. While the standard test indicates significance at the 0.05 level, the bootstrap result is only marginally significant at the 0.10 level and is based on a different lag specification. The additional sensitivity check based on d_{max} = 0 further shows that the causality inference is sensitive to the assumed order of integration, thereby reinforcing the need for caution when deriving policy implications from the baseline results.

The Toda-Yamamoto and Bootstrap Toda-Yamamoto causality tests were conducted without including the structural break dates in the model. However, ignoring the possible effects of these dates could yield incomplete results from academic and econometric perspectives. Thus, the two tests were repeated with dummy variables added. When structural-break dummies are included as exogenous controls, the previously detected causality from greenhouse gas emissions to agricultural PPI is no longer statistically significant. This suggests that the emissions–price nexus is sensitive to structural breaks and should not be interpreted as a stable causal relationship over the entire sample period.

The results are consistent with previous studies on the effects of greenhouse gas emissions on agricultural production and prices. Similarly to studies reporting significant effects of emissions on cereals, maize, or general indicators of agricultural production, this study provides conditional evidence that greenhouse gas emissions may be associated with causal dynamics in agricultural producer prices. Furthermore, evidence on two-way or one-way causality between greenhouse gas emissions and agricultural value added or production suggests that the causality from greenhouse gas emission → agricultural PPI found in this study is meaningful in a wider context.

The variation in results across alternative econometric specifications further suggests that policy design should not rely on a single causality estimate. The stronger evidence from the standard Toda-Yamamoto test, the weaker evidence from the Bootstrap Toda-Yamamoto test, and the absence of significance in the dummy-augmented models collectively point to a specification-sensitive relationship. For this reason, policymakers and relevant public institutions should periodically re-estimate the relationship between greenhouse gas emissions and agricultural PPI using updated data, alternative lag structures, bootstrap inference, and explicit structural-break controls. Such a procedure would reduce the risk of overinterpreting model-dependent findings and would align policy monitoring with the uncertainty revealed by the empirical analysis.

According to the econometric analysis, several points should be given particular consideration when formulating a policy recommendation. First of all, policies should not be based on the assumption that greenhouse gas emissions have a definite and immutable effect on agricultural prices, but rather on the conclusion that emissions are a potential and conditional risk indicator that should be monitored in terms of the agricultural PPI. Within the framework of these findings, it is recommended that greenhouse gas emissions be used as a complementary indicator in analyses of agricultural price stability. When the statistically supported predictive direction, where present, runs from greenhouse gas emissions to the agricultural producer price index (PPI), policy monitoring may use emission dynamics as a complementary risk signal for price dynamics. Therefore, emission-reduction measures should not be justified solely on the expectation that they will directly reduce agricultural producer prices.

The results indicate that policy implications should be framed within a continuous risk-assessment and evidence-updating framework rather than as definitive intervention prescriptions. Accordingly, policymakers should neither overstate nor disregard the role of emissions in agricultural price formation; instead, they should reassess the relationship as new data become available and as structural conditions evolve.

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Competing Interests

The author has declared that no competing interests exist.

Data Availability Statement

The author obtained the data used in the study from the official websites of TUIK and EDGAR. These data were used by the author in the econometric analysis. Since the structure of the study did not require ethical approval, no ethics committee approval was obtained.

AI-Assisted Technologies Statement

The author declares that the AI-assisted tools Ahrefs and Grammarly were used solely for language editing, paraphrasing, and grammar correction. These tools did not contribute to the generation of research content, data analysis, or interpretation. The author takes full responsibility for the content and integrity of the manuscript.

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