

## Climatic effects and agricultural productivity: The case of El Salvador

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**ABSTRACT:** We analyze Total Factor Productivity (TFP) using a large farm level panel data set from El Salvador, a country highly vulnerable to climatic events. For this purpose, alternative stochastic production frontier models are implemented to evaluate the robustness of the analysis. Key findings show that temperature shocks adversely impact output, aggregate rainfall has a positive effect, while mean temperature exhibits no significant effect. Furthermore, TFP declined by -5.36 % on average, while average technological change and technical efficiency declined by -2.25 % and -1.36 %, respectively with considerable variability across time and space.

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### Efectos climáticos y productividad agrícola: El caso de el Salvador

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**RESUMEN:** En este trabajo se analizan cambios en la Productividad Total de Factores (PTF) utilizando datos de panel a nivel predial para El Salvador, país altamente vulnerable a la variabilidad climática. Para este efecto, se implementan modelos de fronteras de producción estocásticos alternativos para evaluar la robustez del análisis. Los hallazgos muestran que las variaciones en temperatura afectan negativamente la producción, la lluvia acumulativa tiene un efecto positivo, mientras que la temperatura media no tiene efecto significativo sobre la productividad. Además, la PTF disminuyó en un -5,36 % en promedio, el cambio tecnológico promedio y la eficiencia técnica disminuyeron en un -2,25 % y -1,36 %, respectivamente.

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**KEYWORDS / PALABRAS CLAVE:** El Salvador, panel data, Stochastic Production Frontiers, productivity, climatic effects / El Salvador, Datos de panel, Fronteras de Producción Estocásticas, productividad, efectos climáticos.

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## 1. Introduction

Growing evidence confirms that climate change is intensifying food insecurity in low-income populations around the globe (Mirzabaev, *et al.*, 2023). In particular, the Latin American and Caribbean (LAC) Region experienced 548 floods, 74 droughts, and 50 extreme temperature events between 2000 and 2019 leading to USD\$280 billion in losses of from crop and livestock production (OCHA, 2020; FAO, 2021). Moreover, according to the Emergency Events Database, which provides information on catastrophic events, Central America was the most affected sub region (Delforge *et al.*, 2023).

Food insecurity in LAC has been on the rise since 2015 and was aggravated by the Covid-19 pandemic remaining above the world's average since 2014. FAO estimates for 2022 reveal that about 38 % of the LAC population experienced food insecurity (247 million people) and 6.5 % experienced hunger (43 million people) (FAOSTAT, 2023). In a context of increasing food insecurity and harsh climatic conditions, accelerating productivity and farm output growth is a central policy concern in countries like El Salvador (USDA & CATIE, 2023).

The Salvadorean agricultural sector contributes just 5.8 % to the countries' GNP; however, farming continues to have a critical function in staple food production, on the well-being of rural areas and in the generation of income and jobs, providing employment to 18.6 % of the economically active population. The food system in El Salvador confronts rising challenges involving land constraints, rapid population growth, high poverty and heavy reliance on imported basic grains to meet a growing demand (WFP, 2025; FAO, 2012). In addition, the country has undergone extensive water and land degradation and is prone to harsh natural disasters made more acute by climate change (Gies, 2018; Derlagen *et al.*, 2020). In fact, El Salvador is one of the most vulnerable countries to climate change in the world according to the Climate Change Vulnerability Index and it ranks second highest for risk exposure to natural hazards (CAF, 2014). Since 1950, the country's temperature has increased by 1.3 degrees Celsius on average, precipitation patterns have become more volatile, and periods of drought have become longer (USAID, 2020). Projected scenarios using the Intergovernmental Panel on Climate Change (IPCC) methodology suggest a rise in temperature of 1.5 degrees Celsius by 2030 and from 2 to 5 degrees Celsius by 2100 (Bouroncle *et al.*, 2015; Ordaz *et al.*, 2010).

The farming sector in El Salvador has a dual structure: (a) small-scale family farming, which represents over 80 % of agricultural operations; and (b) a commercial sub-sector oriented towards export crops such as coffee and sugarcane (CGIAR, 2024). Coffee, historically a major source of export earnings, has experienced a decline in prominence due to a range of structural and market-related challenges. Land distribution in El Salvador remains highly unequal, with 9 % of producers controlling 72 % of the arable land, while the remaining 91 % cultivate only 28 % (FAO, 2025). Green coffee, basic grains, sugarcane, and other crops account for

approximately 61 % of total production. Livestock represents 31 %, while fishing and hunting contribute 3 %, and forestry the remaining 5 %. Of the total cultivated area, 55 % is dedicated to basic grains, 42 % to agro-industrial crops, and the remaining 2 % and 1 % to fruit and vegetable production, respectively. The principal basic grains cultivated are maize, beans, sorghum, and rice (Braude *et al.*, 2025). However, the primary agricultural contributors to GDP are coffee and sugarcane. Livestock production in El Salvador is predominantly small-scale and the main activities include cattle, pig farming, poultry production, and beekeeping. Cattle farming is largely dual-purpose, serving both dairy and meat production needs (CGIAR, 2024).

Despite the importance of productivity growth in any agricultural strategy in El Salvador, as well as in many other areas across the developing world, the farm productivity literature in LAC is scant (Byerlee *et al.*, 2008). This study contributes to this limited literature by presenting a robust micro-econometric analysis of the link between agricultural productivity including climatic effects. Our specific goal is to quantify the role that various key components have on output and productivity growth. The article is organized in five sections, starting with the preceding introduction, followed by an overview of the related literature including key conceptual contributions and empirical TFP studies that have bearing on El Salvador. Section 3 presents the data and methodology followed by Section 4 where we discuss model selection and results, followed by Section 5 containing a summary and concluding remarks.

This study provides a detailed quantitative analysis of the agricultural productivity drivers based on farm level data from all Salvadorean Departments. The results reveal negative productivity changes with considerable variability across the country. Our primary contribution is to narrow the knowledge gap existing in El Salvador regarding agricultural productivity growth analysis which is essential for policy making on several areas including actions needed to curtail the damages imposed by recurrent climatic shocks. The results show that the two key drivers of farm productivity, technological change and managerial performance, are lagging substantially; thus, investments in agricultural extension and research are indispensable. In addition, the clear geographic heterogeneity in our productivity estimates underscore the value of disaggregated data, ideally at the farm level, to undertake meaningful productivity analyses.

A salient geographic feature in Central America is the Dry Corridor (Corredor Seco), a climatically vulnerable region, encompassing areas of El Salvador, Guatemala, Honduras, and Nicaragua. This region is characterized by acute weather variability including, recurrent dry spells, and a clear trend toward increased frequency and intensity of droughts, severely compromising the sustainability of agricultural systems and food security in the region (FAO, 2021). In El Salvador, the Dry Corridor spans primarily the eastern and northern departments, including Morazán, San Miguel, La Unión, Chalatenango, Cabañas, and parts of Usulután, where the impacts of climatic stressors are most acutely felt due to the predominance of

subsistence farming and rainfed agricultural practices (FAO, 2021). It is estimated that about 80% of rural producers in the “Dry Corridor” live in poverty and the majority faces severe food insecurity (FAO, 2021; WFP, 2021).

## 2. Related Literature

Theoretical and empirical work focusing on productivity measurement and analysis has undergone significant evolution over the past several decades. Kumbhakar & Lovell (2000) argue that Nishimizu & Page (1982) pioneered the decomposition of productivity change into technological and technical efficiency change and their conceptual framework was subsequently implemented in agricultural economics by Fan (1991), and Ahmad & Bravo-Ureta (1995; 1996).

Substantial advances have been made in the application of the stochastic production frontier methodology building on the pioneering work of Aigner *et al.* (1977), and Meeusen & van den Broeck (1977), to measure and analyze TFP change (O'Donnell, 2016; 2018; Sickles & Zelenyuk, 2019). O'Donnell has also introduced the ‘proper’ TFP index used in this study, which satisfies several axioms arising from measurement theory, and allows for the exhaustible separation of TFP change into various components including technological, scale, and technical efficiency change, environmental effects, and statistical noise. Moreover, O'Donnell contends that commonly used TFP indexes (e.g., Fisher, Törnqvist) are not ‘proper’ since they are inconsistent with measurement theory and violate critical index number axioms. Applications of the O'Donnell methodology include Njuki *et al.* (2018; 2019; 2020).

Despite a robust literature focusing on the empirical analysis of TFP measurement, micro level studies for LAC countries are rare. Table 1 provides a list of 10 studies that present evidence of agricultural productivity change for El Salvador, all based on macro data, and only six of the 10 rely on econometric procedures. From the list we focus on Lachaud *et al.* (2017) who use FAO country level data for the years 1961-2012 and studied Climate Adjusted (CAD) TFP for 28 LAC countries using a random parameters SPF approach along with the decomposition approach of O'Donnell (2016). The results show that climatic variability has had negative productivity effects in 20 of the 28 countries analyzed and such effects have been more severe in Central America than elsewhere. The average annual TFP growth for El Salvador is 0.41% while the CAD-TFP is 0.52 %. The respective averages for LAC are 1.08 % and 0.69 %. The best performing country was Chile with 2.44 % TFP and 1.82 % CAD-TFP rates. The analysis indicates that technological progress has been the dominant contributor to TFP growth for all countries. The last study on the list shown in Table 1 (Lachaud & Bravo-Ureta, 2021) uses the same 28 country data set and concludes that countries with low CAD-TFP rates, like El Salvador, will not be able to achieve the productivity levels of the better performing peers unless specific growth oriented and well targeted policies are implemented.

TABLE 1

Studies reporting total factor productivity (TFP) measures for agriculture in El Salvador

| Study                          | Data Source | Product             | TFP Annual Change (%) | Method                            | Years in Dataset                    |
|--------------------------------|-------------|---------------------|-----------------------|-----------------------------------|-------------------------------------|
| Arnade (1998)                  | USDA, FAO   | Agriculture         | -0.75<br>-0.82        | DEA-Malmquist Index               | 1961-1993                           |
| Martin & Mitra (2001)          | World Bank  | Agriculture         | 1.43<br>1.05          | Translog Cobb-Douglas (CD)        | 1967-1992                           |
| Nin <i>et al.</i> (2003)       | FAO         | Livestock Crops     | 0.60<br>-0.92         | Non-Parametric Malmquist Index.   | 1965-1994                           |
| Rao & Coelli (2004)            | FAO         | Agriculture         | 0.99                  | DEA-Malmquist Index               | 1980-1995                           |
| Coelli & Rao (2005)            | FAO         | Agriculture         | 1.00                  | DEA-Malmquist Index               | 1980-2000                           |
| Días Avila & Everson (2010)    | FAO         | Livestock Livestock | 3.64<br>2.48          | Growth Accounting                 | 1961-1980<br>1981-2001              |
| Días Avila & Everson (2010)    | FAO         | Crops Crops         | 2.95<br>-0.17         | Growth Accounting                 | 1961-1980<br>1981-2001              |
| Nin-Pratt <i>et al.</i> (2015) | FAO         | Agriculture         | -1.10<br>0.80<br>1.70 | CD Production Function            | 1981-1990<br>1991-2000<br>2001-2012 |
| Lachaud <i>et al.</i> (2017)   | FAO         | Agriculture         | 0.41<br>0.52          | CD Stochastic Production Frontier | 1961-2012                           |
| Lachaud & Bravo-Ureta (2021)   | FAO         | Agriculture         | 0.60<br>0.85<br>0.71  | CD Stochastic Production Frontier | 1961-1970<br>2001-2010<br>1961-2014 |
| Simple Average                 |             |                     | 0.65                  |                                   |                                     |

Source: Elaborated by the authors.

A major limitation of the studies cited in Table 1 is the failure to capture the heterogeneity that most likely characterizes different regions within a country which is vital in targeting interventions intended to promote productivity improvements. The only way to quantify this heterogeneity is to use farm level data and robust econometric methods, which is the task we pursue in the remainder of this study.

### 3. Data and Methodology

The data for this study comes from the *Encuesta Nacional Agropecuaria de Propósitos Múltiples* (ENAPM), which is undertaken annually by the Agricultural Statistics Division of the Salvadorean Ministry of Agriculture and Livestock. The data spans six agricultural years (May 2013-April 2014 to May 2018-April 2019). The raw data set includes 24,687 farm households located in 14 departments and 178 municipalities. After deleting observations with missing data, we have 18,122 observations. The total number of farmers per year varies from a high of 4,032 in 2013-2014 to a low of 1,740 in 2016-2017. The highest number of municipalities is in Usulután (18) and the lowest in Cabañas (7). The average number of households per municipality over the six-year period is 109 making this an unbalanced panel data set at the municipal level.

Table 2 presents names, definitions, and descriptive statistics for all variables used in the analysis. The data shows that farmers in El Salvador have an average value of crops equal to US\$1,529 per year and cultivate 3 *manzanas* (approximately 2.16 hectares), while labor input, measured in worker-equivalent days combining family, permanent, and temporary labor, averages 5.80. Table 2 also includes several binary variables capturing the use of conventional inputs. Mechanization is categorized into high (11 %), medium (44 %), and low (45 %), and the latter is the excluded category in the models below. Most producers report using fertilizers (99 %) and bactericides (98 %), while the use of fungicides (42 %) and irrigation (5 %) is less widespread. Regarding land tenure, 30 % of producers own their land, 51 % rent land, and 19 % fall under a mixed tenure arrangement (excluded category in the estimations). Only a small proportion of producers report access to credit (9 %) or having received technical assistance (6 %), highlighting potential constraints to technology adoption and productivity improvements. The average rainfall experienced by farmers in the sample is about 2,700 mm per year and the average temperature is 27 degrees Celsius. Finally, farmers experienced temperature shocks for about 8 weeks of the year.

TABLE 2

**Variable definitions and descriptive statistics for a sample of 18,122 farmers:  
El Salvador 2012/13 – 2018/19**

| Variable                                                                              | Mean  | S.D.  | Min. | Max.    |
|---------------------------------------------------------------------------------------|-------|-------|------|---------|
| TVC: Total Value of Crops in constant 2018 prices in US \$                            | 1,529 | 4,508 | 0.68 | 192,043 |
| <b>Conventional Inputs-Continuous</b>                                                 |       |       |      |         |
| Land: Manzanas with crops (1 mz=1.736 acres or 0.706 hectares)                        | 3.06  | 8.89  | 0.13 | 300     |
| Labor: Days of family, permanent, and temp. in worker equivalents                     | 5.80  | 10.79 | 0.32 | 1,008   |
| <b>Conventional Inputs-Binary</b>                                                     |       |       |      |         |
| High Mechanization=1 if tractor, mechanical seeder & harrow used                      | 0.11  | 0.32  | 0.0  | 1.0     |
| Medium Mechanization=1 if harvest equip., draft animals & plow used                   | 0.44  | 0.50  | 0.0  | 1.0     |
| Low Mechanization=1 if only manual tools are used (excluded category)                 | 0.45  | 0.50  | 0.0  | 1.0     |
| Irrigation =1 if used                                                                 | 0.05  | 0.21  | 0.0  | 1.0     |
| Fertilizers =1 if used                                                                | 0.99  | 0.07  | 0.0  | 1.0     |
| Fungicides =1 if used                                                                 | 0.42  | 0.49  | 0.0  | 1.0     |
| Bactericides =1 if used                                                               | 0.98  | 0.14  | 0.0  | 1.0     |
| Land Owned=1                                                                          | 0.30  | 0.46  | 0.0  | 1.0     |
| Land Rented=1                                                                         | 0.51  | 0.50  | 0.0  | 1.0     |
| Land Mixed=1 (excluded category)                                                      | 0.19  | 0.39  | 0.0  | 1.0     |
| Credit Access =1 if access                                                            | 0.09  | 0.29  | 0.0  | 1.0     |
| Technical Assistance =1 if received                                                   | 0.06  | 0.23  | 0.0  | 1.0     |
| <b>Climatic Variables and Technical Progress</b>                                      |       |       |      |         |
| Rainfall: Annual Cumulative precipitation in mm                                       | 2,761 | 413.5 | 1818 | 3761    |
| Temperature: Mean Annual in Celsius                                                   | 27.3  | 6.3   | 1.7  | 36.7    |
| Temperature Shock: Number of weeks temperature exceeds 1 std. dev. of max temperature | 8.4   | 4.4   | 1.0  | 23.0    |
| Time trend: Technological Progress, = 1 in year 1, 2 in year 2 etc.                   |       |       |      |         |

Source: Elaborated by the authors.

A formal statement of the production technology can be written as:

$$T^t(z) = \{ (x, q) \in \mathfrak{R}_+^{M+N} : x \text{ can produce } q \text{ in environment } z \text{ in period } t \} \quad [1]$$

A general expression of the SPF model associated with equation [1] can be expressed as:

$$q_{it} = \phi_i + f^t(x_{it}, z_{it}; \beta, \rho) + v_{it} - u_{it} \quad [2]$$

where:  $q_{it}$  is the total value of output<sup>1</sup> for the  $i^{th}$  farm in the  $t^{th}$  year;  $\phi$  is the intercept term;  $f^t$  is the function that approximates the time- $t$  production technology;  $x_{it}$  is a vector of input quantities and  $\beta$  is the corresponding vector of parameters;  $z$  is a vector of environmental variables which can be time variant or invariant and  $\rho$  is the associated vector of parameters;  $v_{it}$  is the idiosyncratic error term with an expectation of zero; and  $u_{it} \geq 0$  is a one-sided error term capturing technical inefficiency. In what follows, we cast the alternative frontier models we implement as variations of equation [2] where the individual farm effects denoted, by  $\phi_i$ , may be a constant parameter or may vary across individual farms depending on the model.

The first SPF we consider is a standard panel data version of the original cross-sectional model from Aigner *et al.* (1977), where each observation is treated as independent from the others. The next model is the True Fixed Effects (TFE) introduced by Greene (2005a) which allows for time varying technical efficiency (TE) through the term  $u_{it}$  while accounting for unobserved farm-level heterogeneity through  $\phi_i$ . The TFE model can be expressed as:

$$q_{it} = \phi + f^t(x_{it}, z_{it}; \beta, \rho) + \zeta_i + v_{it} - u_{it}. \quad [3]$$

We also consider the true random effects (TRE) model by Greene (2005a), which is expressed as:

$$q_{it} = \phi + \sum_{m=1}^M \theta_m \bar{x}_m + \zeta_i + f^t(x_{it}, z_{it}; \beta, \rho) + v_{it} - u_{it} \quad [4]$$

Where  $\zeta_i$  is a random firm specific effect. To control for correlations between the unobserved heterogeneity and the explanatory variables (i.e. heterogeneity bias) we implement the so-called Mundlak TRE (MTRE) model which includes the time-invariant random specific effect, and a group mean term that is orthogonal to the explanatory variables (Abdulai & Tietje 2007). The MTRE can be expressed as:

$$q_{it} = \phi + \sum_{m=1}^M \theta_m \bar{x}_m + \zeta_i + f^t(x_{it}, z_{it}; \beta, \rho) + v_{it} - u_{it} \quad [5]$$

<sup>1</sup> Total value of farm output, or whole farm output, is commonly used as the dependent variable in farm level studies (e.g. Bravo-Ureta *et al.*, 2007; Bravo-Ureta *et al.*, 2017).

Where  $\bar{x}_m$  are the group means of the explanatory variables for each  $m^{th}$  input. All other terms are as in the TRE model in equation [4].

A more recent model, the Generalized True Random Effects (GTRE), affords added flexibility by incorporating a farm-specific time invariant inefficiency term denoted here as  $\omega_i$  (Filippini & Greene, 2016; Colombi *et al.*, 2014; Kumbhakar *et al.*, 2014). A recent study examines the efficiency of pork farms from five EU countries using a GTRE model to differentiate between persistent and transitory TE. The results show that the degree of productive specialization in the five countries has a positive impact on efficiency (Troncoso *et al.*, 2023). The GTRE extends the TRE, by assuming an error structure that has four parts, and can be expressed as follows (Filippini & Greene, 2016):

$$q_{it} = \phi_i + f^t(x_{it}, z_{it}; \beta, \rho) + v_{it} - u_{it} - \omega_i \quad [6]$$

Where  $\omega_i = \xi_i - \eta_i$ , is a time-invariant component with  $\xi_i$  and  $\eta_i$  capturing farm-level heterogeneity and persistent inefficiency, respectively. The GTRE can also deal with the possible correlation between individual effects and regressors by incorporating the group means, as in the MTRE, giving rise to the Mundlak GTRE (MGTRE) model given by:

$$q_{it} = \phi_i + \sum_{m=1}^M \theta_m \bar{x}_m + f^t(x_{it}, z_{it}; \beta, \rho) + v_{it} - u_{it} - \omega_i \quad [7]$$

Distributional assumptions are such that  $\phi_i \sim N(0, \sigma_\phi^2)$ ,  $v_{it} \sim N(0, \sigma_v^2)$ ,  $u_{it} \sim N^+(0, \sigma_u^2)$  and  $\omega_i \sim N^+(0, \sigma_\omega^2)$ .

Finally, we explore parameter heterogeneity by modeling cross firm heterogeneity in the form of continuous parameter variation (Green, 2005a, 2005b). This is the random parameters (RP) model (e.g., Njuki *et al.*, 2019) and is written as:

$$q_{it} = \phi_i + f^t(x_{it}, z_{it}; \beta_{mit}, \rho_{kit}) + v_{it} - u_{it} \quad [8]$$

Where  $\phi_i \sim N(0, \sigma_\phi^2)$ ,  $v_{it} \sim N(0, \sigma_v^2)$  and  $u_{it} \sim N^+(0, \sigma_u^2)$ . Similarly,  $\beta_{mit}$  and  $\rho_{kit}$  represent farm- and time-varying environmental factors with distributional parameters  $\rho_{kit} \sim N(\rho_k, \sigma_{\rho_k}^2)$  and  $\beta_{mit} \sim N(\beta_m, \sigma_{\beta_m}^2)$ . As discussed below, we use the RP model in our analysis.

An added issue in the estimation of production frontier models has to do with identification or, in other words, the potential endogeneity of inputs. A well-established rationale underscoring the identification of production models is “that... entrepreneurs maximize the mathematical expectation of profit” (Zellner *et al.*, 1966, p. 787). This reasoning was later endorsed by Hodges (1969) and by Blair & Lusk

(1975). This rationale is invoked in this paper, as has been done recurrently over the past several decades in agricultural production economic research, either explicitly (Bravo-Ureta *et al.*, 2020; 2021; Picazo-Tadeo & Wall, 2011; Dawson & Lingard, 1982) or implicitly (Abdul-Rahaman & Abdulai, 2018; Piesse *et al.*, 2018).

### 3.1. Empirical Models

The C-D functional form is used here, which can be written, as:

$$\ln q_{it} = \phi_i + \sum_{m=1}^M \beta_m \ln x_{mit} + \sum_{j=1}^J \rho_j \ln z_{jit} + \gamma_t t + \gamma_{tt} t^2 + v_{it} - u_{it} - \omega_i \quad [9]$$

The terms in equation [9] are defined as follows:  $\ln q_{it}$  represents the log of output value for the  $i^{th}$  farm in year  $t$ ;  $x_{it}$  is a vector of inputs;  $z_{it}$  are climatic variables; and  $T$  is a time trend representing technical change. The expressions  $v_{it}$ ,  $u_{it}$  and  $w_{it}$  are as defined earlier, and all other Greek characters are parameters to be estimated. Based on our earlier discussion, alternative assumptions will be made regarding  $\phi_i$ , and some elements are omitted/added depending on the model being estimated.

The estimated SPF parameters are used as weights to decompose the TFPI into various elements. Following O'Donnell (2016; 2018), the TFPI that compares the rate of change in productivity of farm  $i$  in period  $t$  relative to the rate of change in productivity of farm  $k$  in period  $s$  is given by:

$$TFPI_{ksit} = \frac{[Q(q_{it})/X(x_{it})]}{[Q(q_{ks})/X(x_{ks})]} \quad [10]$$

Where  $Q(\cdot)$  and  $X(\cdot)$  are nonnegative, non-decreasing, and linearly homogeneous aggregator functions. Note that in equation 10, farm  $k$  in period  $s$  represents the reference observation and farm  $i$  in period  $t$  represents the comparison observation. All TFP comparisons are made vis-à-vis the same reference observation, which is chosen arbitrarily.

Finally, the expression of the TFP index for the Random Parameter (RP) model, our chosen specification, is denoted as (e.g. Njuki *et al.*, 2019):

$$TFPI_{ksit} = \left[ \frac{\exp(\gamma_t)}{\exp(\gamma_s)} \right] \left[ \prod_{m=1}^M \left( \frac{x_{mit}^{\beta_{mit} - b_m}}{x_{mks}^{\beta_{mks} - b_m}} \right) \right] \left[ \prod_{j=1}^J \left( \frac{z_{jit}}{z_{jks}} \right)^{\rho_j} \left( \frac{\exp(\phi_i)}{\exp(\phi_k)} \right) \right] \left[ \frac{\exp(u_{it})}{\exp(u_{ks})} \right] \left[ \frac{\exp(v_{it})}{\exp(v_{ks})} \right] \quad [11]$$

Where the first right hand side term in [11] is an output-oriented technology index (OTI) that captures technological progress; the second is an output-oriented scale

efficiency index (OSEI) reflecting productivity gains (positive values) or losses (negative values) associated with economies or diseconomies of scale, where  $b_m = \frac{\widehat{\beta}_m}{\sum_{k=1}^M \widehat{\beta}_k}$ , and  $\widehat{\beta}_m$  is an estimator of the mean of the distribution of  $\beta_{mit}$ ; and  $\sum_{k=1}^M \widehat{\beta}_k$  is the returns to scale measure; and the third is an environmental index (EI) that measures the impact of observed weather (i.e., rainfall and temperature variables) and unobserved time-invariant farm-specific heterogeneity on productivity; the fourth term is an output-oriented TE index (OTEI); and the last is a statistical noise index (SNI) that accounts for unexplained factors.

#### 4. Model Selection and Results

As discussed earlier, several models are estimated and the most relevant for our analysis are Pooled, TRE, TRE-M, and RP. In all estimations standard errors are clustered at the municipality level. The FE and TFE models are not suitable in our context because of the incidental variables problem, while the FE and TFE cannot accommodate both time invariant farm effects along with time invariant dummy variables (Belotti *et al.*, 2013). We also estimated the GTRE model with and without the Mundlak correction, and both exhibited the wrong skewness for the inefficiency term, so they were discarded. The parameters considered random in the RP model are those for all continuous variables (*Land, Labor, Rainfall, Temperature, and Temperature Shock*). In Table 3 we report the means of these random parameters obtained using Limdep version 6.

Some of the estimated models are nested, i.e., one model (restricted) is subsumed in a more general specification (unrestricted), but both have the same statistical structure. The True Random Effects (TRE) model is nested in the True Random Effects with Mundlak correction (TRE-M), and the Random Parameters (RP) model is nested in the Random Parameters with Mundlak correction (RP-M) model. Choosing between the restricted and the unrestricted models is done using Loglikelihood ratio and Wald tests. Details on these tests can be found in NIST (2012), Coelli & Rao (2005), and Greene (2012).

We test the Pooled model denoted in equation [3] versus the TRE in equation [5] and we fail to reject the null hypothesis that the farm-specific random effects are zero; therefore, we reject the TRE in favor of the Pooled and the TRE vs TRE-M. Next, the test of the Pooled against the RP in equation [9] supports the notion that the farm-specific and the slope parameters for the continuous variables are random, so we reject the Pooled in favor of the RP. We also contrast the TRE vs. the RP and again the latter is favored. Finally, a Wald test is conducted to test the significance of the additional parameters,  $\beta_{\bar{x}_1}$ , representing the mean of land and  $\beta_{\bar{x}_2}$  representing the mean of labor, included in the RP-M model. We fail to reject the null hypothesis that the additional parameters are significantly different from zero. Therefore, we select the RP over the RP-M. Table 4 reports the results of the various hypothesis implemented for model selection.

TABLE 3

**Estimates for four alternative stochastic production frontier models: Panel data for El Salvador, 2012/13 - 2017/18 (N=18,122)**

| Variable                         | Pooled    | TRE       | TRE-M     | RP        |
|----------------------------------|-----------|-----------|-----------|-----------|
| <i>TVC=Dependent</i>             |           |           |           |           |
| <i>Constant</i>                  | 4.434***  | 4.774***  | 4.798***  | 4.668***  |
| <i>Land</i>                      | 0.858***  | 0.857***  | 0.858***  | 0.839***  |
| <i>Labor</i>                     | 0.104***  | 0.106***  | 0.094***  | 0.096***  |
| <i>Mean Land</i>                 |           |           | -0.001    |           |
| <i>Mean Labor</i>                |           |           | 0.002     |           |
| <i>High Mechanization</i>        | 0.150***  | 0.158***  | 0.150***  | 0.146***  |
| <i>Mid Mechanization</i>         | 0.040***  | 0.044***  | 0.043***  | 0.046***  |
| <i>Irrigation</i>                | 0.285***  | 0.280***  | 0.274***  | 0.262***  |
| <i>Fertilizers</i>               | 0.160***  | 0.196***  | 0.194***  | 0.189***  |
| <i>Fungicides</i>                | 0.130***  | 0.134***  | 0.133***  | 0.133***  |
| <i>Bactericides</i>              | 0.088***  | 0.116***  | 0.113***  | 0.107***  |
| <i>Land Owned</i>                | -0.030*** | -0.029*** | -0.047*** | -0.018*** |
| <i>Land Rented</i>               | 0.074***  | 0.078***  | 0.058***  | 0.086***  |
| <i>Access to Credit</i>          | 0.107***  | 0.108***  | 0.098***  | 0.103***  |
| <i>Technical Assistance</i>      | -0.034    | -0.020    | -0.021*   | -0.035*** |
| <i>Time Trend</i>                | 0.123***  | 0.114***  | 0.115***  | 0.126***  |
| <i>Time Trend<sup>2</sup></i>    | -0.020*** | -0.019*** | -0.019*** | -0.021*** |
| <i>Rainfall</i>                  | 0.273***  | 0.234***  | 0.234***  | 0.248***  |
| <i>Mean Temperature</i>          | -0.015    | -0.015    | -0.014    | -0.013    |
| <i>Temperature Shock</i>         | -0.131*** | -0.131*** | -0.132*** | -0.137*** |
| <i>Sigma(u)</i>                  | 0.734     | 0.731     | 0.737     | 0.707     |
| <i>Sigma(v)</i>                  | 0.257     | 0.245     | 0.246     | 0.215     |
| <i>lambda</i>                    | 2.84***   | 2.98***   | 2.99***   | 3.28***   |
| LL Function                      | -12,736   | -12,758   | -12,675   | -12,462   |
| Akaike Information Criterion     | 25,542    | 25,585    | 25,434    | 25,008    |
| Average Technical Efficiency (%) | 61.2      | 60.8      | 61.0      | 61.6      |

Note: TRE=True Random Effects; M=Mundlak; RP=Random Parameters

Significant at: 1% \*\*\*; 5% \*\*; 10% \*. NA: Not available

Source: Elaborated by the authors.

TABLE 4

**Loglikelihood ratio and Wald tests for model selection\***

| Model selection                                                                | Null hypothesis<br>H0                             | Test Statistic | P-value | Decision                 |
|--------------------------------------------------------------------------------|---------------------------------------------------|----------------|---------|--------------------------|
| Loglikelihood ratio test (Random Parameters vs. True Random Effects)           | $\sigma_{\beta_m} = 0$                            | 473.548        | 0.000   | Reject H0                |
| Loglikelihood ratio test (True Random Effects vs. Pooled)                      | $\sigma_{\beta_0} = 0$                            | 45.152         | 0.001   | Reject H0                |
| Loglikelihood ratio test (Random parameters vs Random Parameters with Mundlak) | $\sigma_{\beta_{x_1}} = \sigma_{\beta_{x_2}} = 0$ | 8.445          | 0.015   | Fail to reject H0 at 5 % |
| Wald test (Pooled SPF with Mundlak Correction)                                 | $\beta_{\bar{x}_1} = \beta_{\bar{x}_2} = 0$       | 1.580          | 0.453   | Fail to reject H0        |
| Wald test (True Random Effects with Mundlak Correction)                        | $\beta_{\bar{x}_1} = \beta_{\bar{x}_2} = 0$       | 0.101          | 0.750   | Fail to reject H0        |

\* The likelihood ratio statistic (LR) is given by:  $LR = -2[\ln LR - \ln LU] \sim \chi^2(J)$  where:  $\ln LR$  and  $\ln LU$  are the maximum values of the restricted (R) and unrestricted (U) log-likelihood functions, and J is the number of restrictions or the degrees of freedom. The calculated LR is compared with the tabulated value for a predetermined level of statistical significance (NIST, 2012).

Source: Elaborated by the authors.

Likelihood ratio tests and Wald tests are not applicable to non-nested models and one alternative is to use the Akaike Information Criterion (AIC) where the preferred model is the one that exhibits the lowest AIC value (Greene, 2012). According to Table 3, the Pooled and TRE models exhibit the highest AIC, so we no longer consider them. The model with the lowest AIC is the RP. In sum, although the estimates from the four models presented in Table 3 exhibit considerable consistency, our selection process supports the RP model as the preferred specification for our data and is the one we rely on for the ensuing discussion.

Returning to Table 3, we now focus on the last column on the right that displays the estimated coefficients for the RP model, which is our preferred option. The key inputs for which data are available to define continuous variables, *Land* and *Labor*, exhibit parameters that are significant at the 1 %. The respective mean values for the RP are 0.839 and 0.096. In what follows, the coefficients for all dummy variables are expressed in percentage terms (Greene, 2012, p. 150). Therefore, increasing mechanization from medium to low, the excluded category, would raise output by 4.7 % and from low to high by 15.7 %. Thus, higher mechanization, *ceteris paribus*, leads to higher output. Using *Irrigation* also plays a significant positive role increasing output by 29.9 %. The next set of dummy coefficients are for the use

of *Fertilizers*, *Fungicides* and *Bactericides* and the respective increases in output are 20.8 %, 14.2 % and 11.3 % compared to farms that do not use such inputs.

We also include a set of four dummies that can be considered structural. The first such variable takes the value of one for *Land Owned* and the estimate shows that average, landowners generate 1.8 % less output compared to mixed tenure, the excluded category. This result is compatible with the notion that owners may be using land as an investment asset without much concern for farm performance. This could also imply that owners place more emphasis on natural resource conservation. The results for *Land Rented* show a 9.0 % advantage suggesting that renters have an incentive to be more productive than farmers with mixed tenure. The third structural variable is a dummy equal to 1 if the farmer reported having *Access to Credit* and the results show a 10.8 % increase in output implying that additional cash might enable access to more and higher quality inputs. The latter is consistent with Almeida & Bravo-Ureta (2022) who, using a fixed effects model to examine the relationship between farm size and productivity in Nicaragua, identify access to credit as an important positive factor. The last variable in this group is *Technical Assistance* and the parameter is negative and significant which counters what is commonly expected. However, only 5.6 % of the sample reports receiving technical assistance.

The parameters for *Time Trend* and *Time Trend*<sup>2</sup> are 0.126 and -0.021 respectively; thus, technological progress displays a concave pattern where at the beginning of the period analyzed the effect is positive, diminishes and then turns negative as time passes. Regarding weather effects, *Rainfall* exhibits a positive and significant coefficient with a value of 0.248 confirm that irrigation can be a key adaptive mechanism during periods of drought that are expected to become more prevalent in El Salvador. On the other hand, the coefficient for *Mean Temperature* is negative but not significant. However, *Temperature Shock* has a significant negative coefficient (-0.137) suggesting that Salvadorian farmers can adapt to higher temperatures if these are stable and predictable while unanticipated temperature shocks can be problematic. These findings support the promotion of climate smart technologies for adaptation as well as dissemination of weather information (Bouroncle *et al.*, 2015). Finally, the results exhibit significant differences across Departments with respect to La Unión which is the omitted category.

Given the statistical support for the RP specification, we continue our TFP analysis considering only this specification. Table 5 presents the average annual %  $\Delta$  TFP and its components over the six-year period 2012/13-2017/18. These are organized into three groups of departments depending on their relative productivity performance. The Best performers are Cuscatlán, San Vicente, Cabañas, San Miguel, and Morazán with %  $\Delta$  TFP ranging between 0.90 % and -3.54 % with an average %  $\Delta$  TFP -1.90 %. The %  $\Delta$  OTI in this group declined by -2.09 % per year. In contrast %  $\Delta$  OSEI was positive among the group indicating a better than average scale of operation and input-mix. The only department exhibiting a positive TFP change in this group is Cuscatlán. It is also noteworthy that Cuscatlán enjoys a non-negative

%  $\Delta$  OTEI of 2.11 % indicating that, on average, farmers in Cuscatlán enjoyed gains in managerial performance over the period studied.

The next, three departments classified as Middle performers, present a  $\Delta$  TFP ranging from -4.63 % (La Unión) to -5.43 % (San Salvador). Here we see that %  $\Delta$  OTI plays a negative role in productivity with a value of -2.34 %. Another consistent negative contributor to the performance of this group is %  $\Delta$  OSEI with an average value of -1.59 %. This implies that farmers are producing at a scale below optimum; therefore, expanding farm size would lead to higher productivity. The third group includes the six departments that display the worst productivity performance ranging from -6.10 % (Santa Ana) to -12.12 % (Usulután) with an arithmetic mean of -8.47 %. This group also presents a negative %  $\Delta$  OTI of -2.34 %. Another negative contributor is again %  $\Delta$  OSEI with an arithmetic mean of -1.06 %. An even sharper negative contributor to performance for this group is %  $\Delta$  OTEI with an average of -3.25 %.

In sum, OTI and OSEI are consistent drivers of the observed negative TFP performance. The implication of negative OTI and OSEI values is that Salvadoran farms are not benefitting from technological progress and economies of scale, respectively. Similarly, a negative OTEI means that the available technology is not being used efficiently. Finally, the EI component fluctuates the most in terms of negative and positive effects across departments.

A distinct feature of the SPF methodology is the two-sided error term allowing the calculation of the statistical noise index (SNI), which captures factors that contribute to TFP change but that are not identified explicitly by the model (O'Donnell, 2016). Consequently, a relatively smaller SNI component is a desirable result. Table 5 shows that the (arithmetic) average percent change in TFP for all departments and years is -5.36 % while the average for the SNI components is -1.49 %.

Table 6 documents average TFP variations across several groupings of the data. Panel A shows average TFP change and components for three farm size groups: Small with less than three *manzanas* (16,234 farms or 89.6 % of the sample); Medium – those with three to 10 *manzanas* (1,698 or 9.4 %); and Large – those with more than 10 *manzanas* (190 farms or 1 % of the observations). These numbers clearly confirm that agriculture in El Salvador is dominated by small farms which experienced an average annual TFP decline equal to -5.92 % while the decline for mid-size farms was -7.69 %. In contrast, the larger farms experienced a decline on annual average TFP growth of only -0.64 %.

As noted earlier, the sample was divided into three mutually exclusive groups according to their mechanization level: High; Mid; and Low; see Table 2). Panel B in Table 6 shows that 2,035 observations (11.2 %) correspond to the High, 7,936 (43.8 %) to the Medium and 8,151 (45 %) to the Low Mechanization categories. All three groups exhibit negative rates of TFP change and the values are -6.73 %, -4.98 % and -8.38 %, respectively. Thus, the farms with the relatively better TFP

performance (less negative) are those with medium levels of mechanization while those that only rely on manual tools are the poorest performers.

TABLE 5

**Geometric means of total factor productivity (TFP) change by group of departments ranked by TPF performance: El Salvador 2012/13-2017/18 (N=18,122)**

| Performance/<br>Department     | % $\Delta$ TFP | % $\Delta$ OTI | % $\Delta$ OSEI | % $\Delta$ EI | % $\Delta$ OTEI | % $\Delta$ SNi |
|--------------------------------|----------------|----------------|-----------------|---------------|-----------------|----------------|
| <b>Best</b>                    |                |                |                 |               |                 |                |
| Cuscatlán                      | 0.90           | -2.34          | -0.64           | 2.01          | 2.11            | -0.17          |
| San Vicente                    | -1.72          | -2.51          | 2.06            | 0.45          | -2.25           | 0.79           |
| Cabañas                        | -1.99          | -2.42          | 0.01            | 1.13          | -0.15           | -0.55          |
| San Miguel                     | -3.17          | -0.84          | 0.04            | -1.02         | -0.50           | -0.88          |
| Morazán                        | -3.54          | -2.32          | 0.91            | -1.61         | -0.26           | -0.30          |
| Arithmetic Mean                | -1.90          | -2.09          | 0.48            | 0.19          | -0.21           | -0.22          |
| <b>Middle</b>                  |                |                |                 |               |                 |                |
| La Unión                       | -4.63          | -2.34          | -1.53           | -1.82         | 1.72            | -0.70          |
| Ahuachapán                     | -4.66          | -2.34          | -1.71           | 1.45          | -0.03           | -2.08          |
| San Salvador                   | -5.43          | -2.34          | -1.54           | 0.64          | -0.19           | -2.09          |
| Arithmetic Mean                | -4.91          | -2.34          | -1.59           | 0.09          | 0.50            | -1.62          |
| <b>Worse</b>                   |                |                |                 |               |                 |                |
| Santa Ana                      | -6.10          | -2.34          | -1.40           | -0.19         | -0.27           | -2.03          |
| Chalatenango                   | -6.56          | -2.34          | -0.22           | 1.30          | -2.97           | -2.44          |
| La Paz                         | -6.77          | -2.40          | -0.44           | -0.48         | -2.78           | -0.84          |
| La Libertad                    | -8.38          | -2.25          | -1.66           | 1.89          | -3.65           | -2.91          |
| Sonsonate                      | -10.88         | -2.34          | -2.07           | 1.74          | -4.81           | -3.77          |
| Usulután                       | -12.12         | -2.34          | -0.59           | -1.91         | -4.99           | -2.87          |
| Arithmetic Mean                | -8.47          | -2.34          | -1.06           | 0.39          | -3.25           | -2.48          |
| <b>Overall Arithmetic Mean</b> | <b>-5.36</b>   | <b>-2.25</b>   | <b>-0.63</b>    | <b>0.26</b>   | <b>-1.36</b>    | <b>-1.49</b>   |

Source: Elaborated by the authors.

TABLE 6

**Average total factor productivity (TFP) change by farm size, mechanization, irrigation, Credit, and Technical Assistance: Random Parameters model**

| Variable                   | Farms  |      | Percent change |       |       |       |       |       |
|----------------------------|--------|------|----------------|-------|-------|-------|-------|-------|
|                            | Number | (%)  | TFP            | ATI   | OSEI  | EI    | OTEI  | SNI   |
| <b>A. Land</b>             |        |      |                |       |       |       |       |       |
| <3 Mz                      | 16,234 | 89.6 | -5.92          | -2.32 | -1.08 | 1.04  | -1.54 | -2.13 |
| 3-10 Mz                    | 1,698  | 9.4  | -7.69          | -2.28 | -1.00 | -2.99 | -0.96 | -0.69 |
| >10 Mz                     | 190    | 1.0  | -0.64          | -2.22 | -0.71 | 0.18  | 1.71  | 0.45  |
| <b>B. Mechanization</b>    |        |      |                |       |       |       |       |       |
| High                       | 2,035  | 11.2 | -6.73          | -2.23 | -0.29 | -2.01 | -2.39 | 0.03  |
| Mid                        | 7,936  | 43.8 | -4.98          | -2.31 | -0.97 | 0.94  | -0.68 | -2.03 |
| Low                        | 8,151  | 45.0 | -8.38          | -2.34 | -2.19 | 1.25  | -2.09 | -3.24 |
| <b>C. Irrigation</b>       |        |      |                |       |       |       |       |       |
| Yes                        | 818    | 4.5  | -6.70          | -2.23 | -0.23 | -2.25 | -2.69 | 0.55  |
| No                         | 17,304 | 95.5 | -6.26          | -2.32 | -1.36 | 0.74  | -1.24 | -2.21 |
| <b>D. Access to Credit</b> |        |      |                |       |       |       |       |       |
| Yes                        | 1,624  | 9.0  | -4.51          | -2.28 | -0.68 | -0.77 | -0.32 | -0.53 |
| No                         | 16,498 | 91.0 | -6.33          | -2.32 | -1.32 | 0.70  | -1.37 | -2.17 |
| <b>E. Tech. Assistance</b> |        |      |                |       |       |       |       |       |
| Yes                        | 1,010  | 5.6  | -8.18          | -2.20 | -1.16 | -1.58 | -2.33 | -1.17 |
| No                         | 17,112 | 94.4 | -6.40          | -2.32 | -1.43 | 0.66  | -1.24 | -2.20 |

Source: Elaborated by the authors.

The next set of comparisons are for farmers that report irrigation use. Panel C in Table 6 shows that 4.5 % of the sample (818 farmers) used irrigation achieving a -6.70 % change in TFP compared to -6.26 % for those that did not. This is contrary to what we would expect but the sample size for irrigation adopters is small. Panel D presents the average outcomes for farmers that report having access to credit (1,624 or 9.0 % of the sample). Those with such access have a -4.51 % TFP change which contrasts with -6.33 % for those without access. Finally, Panel E presents results for technical assistance, where those who receive this service experience a TFP change of -8.18 % compared to -6.40 % for those who do not receive it. Again, this is an unexpected result but the sample size for farmers with technical assistance is only 5.6 % of the sample (1,010 farms).

## 5. Summary and Concluding Remarks

Accelerating agricultural development and farm output growth have been and remain important subjects in policy and political debates in El Salvador. Farmland has been an increasingly constraining resource for decades which highlights the relevance of smart and sustainable agricultural intensification schemes to foster equitable productivity growth and food security. However, research focusing on the productivity analysis required for policy making in El Salvador is almost nonexistent. The econometric estimates and TFP analyses reported here use farm level data covering all areas of El Salvador and reveal considerable heterogeneity across departments.

The analysis supports the following conclusions. Temperature shocks adversely impact agricultural output while aggregate rainfall has a positive effect albeit with substantial heterogeneity across departments. Technological change has made a negative contribution to the TFP performance while technical efficiency change has had a consistent negative effect in the worse performing departments over the last decade. These findings imply that considerable efforts are needed to improve productivity in both of its two key dimensions, technological progress, and technical efficiency. Accordingly, resources should be devoted to promoting the adoption and diffusion of improved technologies while enhancing managerial capabilities through appropriate and relevant extension and training activities with the goal of promoting the correct application of both new and existing technologies. Effective strategies to foster climate change resilience are also needed.

## Authorship contributions

**Boris E. Bravo-Ureta:** Conceptualization, Writing – original draft, Writing – review & editing Methodology. **Eric Njuki:** Data curation, Writing – original draft, Writing – review & editing, Software. **Roberto Jara-Rojas:** Data curation, Writing – original draft, Writing - review & editing. **Lina Salazar:** Writing – original draft, Writing – review & editing.

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The codes to estimate the models are available upon request from Eric Njuki; e-mail: Eric.Njuki@usda.gov

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