Colegio de Postgraduados

Agriculture and Poverty in Mexico: The Role of Agriculture in Poverty, 2010-2022

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ABSTRACT
Objective: To estimate a model incorporating the variables poverty, extreme poverty, and agricultural income using generalized least squares, in order to demonstrate the effect of agricultural income on poverty and extreme poverty. This analysis aims to inform the design of agricultural public policies that effectively contribute to poverty reduction in the sector.
Methodology: The generalized least squares (GLS) method was employed. The primary variables analyzed were poverty and extreme poverty, while agricultural income, planted area, number of workdays, and daily wages were included as control variables.
Results: Between 2018 and 2022, agricultural income was found to significantly reduce extreme poverty. In prior years, no statistically significant relationship was identified. The number of workdays and daily wages were positively associated with poverty suggesting that increases in planted area, workdays, and wages may, paradoxically, be linked to higher poverty levels.
Limitations: The limited availability of multidimensional poverty and extreme poverty data at the state level poses a constraint on conducting robust time-series analyses.
Conclusions: The findings underscore the need to reassess public policies directed at the agricultural sector, with the objective of enhancing their effectiveness in poverty alleviation.

Keywords: Rural poverty, agricultural income, agricultural production.

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INTRODUCTION

Between 2010 and 2022, agricultural production in Mexico increased from 508 million to 708 million tons (Agri-Food and Fisheries Information System, SIAP, 2024). According to the National Institute of Statistics and Geography (INEGI, 2023), primary sector activities contributed 3.9% to the national GDP, with agricultural activities accounting for 90.9% of that total. These figures highlight both the significant growth in agricultural production over a 12-year period and the dominant role of agriculture within the primary sector. Data from the Agri-Food Outlook (2022) indicated that Mexico ranked 11th in global food production and was the leading exporter of several agricultural products: avocado (49% of the global market), tomato (30.7%), asparagus (31.4%), mango (24.7%),

and berries (16%). Additionally, Mexico is the top exporter of agro-industrial products such as beer and tequila. Consequently, the country maintained a positive agri-food trade balance (Secretariat of Agriculture and Rural Development, SADER, 2022). In contrast to the success of certain agricultural products in international markets, Mexico continues to face serious challenges in rural areas, including poverty and extreme poverty. In 2022, 36.6% of the population was living in poverty, and 7.1% in extreme poverty. While these figures represent a decrease from 2010 —when 44.4% of the population was in poverty and 11% in extreme poverty— they remain concerning (National Council for the Evaluation of Social Development Policy, CONEVAL, 2023). Poverty in Mexico is measured multidimensionally, based on income and six social rights: education, health services, social security, housing quality and space, adequate housing, and food access (CONEVAL, 2022). This methodology aims to identify the most vulnerable populations and guide the implementation of appropriate welfare policies. Eradicating poverty is one of the United Nations Sustainable Development Goals (SDGs). Several authors have examined the relationship between agriculture and poverty, suggesting that agriculture can play a key role in poverty reduction (Hammed *et al.*, 2023; Omodero, 2021). Johnston and Mellor (1961) were among the first to assert a direct causal relationship between agriculture and poverty, identifying agricultural income as the primary transmission mechanism —higher agricultural income reduces household poverty levels. Similarly, Sen (1981), through his capabilities approach, emphasized that agriculture contributes to poverty reduction by enhancing access to food, thereby reducing vulnerability among the poor. Ellis and Biggs (2005) also argue for a causal link between agriculture and poverty reduction, particularly in low-income countries, where most of the population resides in rural areas and depends on agriculture for survival. In the same vein, Mellor and Malik (2017) state that growth in agricultural production and smallholder income is the most effective pathway for rural poverty reduction. This occurs through increased spending by commercial farmers in the rural non-agricultural sector, which raises non-farm rural incomes and lowers poverty levels. Schneider and Gugerty (2011) suggest that the link between increased agricultural production and poverty reduction is mediated by job creation in both agricultural and non-agricultural sectors, through backward and forward linkages. These mechanisms help reduce both urban and rural poverty and contribute to lowering food prices. De Janvry and Sadoulet (2010), in a study conducted in Vietnam, found that reductions in rural poverty were associated with increased agricultural productivity. They argue that the agricultural sector is not only crucial for poverty alleviation but also has the capacity to stimulate overall economic growth through its linkages with other sectors. This perspective is reinforced by Ogundipe *et al.* (2017), who highlight that job creation, increased demand for goods and services, and rising agricultural income are essential components in reducing poverty. In Indonesia, Mariyah and Nugroho (2022) found that agricultural production had a statistically significant impact on poverty reduction between 2011 and 2020. They concluded that this effect is primarily achieved through labor absorption, improved agricultural productivity, and a focus on high-value agricultural products. In Burkina Faso, agriculture plays a vital role in the national economy. Despite widespread poverty —particularly in rural areas— increased agricultural productivity has had positive impacts on education, and agricultural value-added has contributed to improvements in life expectancy (Traore *et al.*, 2022). A similar situation has occurred in China, where poverty eradication efforts since 2020 have focused heavily on agricultural subsidies. However, a recent study by Wang *et al.* (2024) found mixed results: while agriculture has been effective in reducing poverty in the northern region, its efficiency score for poverty reduction in the southern region remains low. In Mexico, there is limited research on the relationship between agriculture and poverty reduction. This study aims to estimate an econometric model that incorporates poverty, extreme poverty, and agricultural income using generalized least squares, to evaluate the impact of agricultural income on poverty and extreme poverty. The findings are intended to inform the design of public policies that support the agricultural sector in poverty alleviation. The central hypothesis is that increased agricultural income has contributed to poverty reduction over the study period.

MATERIALS AND METHODS

The study was conducted using state-level data. Multidimensional poverty and extreme poverty figures by federal entity were analyzed for the period 2010-2022. This timeframe was selected due to the consistency of poverty data available biennially and the observed increase in agricultural income alongside a reduction in poverty levels. The years included in the analysis were 2010, 2012, 2014, 2016, 2018, 2020, and 2022. The sample consists of 31 Mexican states and Mexico City.

Selected variables

The poverty and extreme poverty variables refer to multidimensional poverty as defined by CONEVAL, which considers a person to be in poverty if they lack sufficient income to meet basic needs and experience at least one of six social deprivations: educational lag, lack of access to health services, social security, housing quality and space, access to basic housing services, and access to adequate nutrition. Extreme poverty refers to individuals who, even when allocating all their income to cover basic needs, fall short and experience three or more social deprivations (CONEVAL, 2022). Both variables were measured by the number of people living in poverty and extreme poverty, with data obtained from the National Council for the Evaluation of Social Development Policy (CONEVAL, 2023).

Agricultural variables

The agricultural income variable corresponds to the value of agricultural production and is calculated as the product of total agricultural output and the rural average price, expressed in monetary units. Planted area refers to the total number of hectares allocated to agricultural cultivation. Data for these variables were sourced from the Agri-Food and Fisheries Information System (SIAP) for the years 2010, 2012, 2014, 2016, 2018, 2020, and 2022. Due to the availability of agricultural census data for 2022, two additional variables were included: agricultural laborers and daily wages. The former refers to individuals employed in agricultural activities receiving a daily wage; this was measured by the number of laborers per state. The latter represents the amount, in monetary units, received by workers for agricultural labor. These variables were only included in the econometric models for the year 2022. The selection of variables was based on theoretical linkages. As Mellor and Malik (2017) suggest, agricultural income is theoretically tied to poverty reduction particularly in rural áreas since higher agricultural income correlates with lower poverty levels. Income growth may result from increased productivity or higher prices. Planted area is associated with this relationship because its expansion can lead to increased food production, job creation, higher income, and ultimately, poverty reduction (Li *et al.*, 2022). Regarding agricultural laborers, their link to poverty is primarily through labor conditions, informality, and low wages, which according to Yacoub and Restiatun (2024) contribute to the persistence of poverty. It is important to note that for the regression analyses, the explanatory variables were categorized as monetary and non-monetary. The first group includes agricultural income and daily wages, while the second comprises planted area and the number of laborers.

In Mexico, multidimensional poverty data is only available every two years, which limits the feasibility of time-series or panel data analysis. Therefore, a cross-sectional analysis was conducted using the ordinary least squares (OLS) method. OLS is a statistical technique used to establish a functional relationship between two variables, X and Y, where Y is the dependent variable and X the independent variable (Mballa & Sauceda, 2018).

To define the model, the Ordinary Least Squares (OLS) method was employed, which aims to minimize the variance of the errors. According to Madala (2004), the model specification is presented in Equation 1.

$$Y_i = \beta_1 + \beta_2 X_i + u_i \tag{1}$$

Where: Y_i=is the variable to be explained. β_1=is the intercept. β_2=is the parameter associated with X_i. X_i=explanatory variable. u_i=is the error term.

The OLS method seeks to minimize errors, therefore, it starts from:

$$Y_i = \beta_1 + \beta_2 X_i + u_1$$

$$Y_i = \hat{\beta}_1 + \hat{\beta}_2 X_i + u_i \tag{1}$$

$$\hat{u}_i = Y_i - \hat{\beta}_1 - \hat{\beta}_2 X_i \tag{2}$$

Equation (2) shows that the residuals are the difference between the observed and estimated values of Y.

$$\sum \hat{u}_i^2 = \sum \left(Y_i - \hat{Y}_i\right)^2$$

$$\sum \hat{u}_i^2 = \sum \left(Y_i - \hat{\beta}_1 - \hat{\beta}_2 X_i\right)^2 \tag{3}$$

and how $\sum \hat{u}_i^2 = f\left(\hat{\beta}_1 + \hat{\beta}_2\right)$ then the differentiation process is obtained:

$$\sum Y_i = n\hat{\beta}_1 + \hat{\beta}_2 \sum X_i \tag{4}$$

$$\sum Y_i X_i = \hat{\beta}_1 \sum X_i + \hat{\beta}_2 \sum X_i{}^2 \tag{5}$$

n is the sample size and these equations are known as normal equations, by algebraic manipulation the β are obtained.

$$\hat{\beta}_2 = \frac{n\sum X_i Y_i - \sum X_i \sum Y_i}{n\sum X_i^2 - \left(\sum X_i\right)^2}$$

$$\hat{\beta}_2 = \frac{\sum\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sum\left(X_i - \bar{X}\right)^2} \tag{6}$$

$$\hat{\beta}_2 = \frac{\sum x_i y_i}{\sum x_i^2}$$

Where $\bar{X}$ and $\bar{Y}$ are the sample means of X and Y

$$\hat{\beta}_1 = \frac{\sum x_i^2 \sum Y_i - \sum X_i \sum X_i Y_i}{n\sum x_i^2 - \left(\sum x_i\right)^2}$$

$$\hat{\beta}_1 = \bar{Y} - \hat{\beta}_2 \bar{X} \tag{7}$$

Since the estimates presented heteroscedasticity problems, the correction was applied using generalized least squares.

It is required that $E(u) = 0$, now the variance of the errors will be: $Var(u) = \Omega$.

$$Q(\beta) = \left(y - X\beta\right)' \Omega^{-1}\left(y = X\beta\right) \tag{8}$$

Developing, deriving, and equating to 0

$$\frac{\partial Q}{\partial \beta} = -2X'\Omega^{-1}Y + 2X'\Omega^{-1}X\beta$$

$$-2X'\Omega^{-1}Y + 2X'\Omega^{-1}X\hat{\beta}_{MCG} = 0 \tag{9}$$

$$\hat{\beta}_{MCG} = \left(X'\Omega^{-1}X\right)^{-1} X'\Omega^{-1}y$$

After the explanation of the estimation of the coefficients, the model was formulated, whose specification is as follows:

$$P = \beta_0 + \beta_1 Inga + \beta_2 Sup\_S + u \tag{10}$$

$$PE = \beta_0 + \beta_1 Inga + \beta_2 Sup\_S + u \tag{11}$$

Where *P* is poverty, *PE* refers to extreme poverty, *Inga* is agricultural income, measured as the value of agricultural production, and *Sup_S* is the planted agricultural area.

Regarding 2022, the availability of data from the 2022 Agricultural Census made it possible to integrate variables to strengthen the analysis. Thus, in the 2022 linear regression analysis, four regressions were performed (Equations 12 to 15), differentiating between monetary and non-monetary variables. The model specification is as follows:

Monetary variables:

$$P = \beta_0 + \beta_1 Inga + \beta_2 Pag\ J + u \tag{12}$$

$$PE = \beta_0 + \beta_1 Inga + \beta_2 Pag\ J + u \tag{13}$$

Where *Inga* corresponds to agricultural income and *Pag J* refers to the payment for day labor, representing the wages received by individuals employed in agricultural activities.

Non-monetary variables:

$$P = \beta_0 + \beta_1 Jor + \beta_2 Sup\_S + u \tag{14}$$

$$PE = \beta_0 + \beta_1 Jor + \beta_2 Sup\_S + u \tag{15}$$

The variable *Jor* refers to the number of day laborers employed in agricultural activities per state, and *Sup_S* corresponds to the planted agricultural area.

The analysis consisted of 16 regressions following the aforementioned general framework. The EViews 12 software was used for model estimation. All models were subjected to the White test for heteroscedasticity in the error terms, which is considered one of the most robust diagnostic tests (Toro *et al.*, n.d.). Additionally, following Hair *et al.* (2021), the models were tested for multicollinearity using the Variance Inflation Factor (VIF), where a value greater than five indicates the presence of collinearity. After conducting the diagnostic tests, heteroscedasticity was detected in some models. These models were subsequently adjusted and corrected using the Generalized Least Squares (GLS) method (Gujarati, 2010). Hypothesis testing was then performed to verify the predictive validity of the models.

RESULTS AND DISCUSSION

According to the results of the hypothesis tests based on the Prob(F) statistic, it was determined that the independent variables jointly have explanatory power over the dependent variable in each of the models. The R^2 statistic measures goodness-of-fit, which "indicates how well the sample regression line fits the data" (Gujarati, 2010, p. 73), and reflects the percentage of variation in the dependent variable explained by the model. A positive coefficient indicates an increase in poverty, while a negative coefficient suggests a reduction in poverty. The regression results, presented in Table 1, show that agricultural income had no effect on poverty levels during the years analyzed.

Table 1. Regression Results: Poverty

Dependent variable: POVERTY						
Model	**Year**		**Coefficients**	**Standard error**	**T-Student**	**P-value**
1	2010	Constant	15.09378	245.8	2.11	0.0436
		Inga	0.00001	0.00003	0.41	0.6829
		Sup_S	0.001493	0.00051	2.90	0.007***
		$R^2=0.36$	Prob(F)=	0.002		
2	2012	Constant	546.7498	242.017	2.26	0.0316
		Inga	0.000003	0.00002	0.12	0.9080
		Sup_S	0.001638	0.00048	3.43	0.0018***
		$R^2=0.31$	Prob(F)=	0.004		
3	2014	Constant	561.6029	260.772	2.15	0.0397
		Inga	0.0000	0.00	0.06	0.9518
		Sup_S	0.00172	0.00051	3.38	0.0021***
		$R^2=0.27$	Prob(F)=	0.009		
4	2016	Constant	0.000	0.000	−0.30	0.7673
		Inga	0.000	0.000	−0.30	0.7673
		Sup_S	0.002	0.0005	3.56	0.0013***
		$R^2=0.27$	Prob(F)=	0.009		
5	2018	Constant	−0.00001	0.00001	−1.30	0.2026
		Inga	−0.00001	0.00001	−1.30	0.2026
		Sup_S	0.00214	0.00054	3.94	0.0005***
		$R^2=0.29$	Prob(F)=	0.007		
6	2020	Constant	747.867	316.322	2.36	0.0250
		Inga	−0.00001	0.00001	−0.73	0.4737
		Sup_S	0.00169	0.0006	2.83	0.0084***
		$R^2=0.19$	Prob(F)=	0.04		

Source: Own elaboration based on data from CONEVAL and SIAP.
Note: * Significant at the 90% confidence level, ** Significant at 95%, *** Significant at 99%.
Hypothesis test (Prob(F)) for the model at $\alpha=0.05$:
H_0: The coefficients of the explanatory variables are less than or equal to zero; they do not explain the dependent variable.
H_1: At least one coefficient is different from zero; the model explains the dependent variable.
Decision rule: Reject H_0 if Prob(F)<0.05.

In Model 1, an $R^2=0.34$ was obtained, indicating that in 2010, 34% of the variation in multidimensional poverty in Mexico was explained by the model. The coefficient for Sup_S (planted area) suggests that for each additional hectare, poverty increases by 0.0014 persons, with 99% statistical significance. In Model 2, an $R^2=0.31$ was obtained. In that year, a one-hectare increase in planted area was associated with an increase in poverty of 0.0016 persons, also with 99% significance. Model 3 yielded an $R^2=0.28$, and agricultural income (Inga) was not statistically significant. However, planted area was, indicating that each additional hectare increased poverty by 0.0017 persons with 99% probability. In Model 4, the $R^2=0.27$ and the coefficient for Sup_S remained statistically significant at the 99% level, indicating that a one-hectare increase in cultivated area leads to a 0.0018-person increase in poverty. Model 5 produced similar results, with an $R^2=0.29$. Agricultural income was again not a significant factor, while planted area was highly significant (99%) and had a positive effect on poverty: each additional hectare increased poverty by 0.0021 persons. In Model 6, the results followed the same trend. The model had an $R^2=0.19$, and planted area continued to be statistically significant. An increase of one hectare in agricultural area was associated with an increase of 0.0084 persons in poverty, at a 99% confidence level.

The positive association between planted area and poverty contradicts the theory of economies of scale. According to Roest *et al.* (2017), economies of scale imply that the average cost per unit of output decreases as production increases. This theory suggests that an expansion in cultivated land should reduce poverty through increased employment and income. However, in practice, the relationship is more complex, as it is influenced by factors such as land quality, land management, the formation of agricultural cooperatives, and production efficiency, among others (Li *et al.*, 2021). Table 2 summarizes the regression results from Models 7 through 12. The findings indicate that agricultural income had no statistically significant effect on extreme poverty between 2010 and 2016. However, in 2018, a positive relationship between agricultural income and the reduction of extreme poverty was observed.

In 2010, the coefficient of determination was $R^2=0.36$, and agricultural income was not statistically significant. However, the Sup_S (planted area) variable showed a significant effect at the 95% confidence level, indicating that an increase of one cultivated hectare leads to a 0.000633-person rise in extreme poverty. In 2012, $R^2=0.38$, and again, agricultural income was not significant. However, planted area remained relevant; with 95% confidence, it was found that an additional hectare increased extreme poverty by 0.00058 persons. Similar findings were observed in 2014 and 2016: in both years, agricultural income showed no statistical relationship with extreme poverty, while planted area was significant, indicating that land expansion contributes to an increase in extreme poverty. Model 11, corresponding to 2018, yielded an $R^2=0.39$ and demonstrated that a one-unit increase in agricultural income reduces extreme poverty by 0.000008 persons, with 99% confidence (see bold coefficients in Table 2). In 2020, $R^2=0.29$, revealing that a \$1.00 increase in agricultural income results in a 0.000007-person reduction in extreme poverty. Although the coefficient was negative in this year, the confidence level fell to 88%. The results of Models 13 through 16 correspond to the year 2022. In this section,

Table 2. Regression Results: Extreme Poverty.

Dependent variable: Extreme poverty						
Model	**Year**		**Coefficients**	**Standard error**	**T-Student**	**P-value**
7	2010	Constant	15.09378	67.94115	0.22	0.8257
		Inga	−0.000004	0.000013	−0.32	0.7504
		Sup_S	0.000633	0.000277	2.29	0.0296**
		R^2=0.36	Prob (F)=	0.001539		
8	2012	Constant	27.268	54.62579	0.50	0.6214
		Inga	−0.000005	0.000008	−0.62	0.5383
		Sup_S	0.000581	0.000222	2.62	0.0139**
		R^2=0.31	Prob(F)=	0.001092		
9	2014	Constant	6.504879	61.99892	0.10	0.9172
		Inga	−0.00001	0.00001	−0.89	0.3825
		Sup_S	0.000656	0.000253	2.59	0.0148
		R^2=36	Prob(F)=	0.001		
10	2016	Constant	−8.80283	62.86152	−0.14	0.8896
		Inga	−0.00001	0.00001	−1.29	0.2073
		Sup_S	0.00062	0.000234	2.65	0.0128**
		R^2=35	Prob(F)=	0.002		
11	2018	Constant	−27.72477	66.107740	−0.42	0.678
		Inga	−0.000008	0.000004	−1.82	0.0792**
		Sup_S	0.000724	0.00025	2.89	0.0072***
		R^2=39	Prob(F)=	0.001		
12	2020	Constant	70.05538	67.15596	1.04	0.3055
		Inga	−0.000007	0.000004	−1.64	0.1112
		Sup_S	0.000607	0.00023	2.64	0.0133**
		R^2=29	Prob(F)=	0.006		

Source: Own elaboration based on data from CONEVAL and SIAP.
Note: * Significant at the 90% confidence level, ** Significant at 95%, *** Significant at 99%.
Hypothesis test (Prob(F)) for the model at α=0.05:
H_0: The coefficients of the explanatory variables are less than or equal to zero; they do not explain the dependent variable.
H_1: At least one coefficient is different from zero; the model explains the dependent variable.
Decision rule: Reject H_0 if Prob(F)<0.05.

the independent variables were categorized as monetary and non-monetary to assess their specific effects on the dependent variable. This classification led to a significant improvement in model fit: Model 14 had an R^2=0.55, Model 15 reached R^2=0.56, and Model 16 yielded R^2=0.69. Model 13 produced an R^2=0.33. In this case, agricultural income was statistically significant, indicating that a one-unit increase in Inga results in a 0.00001-person reduction in poverty, with 99% confidence. Similarly, the Pag J (payment for day labor) variable was also statistically significant at the 99% level, showing a positive effect: an increase of one monetary unit in daily wage is associated with an increase of 0.66 persons in poverty (see Table 3).

Regarding the non-monetary variables (Model 14), the Jor variable (number of day laborers) was statistically significant at the 99% confidence level and showed a positive relationship with poverty. The result suggests that for each additional person employed in agricultural labor, poverty increases by 0.00188 persons.

The results of Models 15 and 16 refer to extreme poverty. In this context, Model 15, which includes monetary variables, yielded an $R^2=0.56$ and showed that Inga (agricultural income) is negatively associated with extreme poverty. An increase of one unit in income results in a 0.000007-person reduction in extreme poverty, with 99% confidence. Similarly, the Pag_J (payment to day laborers) variable was statistically significant at the 99% level and indicated that an increase in wages is associated with an increase of 0.23 persons in extreme poverty (see Table 4).

Regarding the non-monetary variables, the Jor (agricultural laborers) variable was statistically significant at the 99% confidence level and showed a positive relationship with extreme poverty. Specifically, an increase of one unit in the number of agricultural laborers is associated with an increase of 0.0005 persons in extreme poverty. In contrast to previous years, the Sup_S (planted area) variable did not show statistical significance.

Table 5 summarizes the models in which evidence was found that agricultural income reduced extreme poverty between 2018 and 2022, as well as general poverty in 2022. These findings support the hypothesis proposed at the beginning of this study and are consistent with the results of Warr and Suphannachart (2021), who found that increased agricultural productivity reduces rural poverty in Thailand. Similarly, Chandrarekha *et al.* (2021) observed in India that as agricultural production and *per capita* income rise, poverty decreases particularly in agrarian economies where the majority of the population depends

Table 3. 2022 regression results, poverty.

Dependent variable: Poverty						
Monetary variables						
Model	**Year**		**Coefficients**	**Standard error**	**T-Student**	**P-value**
13	2022	Constant	713.6949	203.4292	3.50832	0.0015
		Inga	−0.00001	0.00001	−1.87134	0.0714*
		PagJ	0.660297	0.134536	4.90795	0.000***
		$R^2=0.33$		Prob (F)	0.003	
Non-monetary variables						
14	2022	Constant	514.9577	210.945	2.44119	0.021
		Jor	0.001748	0.000629	2.77859	0.0095***
		Sup_S	0.000127	0.00045	0.28251	0.7796
		$R^2=0.55$		Prob(F)	0.0000	

Source: Own elaboration based on data from CONEVAL, SIAP, and the 2022 Agricultural Census.
Note: * Significant at the 90% confidence level, ** Significant at 95%, *** Significant at 99%.
Hypothesis test (Prob(F)) for the model at $\alpha=0.05$:
H_0: The coefficients of the explanatory variables are less than or equal to zero; they do not explain the dependent variable.
H_1: At least one coefficient is different from zero; the model explains the dependent variable.
Decision rule: Reject H_0 if Prob(F)<0.05.

Table 4. Regression results 2022. Extreme poverty.

Dependent variable: Extreme poverty						
Monetary variables						
Model	**Year**		**Coefficients**	**Standard error**	**T-Student**	**P-value**
15	2022	Constant	91.46759	37.60456	2.43235	0.0214
		Inga	−0.000007	0.000002	−3.41312	0.0019***
		PagJ	0.232437	0.042901	5.41798	0.000***
		R^2=0.56	Prob(F)	0.000		
Non-monetary variables						
16	2022	Constant	−5.536	43.560	−0.12708	0.8998
		Jor	0.0005	0.0001	5.80702	0.000***
		Sup_S	0.0001	0.0001	0.6539	0.5183
		R^2=0.69	Prob(F)=	0.00		

Source: Own elaboration based on data from CONEVAL, SIAP, and the 2022 Agricultural Census.
Note: * Significant at the 90% confidence level, ** Significant at 95%, *** Significant at 99%.
Hypothesis test (Prob(F)) for the model at $\alpha=0.05$:
H_0: The coefficients of the explanatory variables are less than or equal to zero; they do not explain the dependent variable.
H_1: At least one coefficient is different from zero; the model explains the dependent variable.
Decision rule: Reject H_0 if Prob(F)<0.05.

Table 5. Key regressions.

Dependent variable: Extreme poverty							
Model	**Year**		**Coefficients**	**Standard error**	**T-Student**	**P-value**	R^2
11	2018	Inga	−0.000008	0.000004	−1.82	0.0792**	0.39
12	2020	Inga	−0.000007	0.000004	−1.64	0.1112	0.29
15	2022	Inga	−0.000007	0.000002	−3.41	0.0019***	0.56
Dependent variable: Poverty							
13	2022	Inga	−0.00001	0.00001	−1.87134	0.0714*	0.33

Source: Own elaboration based on data from CONEVAL, SIAP, and the 2022 Agricultural Census. Note: * Significant at the 90% confidence level, ** Significant at 95%, *** Significant at 99%.

on the agricultural sector. The results of this study also align with Umar *et al.* (2023), who reported that increases in agricultural productivity and *per capita* income contributed to poverty reduction in Nigeria. The findings of this research indicate that the effect of agricultural income on reducing extreme poverty was greater than its effect on general poverty. These results contrast with those of Herrero and Bustamante (2025), who, in their analysis of the impact of minimum wage in Ecuador, concluded that wage increases had a stronger effect on general poverty than on extreme poverty. This discrepancy may be due to differences in study periods and variables used. Between 2010 and 2016, no statistical relationship was found between agricultural income and poverty likely due to income levels during that period. These findings are consistent with those of López *et al.* (2016), who, using municipal-level data from Mexico, were unable to establish a clear link between agricultural production and poverty reduction. One possible explanation for the limited impact of agricultural income on poverty reduction relates to the geographic concentration of poverty in southern Mexican states. While regional disparities between the north and south can be attributed to multiple factors, agriculture plays a significant role. According to CONEVAL (2022), Chiapas, Oaxaca, and Guerrero are the states with the highest poverty levels. In these states, agricultural production focuses on grasses, sugarcane, and maize largely for subsistence markets with limited commercialization. In contrast, the states that have experienced agricultural growth are located in the central and northern regions, producing crops such as tomatoes, berries, and avocados, which are part of a more developed agricultural market. For example, states like Guanajuato, Michoacán, Sinaloa, Nayarit, and Baja California have reduced poverty during the study period. With regard to the relationship between planted area and poverty/extreme poverty, it was found that an increase in cultivated land correlates with higher poverty. This contradicts the results of Quin and Zhang (2022), who found in West Java that increasing cultivated area reduced poverty but only through the implementation of regional agricultural clusters and specialization. However, when analyzing farmers within horizontal integration models, their results were consistent with those found in this study, concluding that increased planted area does not reduce poverty. These findings also contrast with Li *et al.* (2020), who reported that plantation land is associated with higher farmer income, though they emphasized the importance of crop diversification. Similarly, Heger *et al.* (2020) identified a link between planted area and poverty reduction in Sub-Saharan Africa, but noted that the effect depends largely on improvements in land quality. The results of this study suggest that expanding cultivated land may increase poverty potentially due to stagnant agricultural productivity. Rural farmers often face capital constraints that limit investment in productivity improvements. Low productivity restricts income, which in turn limits reinvestment in soil quality, perpetuating poverty. Another key factor is land distribution: if agricultural land is concentrated among a small group of farmers, the positive effects of land expansion on poverty reduction are diminished. On the other hand, the relationship between the number of agricultural laborers and both poverty and extreme poverty was found to be positive. This relationship is complex and may be linked to so-called poverty traps situations where poverty persists due to self-reinforcing mechanisms (Millán, 2018). As Nevárez and Castro (2025, p. 4) describe, it is "a condition in which the income of poor individuals does not rise above a certain threshold, causing them to remain in poverty." In rural settings, these traps are often multidimensional, involving economic, biophysical, and social processes that interact to create reinforcing dynamics that maintain the trap (Radosavljevic *et al.*, 2021). In this study, the estimates show that when a person enters the agricultural labor force, poverty increases. These results are plausible: agricultural jobs typically require lower skills and qualifications than those in other economic sectors. For individuals who lack education or training and are not qualified for work outside of agriculture, remaining in that sector may be their only option —even if it means staying in poverty. It is worth noting that since 2021, agricultural laborers have been included in the list of minimum wage earners. According to the National Minimum Wage Commission (CONASAMI, 2024), in 2021, the minimum wage for agricultural workers was $213.30 MXN/day in the northern zone and $160.19 MXN/day in the rest of the country. In

2022, those wages rose to $260.34 and $195.93, respectively a 22% increase. These figures imply a monthly income (assuming 30 days of work) of $7,810.20 in the north and $5,879.90 elsewhere. However, the extreme poverty line for income the monetary value of the food basket in December 2022 for a household of four was $6,520.84 in rural areas (CONEVAL, 2023). This means that the minimum required expenditure on food exceeds the household income of an average agricultural worker. Despite increases in the minimum wage for agricultural laborers, poverty persists. This is largely because most agricultural workers are employed on a temporary or casual basis, without access to social benefits (Flores, 2021). Employment agreements are often verbal, and in some cases, there is no fixed wage agreement (Posadas, 2018). Additionally, wage increases are not uniformly applied across the country. According to Barrón *et al.* (2019), in the third quarter of 2021, 44% of agricultural workers earned less than the value of the basic food basket. Furthermore, while agricultural income has grown at an average annual rate of 18% between 2010 and 2022 (based on SIAP data, 2023), its poverty-reducing effects were only observed during the 2018–2022 period. Ceddia (2019) attributes this to income inequality and land concentration. Vaquiro (2021) also emphasizes that in southern Mexican states where poverty is more persistent agricultural households must diversify income sources to escape poverty. Lastly, it is important to note that agricultural laborers typically migrate two or three times a year, depending on harvest seasons, in order to stay employed year-round (Barrón *et al.*, 2019). For example, in San Quintín (northwestern Mexico), a strong agricultural labor market has emerged, relying heavily on low-cost indigenous labor from the country's poorest southern states (Villegas & Camarena, 2024). In short, low wages, job insecurity, and high labor turnover all reinforce the poverty trap that perpetuates the precarious conditions faced by agricultural workers. Wage increases are necessary but alone, they are insufficient to significantly reduce poverty.

CONCLUSIONS

Although agricultural production increased during the study period, agricultural income only began to have an effect on the reduction of multidimensional extreme poverty starting in 2018, and its effect on general poverty was observed only in 2022. This suggests that, while agriculture is a potentially powerful tool for poverty reduction, in the case of Mexico, other factors must be considered such as land tenure, market conditions, climate change, and public policy. The marginal impact of agriculture on poverty reduction found in this study highlights the need for deeper analysis in future research to evaluate the behavior of these variables as more data becomes available. It is recommended to reinstate social support programs targeting rural agricultural producers, aimed at reducing poverty through subsidies, financing mechanisms, or direct cash transfers.

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