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AGRICULTURAL PRODUCTIVITY IN EL SALVADOR: A PRELIMINARY ANALYSIS

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Abstract:

The need to enhance food security while reducing poverty along with the growing threat imposed by climate change clearly reveal that it is imperative to accelerate agricultural productivity growth. This paper estimates micro-level production models to identify the major factors that have contributed to productivity growth in El Salvador, including irrigation, purchased inputs, mechanization, technical assistance, and farm size, among others. The econometric framework adopted in this investigation is grounded on recent panel data stochastic production frontier methodologies. The results obtained from the estimation of these models are used to calculate Total Factor Productivity (TFP) change and to decompose such change into different factors, including technological progress, technical efficiency (TE), and economies of scale. The findings imply that efforts are needed to improve productivity in both technological progress and technical efficiency where the latter is a measurement of managerial performance. This in turn indicates that resources should be devoted to promoting the adoption and diffusion of improved technologies while enhancing managerial capabilities through agricultural extension.

AGRICULTURAL PRODUCTIVITY IN EL SALVADOR:
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1. Introduction

The rising globalization across economic sectors, including agriculture, the need to enhance food security while reducing poverty along with the growing threat imposed by climate change clearly reveal that it is imperative to accelerate agricultural productivity growth particularly in lower income countries (Fuglie et al. 2020). Moreover, the international community is committed to battling poverty as was explicitly reflected in the Millennium Development Agenda (United Nations 2015) a pledge that is now continued by the Sustainable Development Goals (UNDP 2016). A new significant challenge to global well-being has been imposed by Covid 19, which has had serious and ongoing adverse effects on farm income and food security particularly in the developing world including most Latin American and Caribbean countries (Salazar et al. 2020). The impact of the pandemic is likely to be long-lasting (World Bank 2020) and this will require substantial development assistance to poor countries. Consequently, the support that is critically needed to combat economic challenges such as climate change in order to improve the sustainability and performance of the farming sector will likely become more limited. In this scenario, the importance of productivity growth, not only in agriculture but in all economic sectors, is ever more urgent.

Accelerating agricultural development and farm output growth have been longstanding issues at the center of policy and political debates. El Salvador, the country of interest in this study, is not an exception. An important early milestone was established with the land tenure law enacted in 1882. This law abolished communally owned lands, significantly diminished the size of *minifundia* farms, and set forth the transformation of the country's farm system from food production for local markets to larger export-oriented farms devoted to coffee, sugar, and later to cotton and livestock (Burke 1976). Browning (1983) observed that the prominence reached by these prosperous agricultural operations focusing on supplying foreign markets, led to a shift away from food production for domestic needs. Production for local markets, largely the domain of small-scale farmers, was relegated to areas with the poorest soils and these operations became increasingly "…neglected in terms of security of land tenure, access to credit or markets, pricing policy and technical assistance" (Browning (1983, p. 402-404).

The process set forth with the 1882 land tenure law has had long lasting adverse effects for small-scale farmers in El Salvador despite the subsequent complementary agrarian reform efforts undertaken in the country (McReynolds 2002). Although agriculture contributes only 5.8% to GNP, farming continues to have a critical function in staple food production, in the well-being of rural areas and in the generation of income and jobs, providing employment to 18.6% of the economically active population. Moreover, the country is a net importer of food products that are significant to satisfy the basic needs of local consumers and that require the allocation of limited foreign exchange that is badly needed to promote overall economic growth and development (Derlagen et al. 2020).

Browning argued back in 1983 that agricultural growth in El Salvador was critical and that this growth had to come from a well-articulated intensification strategy given that all available tillable land had been under cultivation for decades. Therefore, augmenting agricultural output to feed a rapidly growing population needs to be achieved by 'smart intensification' strategies and creative crop-livestock farming systems since bringing additional land into cultivation is not an option (Govers et al. 2017; Herrero et al. 2010).

Consequently, the food system in El Salvador confronts rising challenges including binding land constraints, rapid population growth, high poverty levels and heavy reliance on imported agricultural goods including basic grains to meet a growing demand (WPF 2020; FAO 2012). In addition, the country has experienced extensive water and land degradation, and is prone to harsh natural disasters made more acute by climate change (World Bank, 1997; USAID 2013; Gies, 2018; Derlagen et al., 2020). In fact, El Salvador has been categorized as 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; ECLAC 2018).

El Salvador has faced adverse agricultural conditions stemming from changes in temperature and rainfall with detrimental effects on farm productivity. In fact, 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 increased (USAID, 2017). In addition, 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). In addition, natural hazards generated by climatic variability (i.e., droughts, floods, plagues, etc.) have also occurred more frequently, increasing vulnerability to food insecurity (FAO, 2016). These hazards, which are frequently compounded by seismic activity, are expected to have dire effects on the performance of the agricultural sector. For example, it is estimated that by 2070 maize output could decline by 10 percent, the production beans by 29 percent and coffee yields by about 45 percent (USAID, 2017).

Over the years, migration, primarily to the United States, has been a common mechanism used by many Salvadorean generating significant remittances; however, this is a course of action that is fraught with uncertainty and danger. Moreover, and directly tied to our interest here, is the argument that unfavorable shocks to agriculture in El Salvador has fomented increasing migration of males to the United States (Halliday, 2012). Adverse effects of out-migration on farming practices are also reported by Davis and Lopez-Carr (2014) for Central America including El Salvador. A dynamic agricultural sector that contributes to local food security, poverty alleviation and employment while improving its natural resources and resilience to climate change will remain an important challenge for El Salvador.

Considering the above, productivity growth needs to play an essential role in any agricultural strategy for El Salvador as well as in many other countries across the developing world (World Bank 2008). Nevertheless, the available literature focusing on quantifying farm productivity for El Salvador is almost nonexistent. Hence, the goal of this study is to narrow this gap by performing a robust micro-econometric analysis of productivity for the Salvadorean farm sector. Specifically, the intention of this study is to document the effect of key factors on output and productivity growth which could then inform the design of future policies and development projects.

The specific objective of this study is to estimate micro-level production models to identify the major factors that have contributed to productivity growth including irrigation, purchased inputs, mechanization, technical assistance, and farm size, among others. The econometric framework adopted in this investigation is grounded on recent panel data stochastic production frontier methodologies. The results obtained from the estimation of these models are used to calculate Total Factor Productivity (TFP) change and to decompose such change into different factors, including technological progress, technical efficiency (TE), and economies of scale. The analysis will also focus on the evolution of these different factors over time and their variability across space.

The remainder of this report is organized in five sections. We first provide an overview of empirical TFP studies that have a bearing on El Salvador, followed in Section 3 by a presentation of the methodological framework employed. Section 4 contains a discussion of the data and Section 5 details the empirical models used. Section 6 focuses on the results while the concluding remarks are presented in section 7. The paper narrows a void in the applied agricultural productivity literature by providing detailed evidence of farm level performance and its drivers for El Salvador where no related work seems to be available. We also hope that our work will motivate similar efforts for other understudied developing countries, particularly in Central America, where agricultural productivity growth is essential. Empirical productivity investigations are needed to guide the international donor community as well as domestic policy formulation in order to make the best use of the limited resources available to improve the livelihoods of poor farmers and to ensure their food security.

2. Overview of related literature

Theoretical and empirical work focusing on productivity measurement and analysis has undergone significant development over the past several decades. Substantial advances have been made in the application of the stochastic production frontier methodology, that has built on the pioneering work of Aigner, Lovell and Schmidt (1977), and Meeusen and van den Broeck (1977), to measure and decompose TFP (Kumbhakar and Lovel 2000; O'Donnell 2018; Sickles and Zelenyuk 2019).

Pioneering work on TFP decomposition was undertaken by Caves, Christensen and Diewert (1982a; 1982b). About the same time, Nishimizu and Page (1982) argued that technological progress and technical efficiency (TE) are concepts grounded on the production function, but "…applied work in these fields has evolved largely independently" (p. 920). These authors were forerunners in incorporating technological progress along with TE as a source of productivity change and they estimated a deterministic parametric production frontier following the linear programming approach developed by Aigner and Chu (1968). Early applications of the decomposition approach introduced by Nishimizu and Page (1982) based on a stochastic framework includes the work focusing on US dairy farming by Ahmad and Bravo-Ureta (1995).

Another important contribution to the productivity literature is the work by Färe, Grosskopf, Norris and Zhang (1994) who implemented a non-parametric mathematical programming framework to decompose Malmquist productivity indexes into changes in technological progress and TE for 17 OECD countries. Kumbhakar and Lovell (2000) formulated a translog stochastic production frontier, which they used to calculate productivity change, and then separated the latter into three components: technological progress; returns to scale; and time varying TE. More recently, O'Donnell (2016 and 2018) introduced the 'proper' TFP index, which satisfies several axioms arising from measurement theory, and decomposed TFP changes into various elements including scale, technological, TE, environmental, and statistical noise. Furthermore, O'Donnell (2016, 2018) contends that commonly used TFP indexes (e.g., Fisher, Törnqvist) are not 'proper' since they are inconsistent with measurement theory and violate important index number axioms. Applications of the O'Donnell methodology include Njuki, Bravo-Ureta and O'Donnell (2018), and Njuki, Bravo-Ureta, and Cabrera (2020).

Despite a robust literature focusing on the empirical analysis of TFP measurement, studies for LAC countries are extremely limited. Table 1 provides a list, arranged based on year of publication, of 10 studies that present evidence on agricultural productivity change for El Salvador.

All these studies use aggregate data and are part of multi-country comparisons and six of 10 rely on non-econometric procedures. We start with Arnade (1998) who investigated productivity growth in 70 countries, including El Salvador and four of its regional neighbors, Costa Rica, Guatemala, Honduras and Nicaragua. This study makes use of a non-parametric Malmquist index calculated with DEA and data from FAO and USDA for the period 1961-1993. The results reveal negative rates of productivity growth for El Salvador as well as the other Central American (CA) countries considered except for Costa Rica. The author also finds that research and education have a positive effect on productivity.

Martin and Mitra (2001), with data from FAO, the World Bank and OECD, compared TFP growth between the agricultural and manufacturing sectors in 50 countries with different income levels for the period 1967-1992. Cobb-Douglas and translog production function estimates indicate that the annual TFP growth rates for agriculture in El Salvador are positive (1.43% and 1.04% for the translog and C-D models respectively) but lower than the overall average for the sample studied. Nin-Pratt et al. (2003) used a directional distance function to estimate nonparametric Malmquist TFP indexes separately for livestock and crops using FAO data for 93 developing and 23 high income countries over the 1965-1994 period. This study found negative annual productivity growth for agriculture (-0.19%) in El Salvador, but separate TFP measures show a slight positive rate for livestock (0.06%) but negative for crops (-0.92%).

Rao and Coelli (2004) included 97 countries from the FAO dataset from 1980 to 1995 and applied DEA to estimate a two-output distance function, livestock, and crops, which they used to calculate Malmquist TFP indexes. These authors reported annual TFP growth for El Salvador at 0.99% and this compares with 1.03% for Costa Rica the best performer in CA. In an extension of the previous study, Coelli and Rao (2005) covered 93 countries for the period 1980-2000 and found that TFP growth for el Salvador reached 1.008% whereas Costa Rica was 1.028%, again the top performing in CA.

Días Avila and Evenson (2010) employed FAO data for a total of 78 countries, including El Salvador plus five other Central American countries, for the period 1961-2001. Using an accounting relationship, the authors report a 1.05% annual average TFP growth rate (crops and livestock combined) for El Salvador which is significantly below the 1.74% average for all six Central American countries studied. A productivity decomposition analysis showed that key variables related to productivity growth were investment in agricultural research, public and private extension services, and farmer schooling.

Nin-Pratt, Falconi, Ludena and Martel (2015) implemented a neoclassical growth accounting approach combined with DEA to examine the performance of LAC countries using FAO data over the 1961-2012 period. Key results indicated that El Salvador experienced an annual TFP growth equal to 0.5% for the period 1981-2012, the contribution of TE was 0.1% and that of technological progress was 0.4%. The respective average values for all LAC countries are 1.2%, 0.3% and 0.9%, which placed El Salvador in the group of low TFP growth performers.

Lachaud, Bravo-Ureta and Ludena (2017) also using FAO data for the years 1961-2012, studied Climate Adjusted (CAD) TFP for 28 LAC countries using a random parameters SPF along with the decomposition approach proposed by O'Donnell (2016). The results show that climatic variability has had negative productivity effects in 20 of the 28 LAC countries analyzed and such effects have been more severe in Central America. 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 indicated that technological progress has been the dominant factor in TFP growth for El Salvador as well as for all other LAC countries analyzed.

The last study we include in this overview is by Lachaud and Bravo-Ureta (2021), where the authors measured and examined catch-up and convergence patterns in CAD-TFP using the same 28 country LAC data set as the preceding study. The analysis reveals that countries with low CAD-TFP rates, like El Salvador, will not accelerate their productivity levels to those being achieved by better performing peers unless specific growth oriented and well targeted policies are implemented. The study concludes that convergence patterns provide evidence that productivity gaps will keep rising and will not diminish among LAC countries without the application of suitable development policies and programs.

In sum, the studies just reviewed show consistently low productivity growth for El Salvador when using aggregate country level data. A major limitation of this literature is the failure to capture the heterogeneity that most likely characterizes different types of farms and departments within the country, and this is essential in designing and 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. Methodological framework

3.1 Panel data stochastic production frontiers

The last 15 years have witnessed a significant methodological development concerning panel data stochastic production frontiers. In two influential and related articles Greene (2005a and b) makes the case for extricating time-invariant heterogeneity from time-varying TE to account for unmeasured firm-specific features that affect the technology rather than inefficiency, thus avoiding an incomplete or mis-specified model. A further refinement differentiates time-invariant unobserved heterogeneity from time-invariant TE (Filippini and Greene 2016; Tsionas and Kumbhakar, 2014). Below we briefly highlight the key features of these and related panel data SPF models to provide the foundation for our empirical analysis.

Before moving to a discussion of the alternative models, it is useful to distinguish between the production technology and the characteristics of the production environment. Borrowing from O'Donnell (2016), we define the technology as "… a technique, method or system for transforming inputs into outputs". On the other hand, the production environment, comprises of variables that influence the production process but that cannot be controlled by the farm manager (e.g., weather, national disasters, topography). The following equation displays a more formal statement:

$$T^t\,(z) = \{\,(x,q) \in \Re_+^{M+N}: x \text{ can produce } q \text{ in environment } z \text{ in period } t\}. \tag{1}$$

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

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

where: q_{it} is the output quantity of the i^{th} farm in the t^{th} year; ϕ_i represents the individual farm effects; f^t is the function that approximates the time-*t* production technology; x_{it} is a vector of input quantities and β the corresponding vector of parameters; z is a vector of environmental variables which can be time variant or invariant and ρ 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 – which is a measure of the distance between the observed and potential output for each observation.

In what follows we consider convenient to cast the alternative frontier models to be presented as variations of equation (2) where the individual farm effects denoted by ϕ_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, Lovell and Schmidt (1977), where each observation is treated as independent from the others. This model, often referred to as the Pooled SPF, can be written as:

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

where: ϕ is an overall intercept; v_{it} is a normally distributed symmetric random error term with mean zero, i.e., $v_{it} \sim N(0, \sigma_v^2)$; $u_{it} \geq 0$ is a one-sided error term capturing technical inefficiency assumed to follow a half-normal distribution, i.e., $u_{it} \sim N^+(0, \sigma_u^2)$; and the other terms are as defined above. In this Pooled SPF, and subsequent SPF models, the TE component (TE_{it}) is calculated applying the formula developed by Jondrow et al. (1982) and can be represented as $TE_{it} = exp(-\hat{u}_{it})$.

The next model is the True Fixed Effects (TFE), introduced by Greene (2005a) which allows for the measurement of time varying TE through the term u_{jt} while also accounting for unobserved farm-level heterogeneity. This model can be expressed as:

$$q_{it} = \phi_i + f^t(x_{it}, z_{it}; \beta, \rho) - v_{it} - u_{it} \tag{4}$$

Heterogeneity across farms is obtained from the vector ϕ_i, which are farm dummy variables, and the other terms are as already defined. The TFE specification has the advantage of permitting the individual farm-specific effects and the other regressors to be correlated, but a potential weakness is not allowing the inclusion of time invariant variables.

Greene (2005a) also introduced the True Random Effects (TRE) model written as:

$$q_{it} = \phi_i + f^t(x_{it}, z_{it};\ \beta, \rho) + v_{it} - u_{it.} \tag{5}$$

Equation (5) is similar to (4), but now note that the farm-specific effect is random and distributed as $\phi_i \sim N\left(0, \sigma_\phi^2\right)$. On the plus side the TRE makes it possible to include farm-invariant regressors, an advantage over the TFE, but a shortcoming is that unobserved factors may be correlated with some regressors possibly yielding biased estimates of the production frontier coefficients (Abdulai and Tietje 2007).

Mundlak (1978) argued that the random effects, by ignoring the possible correlation between individual effects and other regressors, can be considered a mis-specified form of the standard fixed effects model. This author went on to tackle this issue by incorporating the group-means of the explanatory variables as additional regressors. Several years later, Farsi, Filippini and Kuenzle (2005) incorporated Mundlak's approach within the context of the TRE model giving rise to the Mundlak TRE (MTRE) model also known as the Correlated TRE. The MTRE can be expressed as:

$$q_{it} = \phi_i + \sum_{i=1}^{N} \varphi_i \bar{x}_{ij} + f(x_{it}, z_{it};\, \beta, \rho) + v_{it} - u_{it} \tag{6}$$

where $\bar{x}_{ij}$ are the group means of the explanatory variables for each j^{th} input in the i^{th} farm and all other terms are as in the TRE model in equation (5). Hence, the MTRE includes the positive elements of the TFE and of the TRE by controlling for unobserved heterogeneity while allowing inclusion of time invariant variables.

As indicated, the TFE and TRE models account for unobserved farm-specific heterogeneity (ϕ_i), time-varying inefficiency (u_{it}), and farm level idiosyncratic errors (v_{it}). 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 ω_i (Filippini and Greene 2016; Colombi et al. 2014; Kumbhakar, Lien and Hardaker 2014; Tsionas and Kumbhakar 2014). Thus, the GTRE extends the TRE, by assuming an error structure that has four parts, and can be expressed as follows:

$$q_{it} = \phi_i + f^t(x_{it}, z_{it};\ \beta, \rho) + v_{it} - u_{it} - \omega_i \tag{7}$$

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 (Filippini and Greene 2016) given by:

$$q_{it} = \phi_i + \sum_{i=1}^{N} \rho_i \bar{x}_{ij} + f^t(x_{it}, z_{it}; \beta, \rho) + v_{it} - u_{it} - \omega_i \tag{8}$$

where $\phi_i \sim N(0, \sigma_\phi^2)$, $v_{ij} \sim N(0, \sigma_v^2)$, $u_{ij} \sim N^+(0, \sigma_u^2)$, and $\omega_i \sim N^+(0, \sigma_\omega^2)$.

The last model we will consider here is another extension of the TRE which allows not only for a random intercept term but also for random parameters for the regressors. The model can be written as:

$$q_{it} = \phi_i + f^t(x_{it}, z_{it}; \beta_{it}, \rho_{it}) + v_{it} - u_{it} \tag{9}$$

In the random parameters model depicted above, $\phi_i \equiv \phi(z_i^*)$ measures the effects of time-invariant unobserved heterogeneity. Similarly, $\beta_{it} \equiv \beta(z_{it}^*)$ and $\rho_{it} \equiv \rho(z_{it}^*)$ are random parameters that capture the effects of unobserved stochastic farm- and time-varying environmental factors with distributional parameters $\rho_{jit} \sim N(\rho_j, \sigma_{\rho_j}^2)$ and $\beta_{mit} \sim N(\beta_m, \sigma_{\beta_m}^2)$. As we discuss below, we use the random parameters model in our analysis.

3.2 Functional form and identification

The next consideration is choosing a functional form to approximate the underlying technology. Aigner, Lovell and Schmidt (1977), and Meeusen and van den Broeck (1977) introduced the SPF paradigm the same year and both made use of the Cobb-Douglas (C-D) functional form. Ever since, the C-D has been the most widely used functional form in TE studies as documented in various meta-analyses (Bravo-Ureta et al. 2007; Bravo-Ureta et al. 2017; Ogundari 2014).

Moreover, Sickles and Zelenyuk (2019) state that the C-D… “production function is the workhorse of applied production economists…” (p. 173).

Another important consideration when choosing a functional form concerns the fulfillment of regularity or curvature conditions that come from the economic theory of production, specifically monotonicity and quasiconcavity. A salient feature of the C-D is that it satisfies both conditions globally but at the cost of imposing inflexibilities regarding partial production elasticities, returns to scale and the elasticity of substitution. In contrast, the translog (TL), which is also popular in applied work, offers some flexibilities while failing to satisfy regularity conditions globally. The forgoing arguments provide the rationale for adopting the C-D functional form in this study. We stress the point that the implications of the regularity conditions are particularly relevant when measuring TFP, as we will do here. Further comments regarding this issue will be provided below (O’Donnell 2016 and 2018).

An added issue in the estimation of production frontier models has to do with identification or, in other words, the potential endogeneity of inputs. The well-established rationale underscoring the identification of production models is “that…entrepreneurs maximize the mathematical expectation of profit” (Zellner, Kmenta and Drèze 1966, p. 787). This reasoning was later endorsed by Hodges (1969) and by Blair and Lusky (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 and 2021; Karagiannis and Kellerman 2019; Picazo-Tadeo and Wall 2011; Dawson and Lingard 1982) or implicitly (Abdul-Rahaman and Abdulai 2018; Piesse et al. 2018). We next introduce the data used in our analysis.

4. Data

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 going from May 2013-April 2014 to May 2018-April 2019. The raw data set includes a total of 24,687 farm households located in 14 departments and 178 municipalities. After deleting all observations with missing data, we end up with a total sample that includes 18,122 farm-level observations. As shown in Table 2, these observations are distributed across the 14 departments and 166 municipalities. 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 the Department of Usulután (18) and the lowest in Cabañas (7). The average number of households per municipality over the six-year period is 109. So, we can categorize these data as an unbalanced panel data set at the municipality level.

Table 3 presents all variables used in the analysis including their names, definitions, and corresponding descriptive statistics. Figure 1 presents a map including all 14 departments along with departmental capitals. Additional details regarding these variables will be presented as needed when we discuss the empirical models in the following section.

5. Empirical models

5.1 Cobb-Douglas Stochastic Production Frontier (SPF)

As stated above, the approximating function estimated here is the C-D functional form, which captures the various SPF formulations estimated below, as:

$$\ln q_{it} = \phi_0 + \sum_{m=1}^{M} \beta_m \ln x_{mit} + \sum_{j=1}^{J} \rho_j \ln z_{jit} + \gamma_t t + \gamma_{tt} t^2 + v_{it} - u_{it} - \omega_i \quad (10)$$

The terms in equation (10) are defined as follows: ln q_{it} represents the log of output 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 that represents technical change. The expressions v_{it}, u_{it} and ω_i are as defined earlier, and all Greek characters are parameters to be estimated. Based on our earlier discussion, alternative assumptions will be made regarding ϕ_i, and some elements are omitted/added depending on the particular model being estimated.

5.2 Total Factor Productivity Indexes (TFPI)

The estimated parameters are used as weights to denote the relative importance of the variables in the production function which in turn are used to decompose a TFPI into various components. TFP change measures the rate of change in aggregate output relative to the rate of change in aggregate input. Following O'Donnell (2016 and 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:

$$TFPI_{ksit} = \frac{[Q(q_{it})/X(x_{it})]}{[Q(q_{ks})/X(x_{ks})]} \tag{11}$$

where $Q(.)$ and $X(.)$ are nonnegative, nondecreasing, and linearly homogeneous aggregator functions. Note that in equation 11 above, 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 arbitrarily chosen.

As noted above, the difference between the TRE and the GTRE models is that the latter makes it possible to separate time-invariant farm-specific effects from persistent inefficiency. The complete specification of TFPI that is associated with the GTRE model takes on the following form:

$$TFPI_{ksit}$$

$$= \left[\frac{exp(\gamma_t)}{exp(\gamma_s)}\right] \left[\prod_{m=1}^{M} \left(\frac{x_{mit}}{x_{mks}}\right)^{\beta_m(1-\frac{1}{r})}\right] \left[\prod_{j=1}^{J} \left(\frac{z_{jit}}{z_{jks}}\right)^{\rho_j} \left(\frac{exp(\phi_i)}{exp(\phi_k)}\right)\right] \left[\frac{exp(\omega_i)}{exp(\omega_k)}\right] \left[\frac{exp(u_{it})}{exp(u_{ks})}\right] \left[\frac{exp(v_{it})}{exp(v_{ks})}\right] \quad (12)$$

where the first component on the right hand side is an output-oriented technology index (OTI) that captures the role of technological progress; the second component is an output-oriented scale efficiency index (OSEI) that captures productivity gains (positive index values) or losses (negative index values) associated with economies or diseconomies of scale, and where $r = \sum_m \beta_m$ is a measure of the elasticity of scale; the third component is an environmental index (ENI) 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 persistent or time-invariant TE index (OPTEI); the fifth component captures output-oriented transient or time varying TE index (OTTEI); and the last term is a statistical noise index (SNI) that reflects productivity change due to unexplained factors.

Finally, the complete specification of the TFP index under the Random Parameter (RP) model is denoted as:

$$TFPI_{ksit} = \left[\frac{exp(\gamma_t)}{exp(\gamma_s)}\right] \left[\prod_{m=1}^{M} \left(\frac{x_{mit}^{\beta_{mit}-b_m}}{x_{mks}^{\beta_{mks}-b_m}}\right)\right] \left[\prod_{j=1}^{J} \left(\frac{z_{jit}}{z_{jks}}\right)^{\rho_j} \left(\frac{exp(\phi_i)}{exp(\phi_k)}\right)\right] \left[\frac{exp(u_{it})}{exp(u_{ks})}\right] \left[\frac{exp(v_{it})}{exp(v_{ks})}\right] \quad (13)$$

Here, the first component on the right-hand is the output-oriented technology index (OTI); the second component is the output-oriented scale efficiency index (OSEI), where $b_m = \hat{\beta}_m / \sum_{k=1}^{M} \hat{\beta}_k$ an estimator of the mean of the distribution of β_{mit}; the third component is the environmental index (ENI) which captures the effects of both weather and time-invariant farm-specific heterogeneity; the fourth term is an output-oriented technical efficiency index (OTEI) that captures fluctuations in productivity due to movements towards and away from the frontier; and the final component is the statistical noise index (SNI) which measures productivity changes due to reasons that cannot be identified.

6. Results

This section starts with the rationale for selecting the model used in the analysis which, as detailed below, is the Random Parameters (RP). We then present an overview of salient findings from the RP model. Next, we discuss the TFP growth results followed by a heterogeneity analysis focused on farm size, mechanization, irrigation, credit, and technical assistance.

6.1 Model Selection

Several different models have been estimated and the results of the most relevant – Pooled, True Random Effects (TRE), TRE with the Mundlak correction (TRE-M), and Random Parameters (RP) – are displayed in Table 4. In all the estimations the standard errors are clustered at the municipality level.

We note that given the structure of the data used, the FE and TFE models are not suitable in our context for two main reasons. First is the incidental variables problem, and second, as already mentioned in sub-section 3.1, is the inability of the FE and TFE to accommodate both time invariant farm effects along with time invariant dummy variables (Belotti et al. 2012). We also estimated the GTRE model with and without the Mundlak correction, equations (7) and (8) above, and both exhibited the wrong skewness for the inefficiency term, so we discard those estimates and do not show these results.

The parameters considered random in the RP model are those for all continuous variables, namely: *Land, Labor, Rainfall, Temperature, Temperature Shock, Time and Time*^{2}. In Table 4 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. Model selection between the restricted and the unrestricted models is done easily using Loglikelihood ratio tests and Wald tests. The Loglikelihood ratio test requires the calculation of the likelihood ratio statistic (*LR*) given by:

$$LR = -2[lnL_R - lnL_U] \sim \chi^2 (J) \tag{14}$$

where: lnL_R and lnL_U are the maximum values of the restricted (*R*) and unrestricted (*U*) log-likelihood functions, respectively, and *J* represents the number of restrictions or the degrees of freedom. The calculated *LR* is compared with the tabulated value for the desired statistical significance (NIST 2012). If the critical value is less than (greater than) the calculated value, then the null hypothesis is rejected (not rejected) (Coelli et al 2005). A Wald test on the other hand evaluates the statistical significance of specific parameters based on the weighted distance between the unrestricted estimate and its hypothesized value under the null hypothesis, where the weight is the accuracy of the estimate (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 and we also contrast of 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 model over the RP-M model. Table 5 reports the results of the various hypothesis tested using the Loglikelihood ratio and Wald tests implemented for model selection.

Likelihood ratio tests and Wald tests are not applicable to non-nested models and one alternative is the Akaike Information Criterion (AIC), which conveys that the preferred model is the one that exhibits the lowest AIC value (Greene 2012). According to Table 4, 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 four models presented in Table 4 exhibit considerable consistency, the selection process implemented supports the RP model as the preferred specification for our data and is the one we rely on for the discussion that ensues.

6.2 Random Parameter (RP) estimates

Returning to Table 4, we will now focus on the last column on the right that displays the estimated coefficients for the RP model. The model selection process leads to choosing the RP specification; however, most of the parameters across the four models are statistically significant at the 1%. In all cases, the two key inputs for which data are available to define continuous variables are *Land* and *Labor*, and the parameters for both inputs are uniformly significant at the 1%. The respective mean values for the RP are 0.839 and 0.098. In what follows we only discuss the results for our chosen model, the RP.

The results reveal that coefficients of the dummies for mechanization have a positive and increasing effect on output with a value of 0.140 (*Hi*) and 0.044 (*Mid*), where *Low Mechanization* is the excluded category. Therefore, higher mechanization levels, *ceteris paribus*, leads consistently to higher output. *Irrigation* also plays a significant positive role with a parameter value for the corresponding dummy equal to 0.253. The next set of coefficients are for dummy variables corresponding to the use of chemical inputs and the values are 0.186, 0.133 and 0.102 for *Fertilizers, Fungicides* and *Bactericides*, respectively.

We include a set of four dummy variables that can be considered structural in nature. The first variable takes the value of one for *Land Owned* and the parameter is -0.051. This result suggest that landowners might be using land as an investment asset without necessarily making it more productive. The corresponding parameter for *Land Rented* is 0.052, this might be due to the pressure of having to pay for rent which might serve as an incentive to be more productive. The third variable is a dummy equal to 1 if the farmer reported having *Access to Credit* and the coefficient is positive (0.095) and significant, which is consistent with the notion that credit access alleviates cash constraints and enables the use of more and better inputs, mechanization, technologies, etc. The last variable in this group is also a dummy and is equal to 1 if the farmer reported having received *Technical Assistance* and in this case the parameter is negative (-0.033) and significant. This negative effect is counter to what is commonly expected but only 5.6% of the sample reports receiving technical assistance (Table 8).

The results for *Time* and $Time^2$ show a significant positive linear coefficient (0.125) and a significant negative quadratic coefficient (-0.021). 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. These parameters are random, so the values reported are averages for the entire sample.

The parameters for the three variables included to account for climatic effects are as follows. *Rainfall* exhibits a positive and significant coefficient with a value of 0.248, highlighting the importance of irrigation as an adaptive mechanism during periods of drought that can be common and expected to rise in El Salvador. *Temperature* has a negative value with a coefficient equal to -0.013 but is not significant. In contrast, *Temperature Shock* has a significant negative coefficient (-0.139) demonstrating that Salvadorian farmers can adapt to stable and predictable temperatures while unanticipated temperature shocks can be problematic. These findings support the promotion of climate smart technologies for adaptation as well as climatic information (Bouroncle et al. 2015). Finally, and as would be expected, the results exhibit heterogeneity across the 14 departments evidenced by the significance of 12 of the 13 coefficients for the regional dummies with La Unión being the omitted category.

6.3 TFP measures and components

Given the statistical support for the RP specification we continue our TFP analysis considering only this specification. Table 6 presents the average aggregate output (QI) and weighted aggregate inputs (XI) indexes. The latter is a weighted index that comprises land, labor, the dummies for mechanization and intermediate materials (fertilizer, fungicide, bactericide), and irrigation[1]. The Table also presents TFPI and its components (OTI, OSEI, EI, OTEI and SNI). All these numbers are generated from results obtained from the RP model and are the basis for analyzing TFP change. Figure A1 in the appendix illustrates the evolution of QI and XI alongside TFPI for all the departments. A common pattern exhibited by the graphs is that aggregate input (XI) increased faster than aggregate outputs (QI), which is consistent with the negative TFP growth that we observe across time and departments as depicted in Table 7.

We remind the reader that all our productivity indexes are calculated for a reference observation. Thus, this observation corresponds to farm *k* in year *s* in equations (11) (12) and (13)

[1] Recall from Equation 11 that TFPI is the ratio of QI and XI. Furthermore, TFPI can be decomposed into various components. Thus, it is a product of its components: $TFPI = TI \times OSEI \times EI \times OTEI \times SNI$, following Equation 13.

above. It is also useful to reiterate that our indexes are transitive and thus any ranking in terms of TFP is invariant with respect to the choice of the reference observation where the latter remains constant for all comparisons.

The TFPI and components shown in Table 6 are constructed using the coefficients from the RP estimates (Table 4 as weights and are the basis for calculating the geometric mean of the TFP indexes. To calculate the %ΔTFP for a given department we aggregate the individual components using a geometric approach which is consistent with the index used. For example, the TFPI for Ahuachapán in 2013 is calculated as the geometric of all the farms in the sample for that particular year. These numbers are illustrated in Table 6 for 2012/13 (0.567) and 2017/18 (0.437). Subsequently, the percent change in TFP is calculated as follows: $(0.437/0.567)^{(1/(2018\text{-}2013)})$ - 1= $(0.770^{(1/5)})$ - 1= -5.1%. Another way of looking at this is that compounding 0.567 at a rate of -5.1% per annum for 5 years we would get a TFPI between the first and the last year equal to 0.437. This same approach can be used to calculate the rates of change of all departments and components of the TFPI.

The average annual %ΔTFP and components over the six-year period 2012/13 - 2017/18, presented in Table 7, is organized into three groups of departments depending on their relative productivity performance. The Best three performers are Cuscatlán, Cabañas, and Morazán with ΔTFP equal to 0.15%, -2.61% and -3.31%, respectively. Hence, the only department exhibiting a positive TFP change is Cuscatlán. The dominant component for the Best performing group is the Technological Index (OTI) with a value of -2.51% for each of the three departments.

As indicated above, the model allows for a linear and a quadratic term for the *Time Trend* and the estimated parameters are positive and negative respectively. So, the rate of technological progress declines over time, i.e., it is higher in earlier years compared to later years. Another point that might need clarification is that in a traditional C-D model, the TI index would be constant for all observations except that in our model the corresponding parameters are random and thus vary across observations. Despite this added flexibility, we see little variation in the TI measures indicating that the random parameters do not vary that much for the *Time Trend* variables. Noteworthy is the fact that all three departments in the Best group enjoy non-negative OTEI with an arithmetic mean of 1.34% indicating that the farmers in these locations enjoyed gains in TE over the period studied. In contrast, OSEI makes a negative contribution to TFP change in the three departments with an arithmetic average of -0.51 indicating suboptimal scale of operation and input-mix.

Next, six departments classified as Middle performers, present a ΔTFP ranging from -4.25% (La Unión) to -6.52% (Santa Ana) with an arithmetic mean for all six of -5.59%. Here we again see that OTI plays a negative role on productivity with a consistent value of -2.51% value. Another consistent negative contributor to the performance of this group is OSEI with an average value of -1.44%. This implies that farmers are producing at a scale below optimum; hence, expanding farm size would lead to higher productivity. The third group includes the six departments that display the worst productivity performance going from -7.23% (San Miguel) to -10.96% (Usulután) with an arithmetic mean of -9.18%. This group also presents a negative OTI but here we see some variability across departments while the arithmetic average for this component is -2.44%. Another consistently negative contributor is again OSEI with arithmetic mean of -1.44%. An even sharper negatively consistent contributor to performance for this group is OTEI with an average of -3.08%.

In sum, consistent drivers of the observed negative TFP performance are OTI and OSEI. The sharpest swing is for OTEI which is non-negative for all departments in the Best group (1.34%

average) and negative for all those in the Worse group (-3.08% average). An interesting pattern is observed for the EI component which is the one that fluctuates the most in terms of negative and positive effects across departments while playing a relatively small role with an arithmetic average of 0.25% (Best), 0.41% (Mid), and -0.16% (Worse). Figure 2 depicts a graphical comparison of %ΔTFP and its components for the best, middle and worse performers.

The findings reveal that four departments with negative EI numbers, Morazán, La Union, San Miguel, and Usulután, are contiguous and located in the eastern part of the country known as the "Dry Corridor" (see Figure 1). The "Dry Corridor" is an area of El Salvador that is highly impacted by climatic events, with long periods of droughts followed by intense floods with devastating consequences for agricultural production and food security (FAO, 2021). In fact, 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).

A distinct feature and an advantage of SPF models, such as the RP, is allowing for a standard two-sided error term which in the TFP decomposition permits the calculation of the statistical noise index or SNI. The SNI provides a measure of factors that contribute to TFP change but that cannot be identified explicitly by the model (O'Donnell 2016). Consequently, a relatively smaller SNI component is a desirable feature. Table 7 shows that the (arithmetic) average percent change in TFP for all departments and years is -6.08 % while the average for the SNI components is -1.68%. Hence, the SNI accounts for about 28% (1.68/6.08) of TFP change, stated differently, the model captures 72% of the variation in TFP change that can be attributed to variables included in the model.

6.4 TFP heterogeneity analysis

Table 8 seeks to document the TFP variation according to several groupings of the data. Panel A in the Table shows the 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 -6.05% while the decline for mid-size farms was -4.11%. In contrast, the larger farms experienced an annual average TFP growth of 11.52%.

As noted earlier the sample was divided into three mutually exclusive groups according to their mechanization level: High; Mid; and Low (see Table 4 for a full definition). Panel B in Table 8 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 -6.72%, -4.97% and -8.34%, 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.

The next set of comparisons are for farmers that report irrigation use. Panel C in Table 8 shows that 4.5% of the sample (818 farmers) used irrigation achieving a -6.70% change in TFP compared to -6.23% for those that did not. This is contrary to what we would expect but the sample size for users is very 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 -4.50% TFP change which contrasts with -6.31% for those that did not. Finally, Panel E concerns technical assistance and those that report no exposure have a TFP change of -6.37% compared to -8.15% for those that do. This again is an unexpected result but the sample size for farmers with technical assistance is only 5.6% of the sample (1,010 farms).

7. Summary and concluding remarks

Accelerating agricultural development and farm output growth have been important subjects in policy and political debates in El Salvador for a long time. Farmland has been a constraining resource for many decades which highlights the imperative of smart and sustainable agricultural intensification schemes to foster productivity growth and food security. However, research focusing on the productivity analysis required for policy making in El Salvador is almost nonexistent. Therefore, this paper endeavored to narrow this gap in the literature by presenting a robust micro-econometric analysis of total factor productivity (TFP) using a novel municipal level panel data set for many farms (18,122) located throughout El Salvador over the period 2012/13 – 2017/18. Alternative stochastic production frontier models are estimated, and the resulting parameters are highly consistent across most of the models. The best option for the data used is deemed to be the Random Parameters model. Most of the estimated parameters are highly significant and reveal positive coefficients for mechanization, irrigation use, credit availability and the application of chemical inputs. The estimates show that total annual rainfall has a positive effect on output while annual mean temperature exhibits no significant effect. However, temperature shocks have significant negative effects on output. The estimates for technological change, display a concave behavior so that an initial positive effect declines over time. In addition, the coefficients for departmental dummies reveal significant heterogeneity across El Salvador.

The average technical efficiency for the sample over the six-year time period is 61.6% revealing substantial room for productivity growth through better farm management. This Average

TFP change for all 14 departments over the 2012/13 – 2017/18 period is -6.08% and this value ranges from 0.15% for Cuscatlán to -10.96% for Usulután. The dominant component contributing to this negative TFP change is the technological Index with an average value of -2.48%. This negative contribution is consistent with low levels of investments in agricultural research and extension, which combined with the high vulnerability of El Salvador to natural disasters would have degraded the farming resource base with adverse effects on the Country's production possibilities frontier (Gies 2018; USAID 2020). In fact, the findings reveal that five of the six worse productivity performing departments are in the "Dry Corridor", an area that is highly vulnerable to climate change hence more susceptible to frequent droughts and intense flooding. To counteract the detrimental productivity effects of climate change on agriculture, El Salvador needs to implement effective adaptation strategies which require sustained investments in agricultural research and extension services.

The evidence available reveals that the simple average annual TFP change across 10 studies for El Salvador is 0.65%. Five of the 20 different indexes reported by these studies are negative but none as negative as the ones we have obtained (see Table 1). However, all 20 indexes are based on aggregate (national) statistics covering different time periods. In fact, the earliest data used in these studies goes back to 1961 and the most recent is for 2014 while in this study we used data for the 2012/13 – 2017/18 period. Moreover, all results found in the literature rely on national level estimates from models that pool data for different groups of countries; therefore, the papers by other authors are not directly comparable with what we have presented.

In sum, the econometric estimates and TFP analyses reported here use farm level data that covers all areas of El Salvador and reveal considerable heterogeneity across departments, but key conclusions arise. Technological change has made a negative contribution to the TFP performance throughout El Salvador while TE change has had a consistent negative effect in the worse performing departments over the last decade. These findings imply that efforts are needed to improve productivity in both of its two key dimensions, namely technological progress and technical efficiency where the latter is a measurement of managerial performance. This in turn indicates that resources should be devoted to promoting the adoption and diffusion of improved technologies while enhancing managerial capabilities through extension activities. The goal is to ensure the correct application of new and existing technologies and the effective implementation of strategies to foster climate change resilience.

El Salvador is a small low-income country, so it is reasonable to argue that productivity improvements should come from efforts devoted to the adaptation of suitable technologies, that have already been developed and tested elsewhere, to the agroecological and socio-economic conditions prevailing in the country. Investing in the capacity to develop home grown innovations would entail relatively large sums of money and a long period of time would likely be needed for the emerging technologies to be ready for promotion and subsequent adoption by producers (Fuglie 2020). It also seems that a particular area of required technological improvements are actions devoted to the adaptation and reduction of the adverse effects of natural disasters associated with climate change.

Table 1. Studies reporting total factor productivity (TFP) measures for agriculture in El Salvador

1st Author, Year	Data Source	Product	TFP Annual Change	Method	Years in Dataset
Arnade, 1998	USDA, FAO	Agriculture	-0.75% -0.82%	DEA-Malmquist Index	1961-1993
Martin, 2001	World Bank	Agriculture	1.43% 1.05%	Translog Cobb-Douglas (CD)	1967-1992
Nin, 2003	FAO	Livestock Crops	0.60% -0.92%	Non- Parametric Malmquist Index.	1965-1994
Rao, 2004	FAO	Agriculture	0.99%	DEA-Malmquist Index	1980-1995
Coelli, 2005	FAO	Agriculture	1.0%	DEA-Malmquist Index	1980-2000
Días Avila, 2010	FAO	Livestock Livestock	3. 64% 2.48%	Growth Accounting	1961-1980 1981-2001
Días Avila 2010	FAO	Crops Crops	2.95% -0.17%	Growth Accounting	1961-1980 1981-2001
Nin, 2015	FAO	Agriculture	-1.10% 0.80% 1.7%	CD Production Function	1981-1990 1991-2000 2001-2012
Lachaud, 2017	FAO	Agriculture	0.41% 0.52%	CD Stochastic Production Frontier	1961-2012
Lachaud, 2021	FAO	Agriculture	0.60% 0.85% 0.71%	CD Stochastic Production Frontier	1961-1970 2001-2010 1961-2014
Simple Average			0.65%		

Table 2. Number of farms by department/year and average per municipality: El Salvador 2012/13 – 2017/18

Department	Municipalities	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	Total
Ahuachapán	11	286	388	380	320	387	227	1988
Cabañas	7	159	187	190	162	201	102	1001
Chalatenango	14	226	266	279	262	236	157	1426
Cuscatlán	8	196	263	222	239	13	164	1097
La Libertad	17	358	496	378	378	366	247	2223
La Paz	13	248	317	240	244	264	149	1462
La Unión	11	140	208	197	173	222	116	1056
Morazán	13	118	156	171	164	41	109	759
San Miguel	10	216	240	264	243	0	108	1071
San Salvador	12	170	270	250	205	0	137	1032
San Vicente	9	189	233	204	215	0	124	965
Santa Ana	13	214	320	307	245	2	202	1290
Sonsonate	10	251	373	370	336	2	223	1555
Usulután	18	252	315	295	182	6	147	1197
Total	166	3,023	4,032	3,747	3,368	1,740	2,212	18,122

Table 3. Variable definitions and descriptive statistics for a sample of 18,122 farmers: El Salvador 2012/13 – 2018/19

Variable	Mean	Std. Dev.	Min.	Max.
TVC: Total Value of Crops in constant 2018 prices in US $	1,529	4,508	0.68	192,043
Conventional Inputs-Continuous				
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
Conventional Inputs-Binary				
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	0.40	0.49	0.0	1.0
Land Rented=1	0.61	0.49	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
Climatic Variables and Technical Progress				
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.				
Departmental Fixed Effects (Dummies)				
Ahuachapán	0.11			
Cabañas	0.06			
Chalatenango	0.08			
Cuscatlán	0.06			
La Libertad	0.12			
La Paz	0.08			
La Unión (Excluded category)	0.06			
Morazán	0.04			
San Miguel	0.06			
San Salvador	0.06			
San Vicente	0.05			
Santa Ana	0.07			
Sonsonate	0.09			
Usulután	0.07			

Table 4. 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
TVC=Dependent				
Constant	4.803***	4.803***	4.798***	4.705***
Land	0.859***	0.859***	0.858***	0.839***
Labor	0.107***	0.107***	0.094***	0.098***
Mean Land			-0.001	
Mean Labor			0.002	
High Mechanization	0.151***	0.151***	0.150***	0.140***
Mid Mechanization	0.043***	0.045***	0.043***	0.044***
Irrigation	0.273***	0.272***	0.274***	0.253***
Fertilizers	0.195***	0.194***	0.194***	0.186***
Fungicides	0.133***	0.133***	0.133***	0.133***
Bactericides	0.114***	0.113***	0.113***	0.102***
Land Owned	-0.048***	-0.048***	-0.047***	-0.051***
Land Rented	0.058***	0.058***	0.058***	0.052***
Access to Credit	0.101***	0.100***	0.098***	0.095***
Technical Assistance	-0.019	-0.019	-0.021*	-0.033***
Time Trend	0.114***	0.113***	0.115***	0.125***
Time Trend^2	-0.019***	-0.019***	-0.019***	-0.021***
Rainfall	0.234***	0.233***	0.234***	0.248***
Mean Temperature	-0.016	-0.016	-0.014	-0.013
Temperature Shock	-0.132***	-0.131***	-0.132***	-0.139***
Ahuachapán	0.388***	0.387***	0.386***	0.387***
Cabañas	0.383***	0.382***	0.382***	0.380***
Chalatenango	0.177***	0.177***	0.176***	0.163***
Cuscatlán	0.395***	0.394***	0.393***	0.393***
La Libertad	0.484***	0.483***	0.482***	0.477***
La Paz	0.248***	0.248***	0.246***	0.239***
La Unión (excluded category)	----	---	---	---
Morazán	-0.196***	-0.196***	-0.195***	-0.191***
San Miguel	0.039**	0.039**	0.039**	0.042**
San Salvador	0.522***	0.521***	0.519***	0.517***
San Vicente	0.305***	0.305***	0.303***	0.301***
Santa Ana	0.359***	0.358***	0.357***	0.359***
Sonsonate	0.357***	0.357***	0.356***	0.357***
Usulután	0.029	0.028	0.029	0.043***
Sigma(u)	0.737	0.737	0.737	0.712
Sigma(v)	0.247	0.246	0.246	0.197
lambda	2.98***	2.98***	2.99***	3.60***
LL Function	-12,683	-12,683	-12,675	-12,462
Akaike Information Criterion	25,435	25,433	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

Table 5. Loglikelihood ratio and Wald tests for model selection*

Model selection	**Null hypothesis Ho**	**Test Statistic**	**P-value**	**Decision**
Loglikelihood ratio test (Random Parameters vs True Random Effects)	$\sigma_{\beta_m} = 0$	441.220	0.000	Reject Ho
Loglikelihood ratio test (True Random Effects vs Pooled)	$\sigma_{\beta_0} = 0$	15.194	0.001	Reject Ho
Loglikelihood ratio test (Random parameters vs Random Parameters with Mundlak)	$\sigma_{\beta_{\bar{x}_1}} = \sigma_{\beta_{\bar{x}_2}} = 0$	8.445	0.015	Fail to reject Ho 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 Ho
Wald test (True Random Effects with Mundlak Correction)	$\beta_{\bar{x}_1} = \beta_{\bar{x}_2} = 0$	0.101	0.750	Fail to reject Ho

* The likelihood ratio statistic (*LR*) is given by: $LR = -2[lnL_R - lnL_U] \sim \chi^2 (J)$ where: lnL_R and lnL_U 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).

Table 6. Average total factor productivity indexes (TFPI) and output-oriented components, for the Random Parameters model: El Salvador, 2012/13 and 2017/18

Department	Year	QI	XI	TFPI	OTI	OSEI	EI	OTEI	SNI
Ahuachapán	2013	0.625	1.102	0.567	1.000	1.030	1.051	0.706	0.741
	2018	0.397	0.910	0.437	0.881	0.940	1.131	0.697	0.668
Cabañas	2013	0.564	1.089	0.518	1.000	1.028	1.069	0.669	0.705
	2018	0.467	1.030	0.454	0.881	1.004	1.128	0.669	0.680
Chalatenango	2013	0.782	1.279	0.611	1.000	1.104	0.894	0.758	0.816
	2018	0.551	1.220	0.452	0.881	1.084	0.946	0.667	0.750
Cuscatlán	2013	0.619	1.112	0.557	1.000	1.031	2.015	0.687	0.390
	2018	0.556	0.992	0.561	0.881	0.985	2.211	0.760	0.385
La Libertad	2013	0.806	1.200	0.672	1.000	1.077	1.955	0.699	0.456
	2018	0.426	0.986	0.433	0.886	0.983	2.129	0.591	0.395
La Paz	2013	0.568	1.147	0.495	1.000	1.053	0.954	0.675	0.730
	2018	0.315	0.993	0.317	0.882	0.981	0.923	0.583	0.682
La Unión	2013	0.416	1.158	0.385	1.000	1.067	0.706	0.696	0.734
	2018	0.363	1.103	0.310	0.881	1.015	0.684	0.727	0.697
Morazán	2013	0.322	1.132	0.277	1.000	1.012	0.661	0.587	0.705
	2018	0.237	1.033	0.234	0.881	1.004	0.592	0.648	0.691
San Miguel	2013	0.470	1.219	0.396	1.000	1.062	0.803	0.637	0.730
	2018	0.302	1.097	0.272	0.890	1.026	0.736	0.595	0.682
San Salvador	2013	0.667	1.093	0.610	1.000	1.031	2.099	0.644	0.438
	2018	0.386	0.871	0.444	0.881	0.918	2.151	0.654	0.390
San Vicente	2013	0.718	1.230	0.588	1.000	1.110	0.981	0.698	0.773
	2018	0.549	1.255	0.441	0.881	1.102	0.993	0.622	0.736
Santa Ana	2013	0.682	1.168	0.583	1.000	1.060	1.047	0.689	0.763
	2018	0.400	0.960	0.416	0.881	0.966	1.036	0.692	0.683
Sonsonate	2013	0.610	1.059	0.576	1.000	1.018	1.054	0.732	0.734
	2018	0.271	0.833	0.326	0.881	0.901	1.150	0.589	0.605
Usulután	2013	0.560	1.241	0.451	1.000	1.090	0.767	0.693	0.779
	2018	0.283	1.122	0.252	0.881	1.042	0.695	0.578	0.685

Table 7. 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 Department	%Δ TFP	%Δ OTI	%Δ OSEI	%Δ EI	%Δ OTEI	%Δ SNI
Best						
Cuscatlán	0.15	-2.51	-0.91	1.87	2.03	-0.26
Cabañas	-2.61	-2.51	-0.47	1.09	0.00	-0.71
Morazán	-3.31	-2.51	-0.16	-2.20	1.99	-0.41
Arithmetic Mean	**-1.92**	**-2.51**	**-0.51**	**0.25**	**1.34**	**-0.46**
Middle						
La Unión	-4.25	-2.51	-0.98	-0.64	0.85	-1.02
Ahuachapán	-5.10	-2.51	-1.82	1.48	-0.26	-2.05
San Vicente	-5.59	-2.51	-0.15	0.23	-2.28	-0.98
Chalatenango	-5.86	-2.51	-0.36	1.13	-2.52	-1.69
San Salvador	-6.19	-2.51	-2.29	0.49	0.31	-2.31
Santa Ana	-6.52	-2.51	-1.85	-0.22	0.07	-2.17
Arithmetic Mean	**-5.59**	**-2.51**	**-1.24**	**0.41**	**-0.64**	**-1.70**
Worse						
San Miguel	-7.23	-2.31	-0.69	-1.73	-1.35	-1.36
La Libertad	-8.43	-2.39	-1.80	1.72	-3.32	-2.85
La Paz	-8.50	-2.48	-1.40	-0.65	-2.90	-1.37
Sonsonate	-10.77	-2.51	-2.41	1.77	-4.24	-3.78
Usulután	-10.96	-2.51	-0.91	-1.94	-3.57	-2.53
Arithmetic Mean	**-9.18**	**-2.44**	**-1.44**	**-0.16**	**-3.08**	**-2.38**
Overall Arithmetic Mean	**-6.08**	**-2.48**	**-1.16**	**0.17**	**-1.08**	**-1.68**

Notes:
As indicated in the text, using Ahuachapán as an illustration, if one compounds the TFPI for 2013, 0.567 at a rate of -5.1% per year across 5 years then we obtain the TFPI for 2018, which is 0.437.

A geometric mean is used to aggregate observations in each year by department.

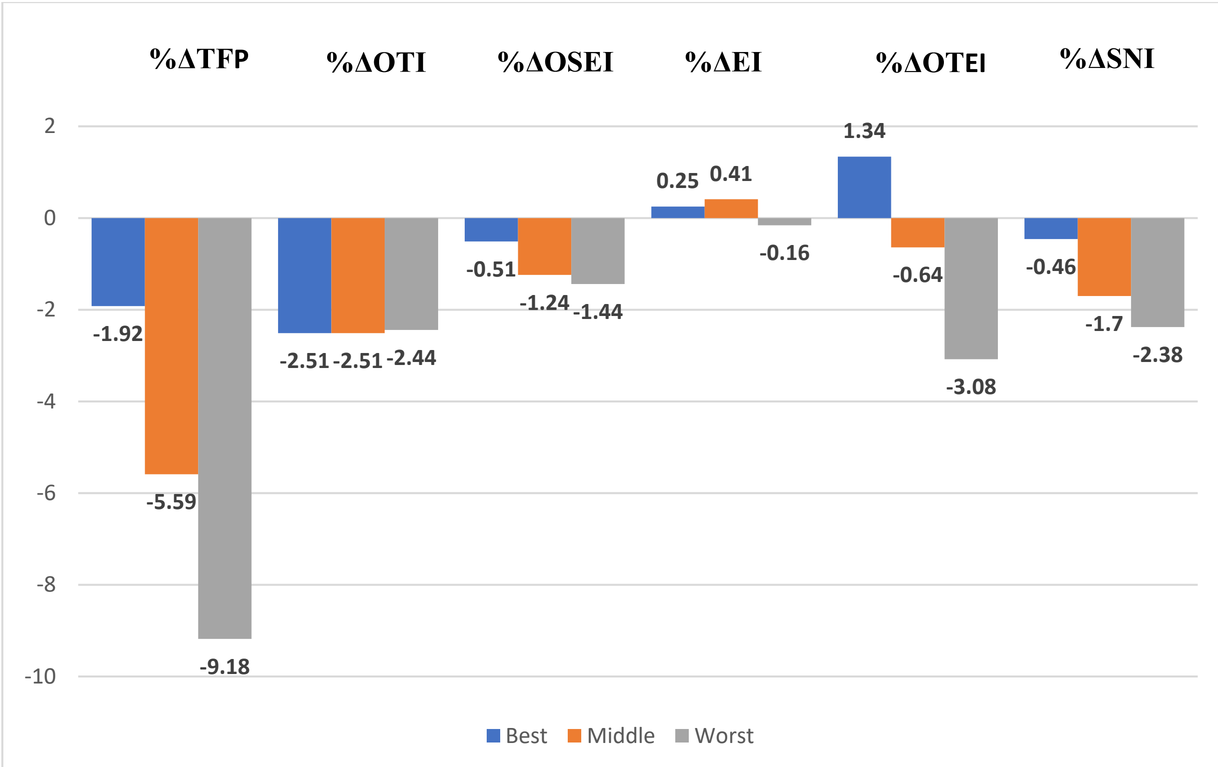
As an additional check, the product of the ratios should equal the original numbers that we started with as reported in Table 6. Therefore:
$(TFPI_{2018}/TFPI_{2013}) = (OTI_{2018}/OTI_{2013}) \times (OSEI_{2018}/OSEI_{2013}) \times (EI_{2018}/EI_{2013}) \times (OTEI_{2018}/OTEI_{2013}) \times (SNI_{2018}/SNI_{2013})$, which is $(0.437/0.567) = 0.769 = 0.881 \times 0.912 \times 1.076 \times 0.987 \times 0.901$

Table 8. Average total factor productivity (TFP) change by farm size, mechanization, irrigation, Credit, and Technical Assistance: Random Parameters model

	Farms		%Δ --------------- %Δ --------------- %Δ --------------- %Δ					
Variable	**Number**	**(%)**	**TFP**	**ΔTI**	**OSEI**	**EI**	**OTEI**	**SNI**
A. Land								
<3 Mz	16,234	89.6	-6.05	-2.49	-1.00	0.73	-1.56	-1.86
3-10 Mz	1,698	9.4	-4.11	-2.43	0.35	-1.91	-0.75	0.60
>10 Mz	190	1.0	11.52	-2.40	0.80	3.27	5.21	4.33
B. Mechanization								
High	2,035	11.2	-6.72	-2.39	-0.28	-2.01	-2.39	0.19
Mid	7,936	43.8	-4.97	-2.48	-0.95	0.92	-0.68	-1.85
Low	8,151	45.0	-8.34	-2.51	-2.14	1.26	-2.09	-3.08
C. Irrigation								
Yes	818	4.5	-6.70	-2.40	-0.22	-2.22	-2.69	0.69
No	17,304	95.5	-6.23	-2.49	-1.33	0.74	-1.24	-2.04
D. Access to Credit								
Yes	1,624	9.0	-4.50	-2.44	-0.66	-0.77	-0.32	-0.36
No	16,498	91.0	-6.31	-2.49	-1.29	0.71	-1.37	-2.00
E. Tech. Assistance								
Yes	1,010	5.6	-8.15	-2.37	-1.14	-1.55	-2.33	-1.02
No	17,112	94.4	-6.37	-2.49	-1.40	0.66	-1.24	-2.04

Figure 1. Map of El Salvador including all 14 departments and capitals

Figure 2: %Δ TFP and its components for Best, Middle, and Worst performing departments



Notes: The best performing departments were Cuscatlán, Cabañas, and Morazán; the medium performing departments were La Unión, Ahuachapán, San Vicente, Chalatenango, San Salvador, Santa Ana; and the worst performing departments were San Miguel, La Libertad, La Paz, Sonsonate, and Usulután. See Table 7 for a complete performance by department.

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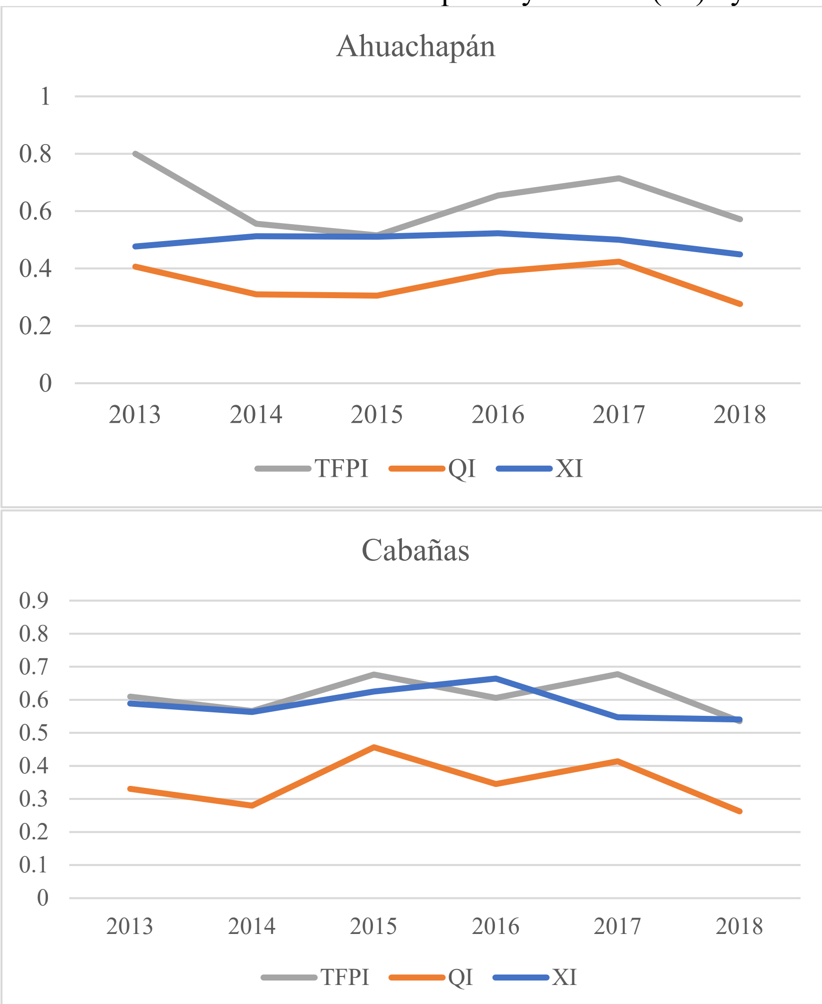
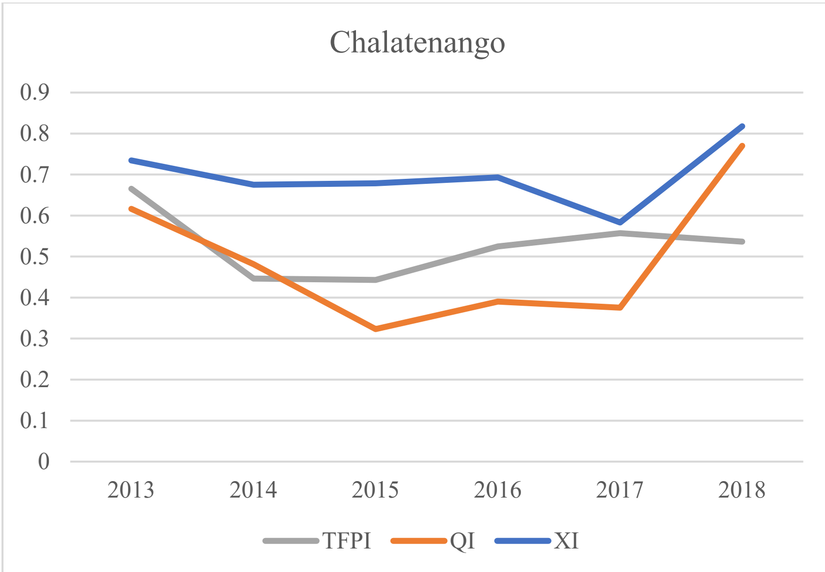
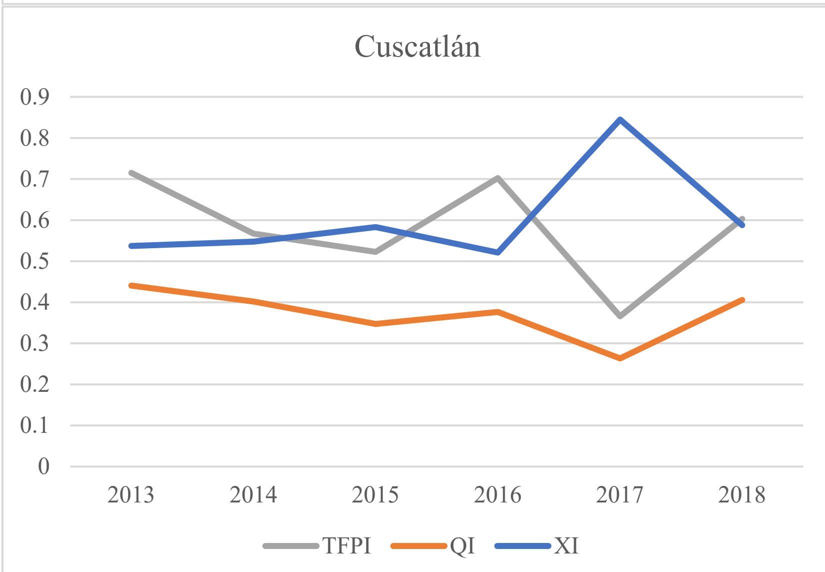
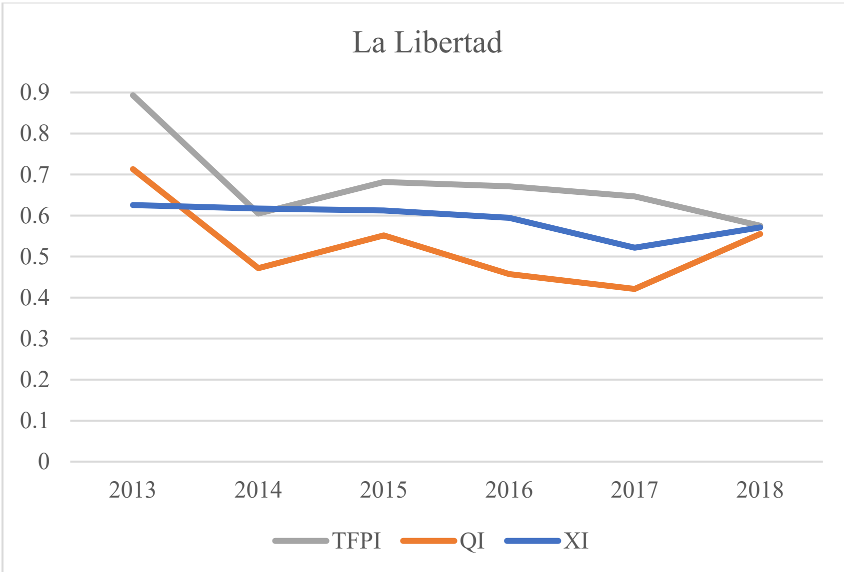
Appendix

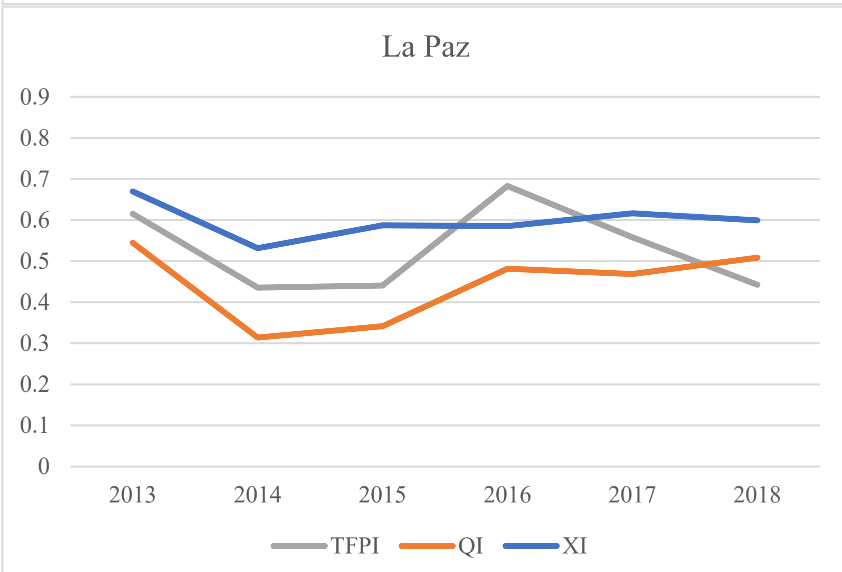
Figure A1: Total factor productivity index (TFPI) and output quantity indexes (QI) and input quantity indexes (XI) by State

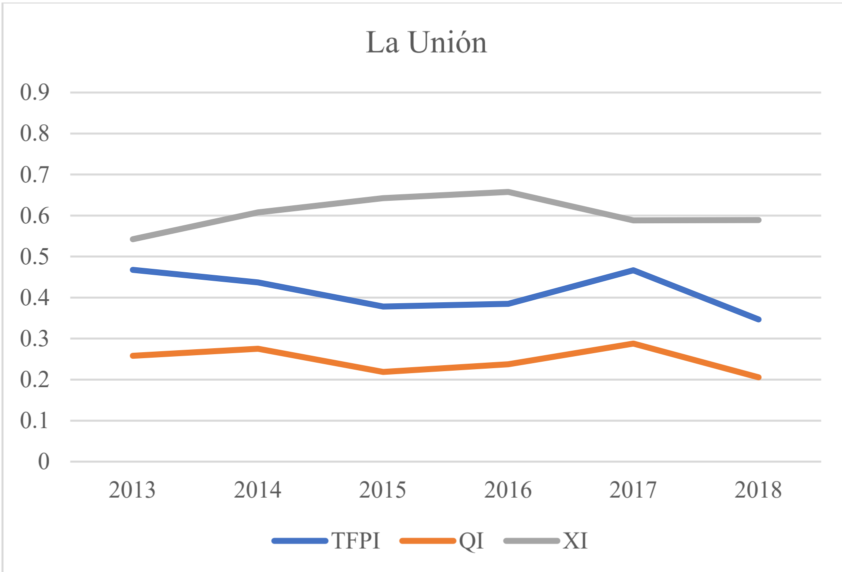


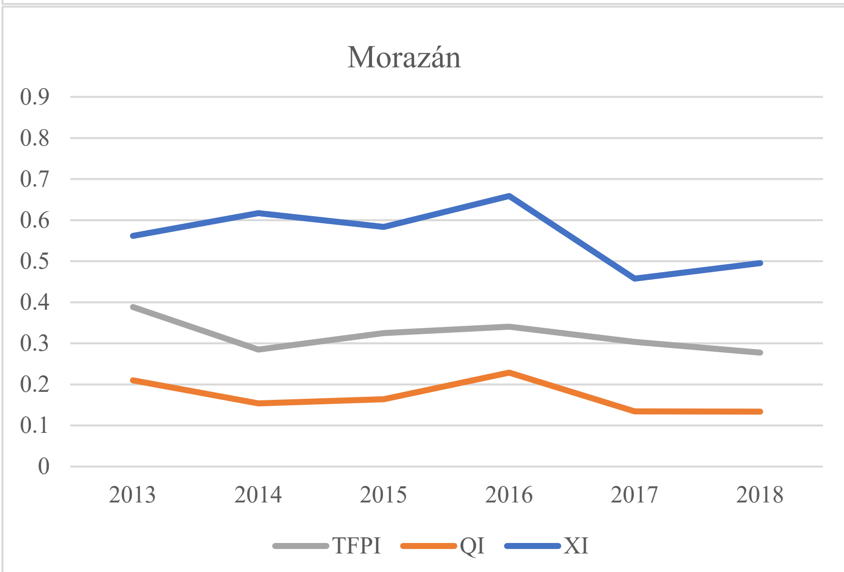

Chalatenango
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2017
2018
TFPI
QI
XI

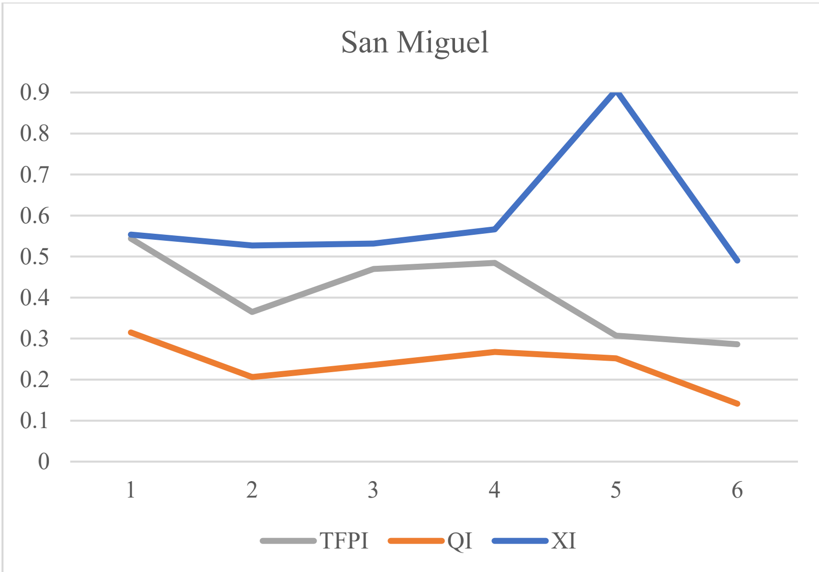

Cuscatlán
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2017
2018
TFPI
QI
XI

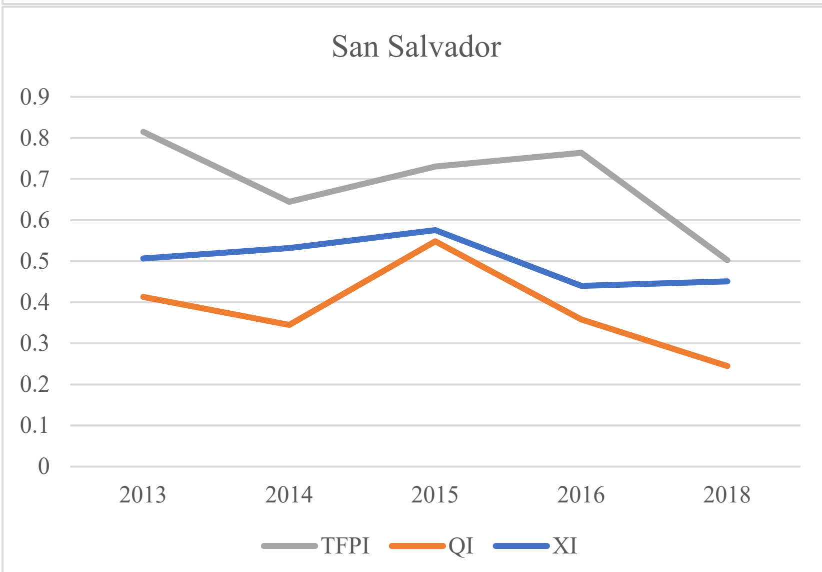

La Libertad
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2017
2018
TFPI
QI
XI

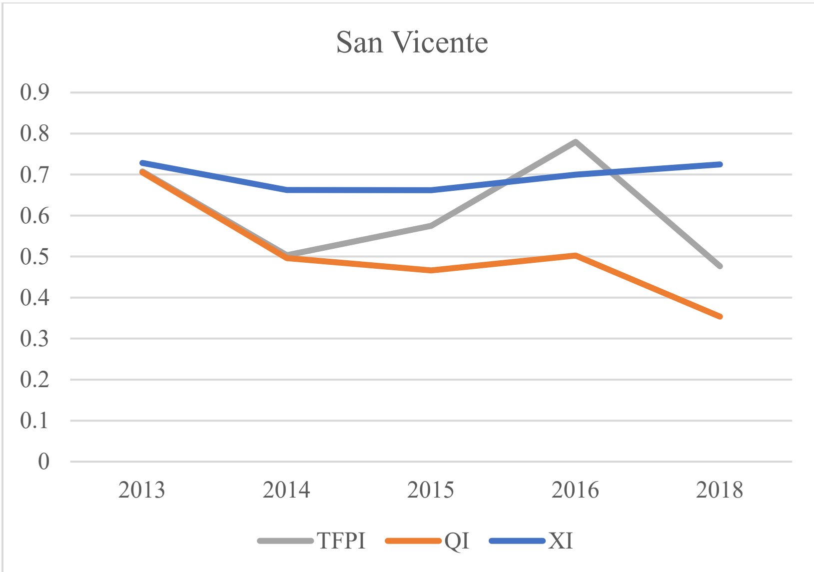

La Paz
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2017
2018
TFPI
QI
XI

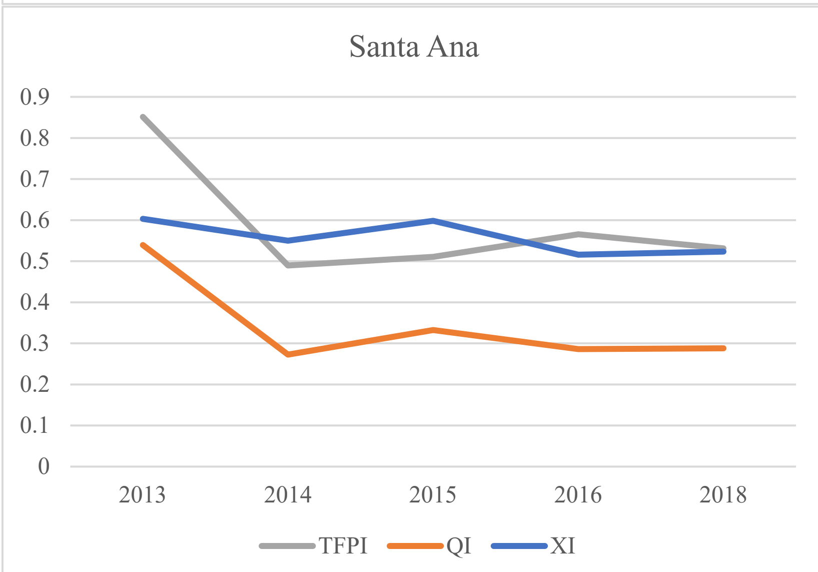

La Unión
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2017
2018
TFPI
QI
XI

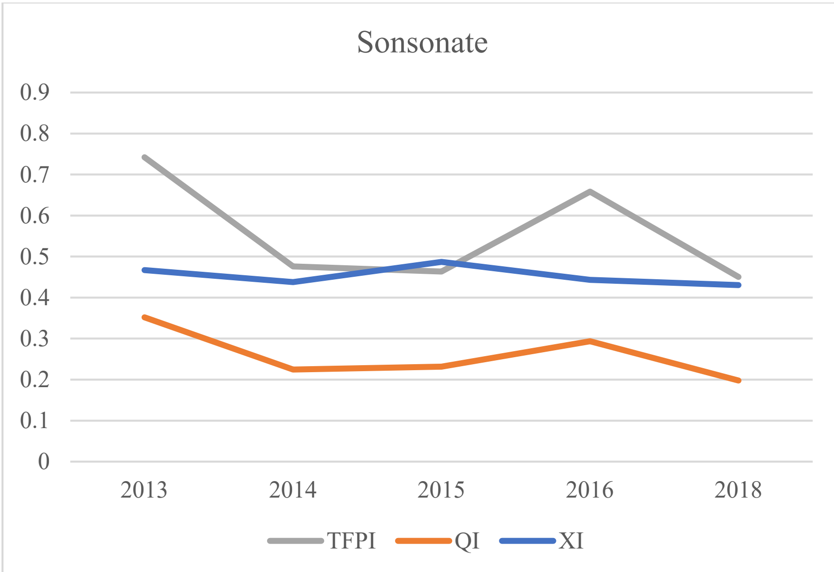

Morazán
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2017
2018
TFPI
QI
XI

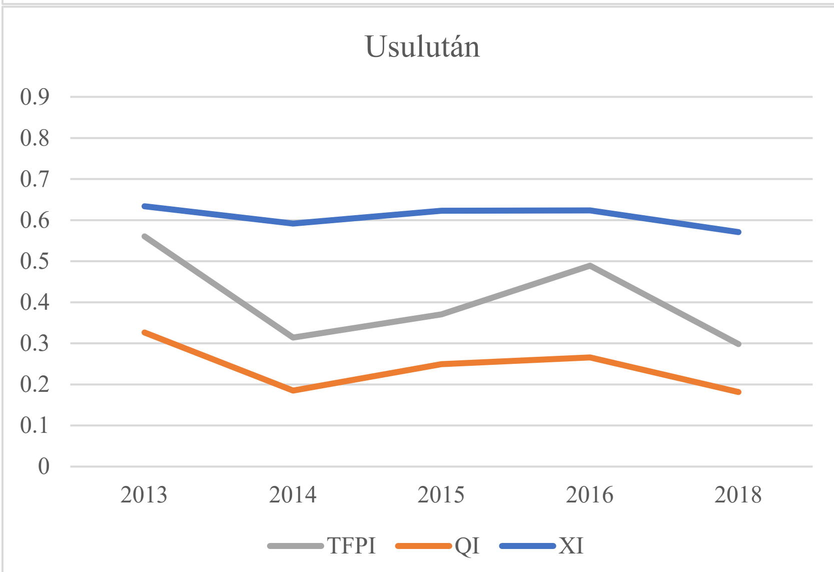

San Miguel
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
TFPI
QI
XI


San Salvador
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2018
TFPI
QI
XI


San Vicente
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2018
TFPI
QI
XI


Santa Ana
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2018
TFPI
QI
XI


Sonsonate
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2018
TFPI
QI
XI


Usulután
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2013
2014
2015
2016
2018
TFPI
QI
XI