Agribusinesses under siege: Firm-level innovation and productivity in adverse economic environments

Gabriel Rosero[*,a], José Salguero[*,b], Bernhard Brümmer[a]

[a] *Department of Agricultural Economics and Rural Development, Georg-August-Universität Göttingen, Platz der Göttinger Sieben 5, Göttingen, Germany, D-37075*
[b] *Institute of Sociology, Philipps-Universität Marburg, Ketzerbach 11, Marburg, Germany, D-35032*

Abstract

The role of agribusinesses can be crucial in improving a country's economic growth, diversification of revenue sources and contributing to its overall development goals. Previous research has focused on innovation in the first step of the agricultural value chain. Despite that, the off-farm segments may have equal weight in the performance of the entire chain; the food and beverage branch alone represents around 40-70% of the value-added cost. The aim of this paper is to analyse whether firm-level innovation improves agribusinesses' economic performance. Our analysis contributes to the current academic debate providing evidence of the agribusiness sector within a hostile business environment, a recurrent issue in several developing countries. We use the World Bank Enterprise Survey (2010, 2016) of El Salvador and follow a sequential Crépon-Duguet-Mairesse (CDM) approach, one of the most influential empirical frameworks in the recent literature on innovation and productivity at the firm level. Our results suggest that investment in innovation activities and the potential innovation outcomes are determined by both specific firm characteristics and the surrounding hostile environment. The agribusiness sector has not expanded its overall production frontier, and the expenditures on insecurity mitigation outweigh the economic gains from innovation outputs.

Key words: Firm-level, Innovation, Agribusiness, CDM, Productivity, El Salvador, Crime, Corruption, Insecurity

1. Introduction

Agribusinesses are crucial for food security and the generation of employment opportunities in developing countries, not less so in economies in which a large part of the population is employed in the informal and service sectors (Barraza et al., 2020; Reardon et al., 2019, 2014; UNODC, 2020). Against the current backdrop of a global economic recession, it is critical to discuss how vulnerabilities might be reduced and how to secure and promote a robust development agenda (i.e., income growth, food security and poverty reduction).

In this regard, we argue that a way to mitigate the effects of unpredictable crises in developing countries may come from diversifying the economy's structure and promoting value-adding industries. Bank (2007) highlights the agribusiness sector's role as a major driver of growth for both agricultural and non-farm

[*] Equal contribution
Corresponding Author:
Email address: gabriel.rosero@uni-goettingen.de (Gabriel Rosero)

outputs. Agribusinesses have the potential to link smallholder farmers in the developing world with consumers and other actors along the agricultural value chain (Santacoloma and Riveros, 2007). More importantly, they can further add value to agricultural goods, translating to higher incomes, food security, and poverty and malnutrition reduction (especially in rural areas), and overall economic growth (UNIDO, 2013).

Moreover, there seems to be a consensus among scholars on the positive effects of innovation in productivity growth to improve economic performance. From a microeconomics perspective, innovation is considered as the critical determinant behind firm-level productivity improvements. Crepon et al. (1998) and Griffith et al. (2006) show that innovation influences both "within" and "between" aspects of productivity growth. Innovation can have different effects on firm-level productivity (Cirera and Sabetti, 2019). For example, process or organisational innovations can reduce production costs, increasing the efficiency of the given production factors. Product innovations can help firms satisfy consumers' changing demand and generate learning-by-doing effects that trickle down to the constant offering of newer and upgraded goods. Organisational innovation can encourage the reallocation of inputs and factors of production across activities within and between firms, enhancing productivity and efficiency.

Nevertheless, despite the economic benefits behind innovation, most of the available literature studying this phenomenon has emerged from the perspective of manufacturing enterprises in high-income countries in Europe and North America. Empirical evidence that may not hold in the context of developing countries, where there is still a significant gap in understanding why improvements in innovation have not come through to firms (Cirera and Maloney, 2017). Indeed, despite the promised benefits of innovations based on the experiences of the Global North, the evidence of its effects on the productivity of firms in Africa, Latin America, or South Asia is relatively scarce and inconclusive. With this work, we seek to address this gap in the literature.

Considering that recent literature suggests that innovation and its effects would vary significantly across economic sectors and industries (Frick et al., 2019; Zhang and Islam, 2020), the importance of the agribusiness sector for the developing world, and the scarce and inconclusive evidence regarding the relationship between innovation and firm-level productivity in the Global South. We seek to contribute to the ongoing discussion by answering the question: what are the determinants of firm-level productivity in the agribusiness sector?" We follow the general framework proposed by Crepon et al. (1998) that links innovation and productivity in a sequential process described by three main stages. First, find the factors that explain the effort a firm makes towards innovation. Second, determine if investments in innovation translate to new products or processes. Third, examine if innovation outputs improve the economic performance of firms. The main advantages of this theoretical approach are: addressing potential issues of endogeneity and selection bias and making a clear distinction between innovation inputs and innovation outputs (Griffith et al., 2006).

The case selection was made to explore the phenomena above plus the economic consequences of hostile business environments, which are common in Latin America. We chose El Salvador since it has a significant dependency on the informal services sector, low economic growth rates coupled with endemic poverty (OIT, 2020; The World Bank, 2021a), and it ranks as one of the most violent countries in the region in terms of homicides per 100,000 inhabitants (UNODC, 2019). The data comes from the World Bank's Enterprise Survey Series for the years 2010 and 2016. In addition, we constructed a subsample of 244 agribusinesses to focus on a sector that, as reported by WFP (2021), remains largely ignored across developing countries. In the case of El Salvador, its improvement could strengthen local agricultural value chains, lead to poverty reduction, foster economic growth and reduce vulnerability to unexpected macroeconomic disruptions.

Our analysis contributes to the current academic debate in two broad ways, methodologically and conceptually. First, previous research on the innovation-productivity relationship has been restricted mainly to a cross-sectional analysis. In contrast, we used a pooled data sample to account for any underlying time effects. Second, we address potential endogeneity problems by following the control function model, which also provides a statistical test for endogeneity. Third, the effects of innovation outputs on firm performance were measured through TFP, while past research has focused exclusively on labour productivity. In addition, we considered a more flexible extension of the linear Cobb-Douglas production function, a Translog functional form. Finally, we provide evidence from a developing country scenario under a hostile business environment.

The main findings of our research indicate that insecurity plays a decisive role in all the aspects of firms' activities under study. Higher perceptions of insecurity reduce the efforts towards innovating (e.g. R&D expenditures) while, at the same time, positively influencing the generation of new products and processes; an effect that, we argue, is a mechanism for local enterprises to cope with their challenging business climate. Finally, we found no evidence of technological change in terms of Total Factor Productivity growth between 2010 and 2016. Moreover, the introduction of new products or processes did not lead to significant increases in total sales. Nevertheless, on the other hand, establishments that did not incur security costs had - on average - 36% lower sales than those that did, even after we controlled for other firm characteristics, such as size and sub-sector. In summary, our results provide robust evidence for the general importance of an enabling or hindering business environment for making innovations come to bear on firm performance in the context of developing countries.

The remainder of this study comprises six sections. First, we detail the relevant macroeconomic background in which Salvadoran agribusinesses operate. Second, we introduce and discuss the CDM conceptual framework and the econometric implementation. Third, data transformations and descriptive statistics are listed. Fourth, we present the main findings of the econometric analysis. Finally, in the last sections, we discuss the policy implications and provide the conclusions of our study.

2. Background

El Salvador has experienced more than a decade of sluggish economic performance. According to The World Bank (2021a), the country only managed to average a 1.9 percent GDP annual growth rate between

2010 and 2016. When compared to its neighbours in Central America, it has also been the slowest performer since 2010. In terms of GDP per capita, the country remains well below the Latin American average.

In contrast, regarding poverty reduction, food security and nutrition standards, El Salvador has made considerable progress. The World Bank (2021b) reports that the poverty rate (based on a US$5.5 per person per day poverty line) declined from 39 percent in 2007 to 29 percent in 2017. Likewise, extreme poverty (US$3.2 per person per day) also declined from 15 percent to 8.5 percent over the same period, being the reduction in rural areas the most prominent (Calvo-González and López, 2015). Additionally, the WFP (2021) states that in El Salvador, the rate of stunting in children under 5 years of age dropped from 19 to 14 percent between 2008 and 2014; and acute malnutrition levels remain low at 2 percent.

Nevertheless, the durability and stability of those development gains, as well as further improvements, remains in question, especially in the face of unforeseeable shocks. Acevedo et al. (2014) point out how the Salvadoran "development strategy" is likely to be unmaintainable over time. Current levels of consumption are mostly sustained by remittances (17% of the GDP) and credit, while the total added value from the manufacturing and agricultural sectors continues to decrease in favour of the services sector (Hernández et al., 2017). Moreover, food production represents only 6 percent of the annual GDP, and the country is heavily dependent on imports of its main staples like rice, wheat, beans, and corn (WFP, 2020, 2019).

The recent COVID19 pandemic was not only a health-related crisis, but also a major reminder of the vulnerability of the development agenda in the country. The general structure of the economy (i.e. informal- and services-oriented) was particularly susceptible to the restriction measures that were put in place during 2020. Around 62% of the working age population is employed in the informal sector, and 80% of those work in services enterprises such as tourism and retailing (OIT, 2020). The lack of diversification of the productive base, alongside an expected contraction of the economy, has resulted in less than auspicious forecasts in terms of unemployment, food security and poverty reduction (Barraza et al., 2020; UNODC, 2020).

The role of the agribusiness sector can be crucial in improving a country's growth sustainability, diversification of revenue sources and keeping development-policy goals. The United Nations Industrial Development Organization states that in large parts of the Global South, the potential of agro-enterprises remains unexploited. They argue that in developing countries, smallholder farms often cannot get their produce to market because of weak infrastructure, hostile business environments, and missing linkages between farm-level production and down-stream activities such as processing, marketing and distribution. While 98 percent of agricultural production in high-income countries undergoes industrial processing, in developing countries, barely 30 per cent is processed. Furthermore, while high-income countries add over US$200 of value by processing one tonne of agricultural products, developing countries add less than US$50 (UNIDO, 2021, 2013).

Strengthening the capacity of agribusinesses in adding value to agricultural commodities can be instrumental in retaining and expanding poverty reduction, improving economic growth, and achieving the SDGs by the year 2030. The agroindustry in El Salvador represents roughly 63.4% of the total

Manufacturing sector, that is, around 14.5% of the GDP on average between 2010 and 2016 (BCR, 2020). Additionally, according to the USDA (2018) around 34 thousand people are employed in the food and beverages branch alone, in other words, around 18% of all the people employed in the manufacturing sector. If these branches could be better linked to the local production of agricultural goods, the living standards of around 14% of the economically active population occupied in farming (WFP, 2021) could be improved.

Despite the potential benefits of strengthening local value chains via the agribusiness sector, it has not been a special focus of policy or research (Oddone, 2018). Addressing the broader private sector (i.e. manufacturing and services), FUSADES (2019) reported that from 2011 to 2017 only 17% of firms -on average- made new capital investments. However, despite the general lack of investment, during that same period, around 56% of all establishments reported having introduced a new product or process (FUSADES, 2021, 2019).

A well-documented explanation behind the general lack of economic development in El Salvador is its hostile business environment. The available estimations show that the total costs of crime and insecurity in the country was 11% and 16% of the annual GDP in 2011 and 2014 respectively (Salguero, 2016), and it is one of the countries with the highest homicide rate x100,000 inhabitants in the world (UNODC, 2019). Other crimes with high incidence include robbery, theft, and extortions. Some of their firm-level economic consequences include investment reduction, increased protection costs and direct output losses (Peñate et al., 2016).

3. Methodology

Based on the seminal paper by Crepon et al. (1998), the main idea behind the CDM model is to answer three specific questions sequentially. First, what determines a firm's efforts or investments towards innovation? Second, is the generation of innovation outputs influenced by those same efforts or investments? Third, do those innovation outputs translate to firm productivity?

Throughout the years, several revisions have been implemented to the original CDM framework. Those expansions range from using new or reconceptualised variables to undertaking distinct econometric approaches. However, the core idea of the model has remained largely intact. Cirera and Cusolito (2019), argue that all CDM applications intend to address two specific (potential) issues; selectivity bias[1] and endogeneity[2]. The first issue is addressed with any model that considers values equal to zero in the estimation, (i.e. Tobit, Poisson, Heckman 2-Steps, Double Hurdle) (Fagerberg et al., 2010; Mohnen and Hall, 2013). The second issue, endogeneity (i.e. as a result of omitted variable bias or due to correlation between the residuals of the sequentially estimated equations), is usually faced by mimicking a Two-Stage Least Squares (2SLS) regression. In brief, during the second and third stages of the CDM method, a model will be estimated using the fitted values of a previous equation as a pseudo instrument, and, later, any

[1]This issue may arise in the first question/stage of the CDM model (i.e. innovation efforts). It describes the potential dangers of only including firms with non-zero innovation efforts/reporting.
[2]Endogeneity is an issue related to the CDM model's second and third questions/stages.

potential issues with the standard errors are corrected through bootstrapping techniques (Cirera, 2015; Crespi and Zuniga, 2012; De Fuentes et al., 2015; Griffith et al., 2006).

In this research, we build from the model developed by Griffith et al. (2006) and expand it in four specific areas. First, we use a pooled data sample to account for underlaying time effects, as previous research is restricted mainly to a cross-sectional analysis. Second, when addressing the issue of endogeneity, we include an extra step by formally testing its presence, following a control function approach. Third, the analysis focuses on an industrial subsample (i.e. agribusinesses) to reduce heterogeneity within the dataset and draw industry-specific conclusions and policy implications. Fourth, when measuring the effects of innovation outputs on productivity at the firm level, a more flexible extension of the linear Cobb-Douglas production function is considered, a Translog functional form. In this section, we present the general conceptual framework of the CDM model along with its relevant equations. The details and shortcomings related to the empirical implementation are discussed.

3.1. Empirical Implementation[3]

All the relevant specificities regarding the empirical implementation of the CDM framework will be outlined in this section. A first consideration has to do with the subsample of firms that were used. Given our interest in focusing on the agribusiness sector -due to its relevance in food security and economic development- a subsample was created. We use the fourth revision of the International Standard Industrial Classification of All Economic Activities (ISIC) published by the Department of Economic and Social Affairs of the United Nations -United Nations (2008). The technical definition of agribusinesses and the specific categories that were used to select them from our data can be found in Appendix A.1

A second consideration has to do with the dataset. Even though El Salvador has three survey waves available (2006, 2010 and 2016), the differences between each one (i.e. changes in survey questions and missing participants between each point in time) did not allow to use of a balanced panel dataset without resulting in several missing variables and observations. Therefore, to address this issue, a pooled cross-sectional dataset was constructed across the two most recent waves available (which had almost identical survey questions). As argued by Wooldridge (2012), the advantages of pooling random samples drawn from the same population are increasing the available sample size, obtaining more precise estimators and overall test statistics with more power. Moreover, we allow the intercept to differ across periods (2010 and 2016) to reflect that firms may have changed across waves by including time dummies.

Furthermore, some econometric decisions were taken at each step of the process when we estimated the sequential model. The relevant equations will be clarified in the following. In the first stage of the CDM sequence (Equation 1), r_i^* accounts for a *firm's broad innovative effort*. In practice, this effort can

[3]According to Cirera and Cusolito (2019), two empirical strategies can be seen in the literature. Asymptotic-Least-Squares: joint estimation of the main equations of the model. The sequential model approach where predicted values of endogenous variables in the first stage are included in the second estimation and from the second to the third. Both empirical strategies do not yield significant differences in measuring the effects of innovation on productivity, as long as endogeneity and selection bias are properly treated (Cirera and Sabetti, 2019), based on Hall (2011), Musolesi and Huiban (2010).

be proxied or measured by any given type of expenditure towards innovation activities[^met3]. However, some firms might carry out these expenditures (and/or report them) while others do not. Thus, if a model were to be estimated without considering the former issue, it would run the risk of selection bias. *Research effort*[4], in the current study is proxied by R&D expenditures, and R&D plus machinery and equipment expenditures (coded as Research Intensity). The empirical literature on innovation in developing countries suggests that specialized R&D departments are often an exception, and exclusive R&D expenditures (or data on filed patents) might not cover the real phenomena of innovation efforts. Following that previous evidence and trying to better fit the model to the realities faced by firms in countries like El Salvador, we considered an aggregate measure of research effort[5]. Consequently, Equation 1 can be formulated such as:

$$\begin{gathered} r_i^* = Z'\beta + \alpha t + \epsilon_i; \quad \epsilon_i | Z \sim (0, \sigma^2), \\ with \quad r_i = r_i^* \quad if \quad r_i^* > 0, \; and \; r = 0 \; otherwise \end{gathered} \tag{1}$$

where r_i^* is either R&D or Research Intensity depending on the model specification,r_i^* is a corresponding latent variable such that firms decide to invest/spend in (or report) innovation. Z' is a matrix of determinants of the innovation effort; β is a vector of the estimated parameters; t is the year of the survey sample, and α is the parameter of interesting; ϵ_i is an error term which follows a normal distribution with variance σ^2. Seeking to further control for any potential heterogeneity issues (besides the previous control that was implemented by using an agribusiness subsample) as the residuals (ϵ_i) from this step will be relevant for the next ones. Moreover, we transform the dependent variables using inverse hyperbolic sine transformation to reduce heteroscedasticity, the effect of possible outliers, and improve model estimation (Bellemare and Wichman, 2020).

The next equation in the model is the *knowledge or innovation production function.* In this step, factors behind the creation of innovation outputs[6] are determined. The main dependent variable is proxied in our estimations by using a joint measure of product and process innovation (coded as *P&P Innovation*), following previous empirical studies such as those by Crespi and Zuniga (2012), De Fuentes et al. (2015), and Cirera and Cusolito (2019). However, Mohnen and Hall (2013) argue that complementary effects are to be expected by these two dimensions of innovation when merged, a situation that may lead, in practice, to non-significant econometric results[7]. Despite the former potential disadvantage, a joint variable was still vastly preferable for three specific reasons. First, conceptually, both product and process innovation outputs can be understood as part of a general effect of "technologically-based" innovation like the one

[4]In the CDM literature, the econometric approach usually mimics a 2SLS regression because there is an interest in modelling the determinants of the binary decision to invest in innovation and subsequentially the magnitude of the investment made by any firm. However, in practice, these econometric estimations do not return the residuals on the whole distribution of values of the dependent variable. Since a particular interest of this research was to test formally for endogeneity in the following step of the CDM model; we use a Tobit model (Equation 1), as it allows us to compute the marginal effects and get all the residuals, not only those from the censored part of the data.

[5]Alternative measures include, for example, expenditures in machinery, specialized software, and employee training. However, the use of one in favour of another depends a great deal on data availability.

[6]According to Joseph Schumpeter (quoted by Cirera and Sabetti (2019)), there exist five types of innovation: Product, Process, business model, source of supply and mergers & divestments. Alternatively, Cirera and Maloney (2017) suggest four types: improved products, improved processes, improved organization, intellectual property (patents).

[7]Studies that encountered this issue were Mairesse et al. (2005), Chudnovsky et al. (2006), and Duguet (2006).

described by Fagerberg et al. (2010). Second, in our dataset, agribusinesses that reported process innovation exclusively were scarce and would not otherwise lead to independently estimating a meaningful model. Third, a disaggregate analysis of product and process innovation outputs is not likely to yield largely different results when applied in the following step of the model (i.e. effects on productivity), mainly since the firm-specific characteristics among agribusinesses types are already being controlled with subindustry dummies (i.e. distribution, production, input) as shown in the Table 2

Another econometric challenge that comes up during this stage is the potential issue of endogeneity, specifically from omitted variable bias. There might be firm characteristics that were not observed/measured and could influence the generation of knowledge outputs. As pointed out by Griffith et al. (2006), omitted variables - in their case- could overestimate the parameter of innovation effort, since they argue that it is reasonable to assume that innovation effort and the error term from the innovation outputs equation could be positively correlated due to unobserved factors that increase innovative efforts.

To address the over/underestimation of the parameter due to omitted variable bias, two solutions could be implemented according to Wooldridge (2010) when the dependent variable is binary, either estimating a 2SLS regression or following a control function approach. In previous CDM applications, a simulation of the 2SLS has been used, where the fitted values of Equation 1 enter the innovation outputs equation as an instrumental explanatory variable. Moreover, plugging the fitted values of a linear model into a non-linear one may not necessarily result in inconsistent parameters. Nevertheless, this approach has three clear disadvantages: i) it leads to inconsistent standard errors, which then require extra steps to correct (i.e. bootstrapping), ii) it does not allow us to perform a formal test for identifying endogeneity, and ii) calculating the marginal effects requires further transformations (Wooldridge, 2010).

Given the issues outlined above, and following Rivers and Vuong (1988), in this paper, we argue for an alternative route, using a control function approach since it would address the three issues mentioned above. The procedure is then to include the observed values of innovation efforts (i.e. R&D or Research Intensity) plus the residuals of Equation 1 to estimate the innovation outputs equation. Thus, we expand the traditional CDM model as follows:

$$g_i = \gamma r_i^* + Z'\delta + \omega\epsilon_i + \alpha t + u_i, \;\; u_i \sim N(0, \sigma^2) \tag{2}$$

where g_i is P&P innovation outputs, r_i^* is the observed value either of R&D or Research Intensity (depending on the regression specification). Z' is a matrix of other factors influencing the production of knowledge. t is the year of the survey sample; γ, δ, and α are the parameters of interest. ϵ_i are the residuals from the first equation with a respective parameter ω, and u_i is an error term. Moreover, if ω is statistically significant, we reject the null hypothesis (H_o) of non-existence of endogeneity in our model

The last stage of the CDM method is the productivity equation, where the effect of the generated innovation outputs (from the previous step) on *firms' performance*[8] is estimated. Previous research articles

[8]Performance can itself be understood or proxied by different observed indicators, such as sales, market shares, or output/production (Cirera, 2015). The selection will depend on a researchers' availability and/or interests.

on this issue were interested in measuring the effect of innovation outputs almost exclusively on labour productivity. For example, Fagerberg et al. (2010) explain how the debates of technological innovation and its potential effects on unemployment and labour displacement shaped the research agenda behind previous CDM applications, especially in the context of the European Union and the United States. In contrast, Cirera and Maloney (2017) argues that the focus when studying innovation in the Global South should be on the generalised lack of innovation efforts, despite the potential returns they offer; a phenomenon the same authors dubbed as "the bounded Prometheus paradox." In other words, in the developing world, the discussion of innovation should focus on determining what is preventing firms from investing in innovation effectively or what blocks them from reaping the benefits linked to innovation.

Moreover, previous CDM empirical applications have mostly considered a Cobb-Douglas production function due to its simplicity and it being easily linearised with the application of natural logarithms (Martins et al., 2012). However, as pointed by Coelli et al. (2005), the disadvantage of using partial measures such as labour, capital or land productivity instead of Total Factor Productivity is that they can provide misleading indications of overall productivity when considered in isolation. Thus, we argue that for the case of developing countries, El Salvador, the focus of analysis should not rest on how innovations translate to employment or labour productivity, but rather on two questions: Are innovative outputs coming to bear in terms of improved firm performance? If not, what are the significant factors hindering this relationship? Concordantly, in our research, we seek to extend the analysis to total productivity gains, provide evidence on the (possible) positive effects of innovation at the firm level and the barriers that might exist to achieve them. Additionally, we seek to extend the model through a more flexible functional form, such as the Translog production function, which allows us to define the productivity equation as follows:

$$\ln y_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln x_i + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln x_i \ln x_j + \sum_{k=1}^{n} \beta_k D_{ik} + \alpha t + v_i \tag{3}$$

where output y_i is the total output (proxied by total sales), x_i is a vector of the observation on inputs j. t is a time dummy controlling for unobservable factors that differ between the two waves. D_{ik} enters as an explanatory variable and refers to the characteristic that can alter the production process[9] (similar to the additions done by Wollni and Brümmer (2012) and Escribano and Guasch (2005) since they consider such characteristics as '*shifters*' of the production frontier). v_i are the random error.

The last econometric challenge that may be encountered at this stage is, similar to the previous ones, the issue of endogeneity due to omitted variables. Previous CDM applications -again mimicking a 2SLS regression- have inserted the fitted values of innovation outputs (Equation 2) as an explanatory variable (i.e. pseudo instrument) in the firms' performance OLS regression to address the potential endogeneity issues. Then, corrected the standard errors through bootstrapping techniques. Just as before, this econometric

[9] Additionally, according to Battese (1997), having a production function where one or many factors can adopt zero values can lead to biased estimations. To correct this issue, the author suggests adding dummies variables with values equal to one when the inputs values are zero. Therefore, in this paper, we created three dummy variables for capital, inputs and security when the values were equal to zero or the firm did not report them.

approach does not lead to inconsistent parameters. However, as remarked by Wooldridge (2010), this possibility comes with the disadvantages of inconsistent standard errors and invalid statistical tests[10]. Given the nature of the main dependent variable (i.e. continuous), the same author suggests an alternative strategy: an IV regression model with a dummy endogenous variable that addresses the weaknesses of prior empirical applications. In this research, we follow this alternative procedure, estimating Equation 3 as an IV regression with the *fitted probability values* from Equation 2 ($\hat{g}_i$) as an instrument for g_i. According to Wooldridge (2010), assuming the usual restrictions on the error term, the IV estimation has standard errors and statistical tests that are asymptotically valid.

4. Data and descriptive statistics

4.1. Data sources and sampling

This study draws from the World Bank's Enterprise Surveys (ES) to analyse the determinants of innovation activities and their effects on economic performance in El Salvador. The Enterprise Survey series contains firm-level information regarding different aspects of an individual firm's characteristics, access to finance, costs of production, experiences with crime and corruption, perceptions of their business environment, innovation practices, and performance metrics. Information for 146 countries is available to date, which constitutes a significant effort for generating standardised instruments that establish comparability across countries and time (Barasa et al., 2017: 283).

There are three waves of the Enterprise Surveys available regarding El Salvador in 2006, 2010, and 2016. They are all based on representative samples of formal private-sector establishments (i.e. manufacturing and services enterprises) (The World Bank, 2021c). Therefore, statistically representative conclusions might not be drawn for other entities strictly working in raw agricultural production. Moreover, changes in the core questionnaires between each round resulted in some cases of missing or incompatible variables. Thus, only the two more recent waves of data were used in the present research to ensure consistency. Both waves followed a stratified random sampling strategy, with three levels of stratification: industry, establishment size, and region. The 2010 data was collected between March 2010 and April 2011, totalling 360 establishments. Similarly, the data for 2016 was collected between March and August of that same year, totalling 719 establishments.

The data collection process consisted of face-to-face interviews[11] with each establishment's manager, owner, or director. In the implementation files of both 2010 and 2016 survey waves, it is specified that the primary sampling unit is the establishment, which is understood as a physical location where businesses are carried out and where industrial operations take place or services are provided. A firm may be composed of one or more establishments. However, for the purposes of the survey, an establishment must make its own financial decisions and have its financial statements separate from those of the entire firm. An establishment

[10]For a more thorough clarification of this econometric issue, please see Wooldridge (2010), pp. 625.

[11]A more thorough discussion of the shortcomings of using this type of survey instruments and design can be read in Cirera (2016); Cirera and Muzi (2020)); Bogliacino et al. (2012); and Mairesse and Mohnen (2010).

must also have its management and control over its payroll (The World Bank, 2021c). Nevertheless, in the current text, both terms (i.e. firm and establishment) are used mutually in the interest of simplicity alongside other synonyms such as businesses and enterprises.

Given the particular research interest to focus on agribusinesses, a subsample was constructed following the definitions suggested by Zylbersztajn (2017), Santacoloma et al. (2005) and the statistical classification notes of the Food and Agriculture Organization, FAO (Ramaschiello, 2015). Furthermore, recent literature suggests that the effects of innovation may vary significantly across economic sectors and industries (i.e., food and beverage vs high-tech firms). Thus, an in-depth analysis of industry subsector (e.g., agribusiness) may provide more robust results and tailored policy-relevant conclusions (Frick et al., 2019; Zhang and Islam, 2020).

Focusing on a specific subsector reduced the heterogeneity of the original sample, which included several companies performing diverse activities within the economy's manufacturing and services branches. Therefore, the agribusinesses pooled subsample for both waves was constructed using the survey's internal classification codes, based on the International Standard Industrial Classification of All Economic Activities (ISIC) - Revision 3.1 (UN, 2002). The final subsample consisted of 244 observations. Further information on the subsampling criteria can be seen in Appendix A.1.

4.2. Main variables and descriptive statistics

The list of variables used in this research, as well as their definitions, are presented in Table 1. We sorted them into four categories: innovation, production function, firm characteristics, and (perceived) obstacles of the local business environment. The selection was made following the previous research by Griffith et al. (2006), Crespi and Zuniga (2012), and Cirera and Sabetti (2019). We took the description of each variable from the Manufacturing questionnaire for each survey year. Other relevant data details or recodifications will be further clarified alongside the corresponding descriptive statistics, as summarized in Table 2.

Table 1: Description of the variables used in the analysis

Variable	Definition	Units
Innovation		
Research Intensity	Sum of R&D, equipment and machinery expenditures.	2010 US Dollars
R&D	Intramural and extramural R&D expenditures.	2010 US Dollars
P&P Innovation outputs	Product and process innovation dummy with value 1 if any new or significantly improved product or process was introduced by an establishment.	1=Yes ; 0=No
Production function		
Total sales	Total sales during the last fiscal year.	2010 US Dollars
Capital cost	Net book value (after depreciation) of machinery, vehicles, and equipment.	2010 US Dollars
Labour cost	Total annual cost of labour, including wages, salaries, bonuses and social security payments.	2010 US Dollars
Inputs cost	Total annual cost of raw materials, intermediate goods and electricity used in production.	2010 US Dollars
Security expenditures	The total annual cost of security during last fiscal year (e.g. equipment, personnel, or professional security services).	2010 US Dollars
Capital dummy	Dummy with value 1 if capital costs were equal to 0 or not reported.	1=Yes; 0=No
Inputs dummy	Dummy with value 1 if inputs cost were equal to 0 or not reported.	1=Yes; 0=No
Security dummy	Dummy with value 1 if security costs were equal to 0 or not reported.	1=Yes; 0=No
Firm characteristics		
Permanent workers	Fulltime individuals working at one establishment during the last fiscal year (contracted for a term of one or more years), including all employees and managers.	Number of workers
Firm age	Total number of years that the firm has carried out operations (depending on the survey wave).	Number of years
Foreign ownership	Percentage of the firm that is owned by private foreign individuals, companies or organizations.	Percentage
Exports	Percentage of total sales that was exported directly during the last fiscal year.	Percentage
Firm size	Categorical variable with brackets according to the number of employees.	Small: 5 - 19 employees; Medium: 20 - 99 employees; Large: 100 or more employees.
Group membership	Dummy if establishment is part of a larger corporation.	1=Yes ; 0=No
Agribusiness category	Categorical variable for agribusinesses based on the International Standard Industrial Classification of All Economic Activities (ISIC Rev. 3.1).	Agribusiness-Inputs: textiles, chemicals, machinery. Agribusiness-wholesale: wholesale storage and trade. Agribusiness-processing: food, beverages, tobacco.
Foreign technology	Use of technology licensed from a foreign-owned company (excluding office software).	1=Yes; 0=No
Business environment obstacles		
Property crime	Dummy if in the last fiscal year an establishment experienced losses as a result of theft, robbery, vandalism or arson.	1=Yes; 0=No
Insecurity	Categorical variable of the perception of crime, theft and disorder as obstacles to the current operations of the establishment.	No issue, Moderate issue, Major issue.
Corruption	Categorical variable of the perception of corruption as an obstacle to the current operations of the establishment.	No issue, Moderate issue, Major issue.
Finance	Categorical variable of the perception of access to finance as an obstacle to the current operations of the establishment.	No issue, Moderate issue, Major issue.
Labour Force Quality (LFQ)	Categorical variable of the perception of inadequately educated workforce as an obstacle to the current operations of the establishment.	No issue, Moderate issue, Major issue.
Business Licensing and Permit (BLP)	Categorical variable of the perception of business licensing and permits issuing as an obstacle to the current operations of the establishment.	No issue, Moderate issue, Major issue.

Note: All the information regarding expenditures, sales and costs of the establishments is presented in 2010 US Dollars. To account for inflationary trends, monetary values were deflated using the Consumer Price Indexes published by the Salvadoran Central Bank (BCR, 2021).

Innovation variables

As suggested by Crepon et al. (1998) and Griffith et al. (2006), the measure for an establishment's innovation efforts is the expenditures towards Research and Development (R&D). Therefore, the corresponding survey question was: "During the last fiscal year, how much did this establishment spend on formal research and development activities, either in-house or contracted with other companies?" In 2010, 19 establishments reported having made such expenditures, while 30 did so in 2016, totalling 49 cases for the pooled subsample of Salvadoran agribusinesses.

Fagerberg et al. (2010) and Cirera and Maloney (2017) argue that measuring the efforts towards innovation in developing countries becomes challenging due to the relatively unusual nature of specialized R&D departments compared to enterprises in other parts of the world, such as the United States or Europe. Thus, the same authors propose that alternative measures that capture other innovation efforts should be implemented.

Following a similar approach to Cirera (2016) and Aboal and Garda (2016), Research Intensity was constructed, adding R&D to machinery and equipment expenditures[12] ("In the last fiscal year how much did this establishment spend on purchases of machinery, vehicles, and equipment (new or used)?"). No changes in the number of firms reporting to spend in innovation were obtained; only the magnitudes were updated. We argue that all establishments engage in innovative activities, but only some of them are doing so in a sufficient (monetary) amount for it to be eventually reported (Crespi and Zuniga, 2012).

Product and process innovation outputs (P&P Innovation[13]) are measured as a joint factor, similar to the work by Hall et al. (2009), De Fuentes et al. (2015) and Hall and Sena (2017). The dummy variable was constructed from two separate questions: i) "Over the last three years, did this establishment introduce any new or significantly improved product (good or service)?" and ii)"Over the last three years, did this establishment introduce any new or significantly improved processes for producing or supplying products (good or service)?" In 2010, 48.39% of the establishments answered affirmatively to at least one of these two questions. Meanwhile, 43.41% did so in 2016. In total, 109 businesses (44.67%) out of 244 in the sample reported having generated an innovation output.

Production function factors

The selection of variables pertinent to the production function was made drawing from the guidelines on productivity analysis[14] by Coelli et al. (2005). Moreover, as mentioned in the methodology section, having a production function where at least one factor can adopt values equal to zero might lead to biased estimations. Therefore, following the procedure to correct this issue suggested by Battese (1997), dummy variables were created that equal 1 when their values (i.e. capital, labour, inputs, and security costs) were not reported and otherwise equal 0. Most notably, 40.1% of all the establishments in the sample reported

[12]Due to constraints in the survey data, different forms of knowledge investments such as staff training, marketing strategies, and trademark licensing could not be included in the analysis.

[13]Other forms of innovation outputs such as organizational or marketing-related could not be included in the analysis because that information was not part of the survey questionnaire.

[14]A noteworthy omission are the expenditures on land and infrastructures. Data limitations were the main reason behind it.

Table 2: Descriptive statistics of the Agribusiness Sector in El Salvador

	2010 (n=62)	2016 (n=182)	Pooled sample (n=244)
Innovation			
Research intensity	61358.06	82878.83	77410.44
	(228408.33)	(436046.66)	(393457.57)
R&D	19080.65	4300.60	8056.18
	(71991.13)	(15231.29)	(38927.97)
P&P Innovation = yes	48.39 %	43.41 %	44.67 %
Production function			
Total sales	9372840.13	5478793.43	6468264.31
	(21369632.21)	(16169288.23)	(17670892.92)
Capital cost	1014004.80	1425153.35	1321348.52
	(2935021.23)	(9515110.92)	(8351054.52)
Labour cost	1438122.03	554591.83	777661.34
	(4820071.32)	(1075996.68)	(2606039.76)
Inputs cost	6011251.61	2292461.37	3231363.86
	(14698089.21)	(9435057.41)	(11081329.01)
Security expenditure	116486.18	82142.44	90813.38
	(321725.60)	(299882.02)	(305095.36)
Capital dummy = no	37.25 %	41.06 %	40.10 %
Inputs dummy = no	25.49 %	1.32 %	7.43 %
Security cost dummy = no	15.69 %	35.10 %	30.20 %
Permanent workers	130.82	85.32	96.89
	(165.13)	(142.85)	(149.80)
Firm characteristics			
Firm age	25.68	26.41	26.23
	(17.89)	(17.35)	(17.45)
Foreign ownership (%)	15.23	8.76	10.41
	(32.31)	(26.42)	(28.11)
Export (%)	13.60	11.24	11.84
	(24.06)	(26.81)	(26.11)
Firm-small	24.19 %	49.45 %	43.03 %
Firm-Medium	32.26 %	25.27 %	27.05 %
Firm-Large	43.55 %	25.27 %	29.92 %
Group membership= yes	25.81 %	23.08 %	23.77 %
Agri-processing	70.97 %	68.68 %	69.26 %
Agri-wholesale	24.19 %	19.78 %	20.90 %
Agri-inputs	4.84 %	11.54 %	9.84 %
Foreign tech. = yes	6.45 %	6.59 %	6.56 %
Business environment obstacles			
Property crime = yes	46.77 %	21.43 %	27.87 %
Insecurity- no issue	30.65 %	28.57 %	29.10 %
Insecurity- moderate	46.77 %	44.51 %	45.08 %
Insecurity- major	22.58 %	26.92 %	25.82 %
Corruption- no issue	30.65 %	32.97 %	32.38 %
Corruption- moderate	46.77 %	47.80 %	47.54 %
Corruption- major	22.58 %	19.23 %	20.08 %
Finance- no issue	14.52 %	30.22 %	26.23 %
Finance- moderate	58.06 %	54.40 %	55.33 %
Finance- major	27.42 %	15.38 %	18.44 %
LFQ- no issue	16.13 %	19.78 %	18.85 %
LFQ- moderate	62.90 %	64.29 %	63.93 %
LFQ- major	20.97 %	15.93 %	17.21 %
BLP- no issue	25.81 %	28.57 %	27.87 %
BLP- moderate	54.84 %	54.95 %	54.92 %
BLP- major	19.35 %	16.48 %	17.21 %

Note: Percentages, means (standard deviations shown in parentheses)

no capital costs, while 70% reported having spent on security measures[15].

[15] In the survey, the magnitude of security expenses was reported either through a direct monetary figure or as a percentage of total annual sales. These two questions were recorded as a single variable expressed in 2010 US Dollars.

Firm characteristics

The survey question for measuring the age of a firm was: "In what year did this establishment begin operations?" On average, the typical agribusiness in the sample is 26.23 years old, with a standard deviation of 17.45 years. Additionally, 35 establishments reported that, on average, 10.41% of the firm was owned by private foreign individuals, companies, or organizations. Likewise, about 11,84% of the total sales of 71 establishments came from direct exports.

The categorical variable for firm size was constructed using the total number of permanent workers. The survey question defines permanent, full-time employees "as all employees that are employed for a term of one or more fiscal years and/or have a guaranteed renewal of their employment and that work a full shift." Based on this definition, the categories in the survey were established as follows: a small firm has between 5 and 19 employees (43% of the pooled sample), a medium-sized firm has between 20 and 99 (27%), and a firm with more than 100 employees is considered large (30%). Moreover, 23.77% of all establishments reported being part of a larger group/corporation[16].

Most of the agribusiness, approximately 69%, operate in the processing branch that deals with the manufacture of food, beverages, leather, tobacco, and wood products. The second-largest share of firms was performing activities such as wholesale trade, warehousing, and auxiliary transport with 21%. Finally, only about 10% of the establishments provide inputs to the industry through specific textiles, chemicals, and machinery (See Appendix A.1).

Obstacles of the business environment

Given the Central American context, a particular focus of the survey and this research had to do with the issues of crime and corruption. Therefore, we combined two items from the questionnaire to measure experiences with property crime[17]: "In the last fiscal year, did this establishment experience losses as a result of theft or robbery (excluding in transit) on this establishment's premises?" and "In the last fiscal year, did this establishment experience losses as a result of vandalism or arson?" Around 28% of all agribusinesses reported having been victims of said types of crimes.

The rest of the variables regarding the business environment of firms had a similar structure in the questionnaire: "Using the response options on the card; to what degree is [insert obstacle] an obstacle to the current operations of this establishment?" with the possible responses: No obstacle, minor, moderate, major, and very severe obstacle. The list of issues surveyed was broad. The ones included in the present analysis were insecurity, corruption, access to finance, quality of the labour force and business licensing and permits. Moreover, some categories registered very few or no observations. Thus, each variable was recoded to have only three possible answers: No issue (sum of no obstacle or minor), moderate (remained the same) and major obstacle (sum of major and very severe). The results can be seen in Table 2.

[16]Being part of a larger group or corporation was denoted to include several distinct locations or establishments, including branch offices or production, distribution, or sales sites.

[17]Other pertinent forms of crime, such as extortions, payments to local gangs, and worker absenteeism due to violence, were considered for inclusion. However, disparities between survey questionnaires prevented it.

5. Empirical findings

5.1. Determinants of innovation efforts

The determinants of innovation efforts (i.e., expenditures in innovation inputs) were estimated through a Tobit model (See Equation 1). The findings are reported in Table 3. R&D and Research intensity are measured in thousands of dollars, and they were transformed using the inverse hyperbolic sine transform (arcsinh). It has the advantage of handling zero values, and the interpretation of the partial effects can be the same as the natural logarithm transformation, as long as the variable's mean is greater than 10 (Bellemare and Wichman, 2020). Columns one and three show the results for each model, respectively. Likewise, columns two and four present their marginal effects that allow us to compare the intensity of each variable under study.

Firm characteristics such as firm size, firm age, percentage of exported sales, foreign ownership, agribusiness subsector, and usage of licensed technology have statistically significant effects on the firm's expenditures towards innovation inputs. Exports and firm size (measured as the number of permanent workers) had a positive effect. The former result might reflect how firms that export relatively more face tougher competition in a foreign market and might also have to meet higher quality standards or certification processes (Baumann and Kritikos, 2016; Hall et al., 2009). Firm size positively and statistically significantly affects both model specifications. A straightforward explanation for this effect is that larger firms are more likely to have more resources at their disposal. Likewise, firm age positively affects both models, but it was only statistically significant for research intensity. We argue that the old firms are more likely to have more resources at their disposal. As it captures investment towards capital goods, the Research Intensity reflects that investment capacity (Cirera, 2015)

The positive effects of foreign technology use on innovation expenditures might be explained by the costs associated with adopting and implementing said technologies in the local market (Crespi and Zuniga, 2012). Under this logic, it is not surprising that this variable holds significant positive effects for Research Intensity. It is important to note that even if the foreign technology effect was not statistically significant with the R&D model, it still had the expected positive sign. Foreign ownership had a negative effect (similar to the results obtained by De Fuentes et al. (2015)), meaning that, on average and everything else being equal, an additional percentage point of foreign ownership of a firm translates into a decrease in expenditure in both Research Intensity (0.6 percent point) and R&D (0.4 percent point). Furthermore, firms located in the wholesale and warehousing subsector where goods such as food and beverages are sold and stored (e.g., warehouses, ancillary logistics) invested on average less in R&D (35%) and Research intensity (48%) than the rest of agribusinesses even after controlling for other effects.

Business environment factors also had relevant effects on firms' investments in innovation, namely, financing obstacles, property crime, perception of insecurity. However, this time the R&D and Research Intensity models differ in the statistical significance of some of their explanatory variables. Using the R&D specification as the benchmark, we find that when firms report insecurity as a major obstacle, the expenditures in innovation efforts are 31 % lower than those reporting it as a minor issue. An explanatory argument for these findings could be that in uncertain business environments, incentives to invest are decreasing, given that the significant opportunity costs might offset the expected returns. Similarly, a more restrictive financing environment (e.g., lack of banking instruments and access to credit) also reduces innovation expenditures by 52%, which is in line with the evidence found by Czarnitzki and Hottenrott (2011) and Baumann and Kritikos (2016).

Table 3: Determinants of Innovation effort

	R&D (I)	R&D Marginal effects (II)	Research intensity (III)	Research intensity Marginal effects (IV)
(Intercept)	-8.089^{***}		-12.771^{***}	
	(2.669)		(3.767)	
logSigma	1.276^{***}		1.599^{***}	
	(0.109)		(0.109)	
Permanent workers	0.008^{***}	0.001^{***}	0.010^{***}	0.001^{***}
	(0.002)	(0.000)	(0.003)	(0.000)
Firm age (arcsinh)	0.894	0.118	1.363^{*}	0.179^{*}
	(0.563)	(0.077)	(0.783)	(0.107)
Export (%)	0.049^{***}	0.006^{***}	0.069^{***}	0.009^{***}
	(0.013)	(0.002)	(0.018)	(0.003)
Foreign ownership (%)	-0.033^{**}	-0.004^{**}	-0.045^{**}	-0.006^{**}
	(0.015)	(0.002)	(0.021)	(0.003)
Foreign tech. = yes	1.882	0.248	2.794^{*}	0.367
	(1.212)	(0.166)	(1.671)	(0.231)
Group membership = yes	0.645	0.085	1.106	0.145
	(0.803)	(0.107)	(1.106)	(0.148)
Property crime = yes	2.541^{***}	0.335^{***}	3.877^{***}	0.509^{***}
	(0.851)	(0.117)	(1.179)	(0.164)
Insecurity- moderate	-0.823	-0.108	-1.026	-0.135
	(0.872)	(0.116)	(1.218)	(0.161)
Insecurity- major	-2.383^{**}	-0.314^{**}	-2.767^{*}	-0.364^{*}
	(1.143)	(0.148)	(1.551)	(0.201)
Finance- moderate	-1.188	-0.157	-1.477	-0.194
	(0.899)	(0.121)	(1.250)	(0.168)
Finance- major	-3.912^{***}	-0.515^{***}	-5.242^{***}	-0.689^{***}
	(1.391)	(0.184)	(1.909)	(0.254)
LFQ- moderate	2.727^{**}	0.359^{**}	3.882^{**}	0.510^{**}
	(1.302)	(0.173)	(1.827)	(0.241)
LFQ- major	2.553^{*}	0.336^{*}	3.298	0.433
	(1.495)	(0.194)	(2.096)	(0.270)
BLP- moderate	0.644	0.085	1.198	0.157
	(0.923)	(0.124)	(1.301)	(0.173)
BLP- major	3.202^{***}	0.422^{**}	5.055^{***}	0.664^{***}
	(1.213)	(0.164)	(1.685)	(0.231)
Agri-wholesale	-2.618^{**}	-0.345^{**}	-3.647^{**}	-0.479^{**}
	(1.187)	(0.162)	(1.623)	(0.223)
Agri-inputs	-0.866	-0.114	-1.387	-0.182
	(1.207)	(0.162)	(1.703)	(0.226)
Year dummy	-1.785^{**}	-0.235^{**}	-1.882^{*}	-0.247^{*}
	(0.800)	(0.108)	(1.109)	(0.147)
Log Likelihood	-183.009		-198.551	
AIC	406.018		437.103	
BIC	475.962		507.046	
Correlation	0.544		0.546	
Num. obs.	244		244	

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

In this model specification, BLP is statistically significant and had a positive sign, which might seem counter-intuitively at first. However, as explored in the literature of "greasing the wheels," institutional imperfections can positively affect investments, especially in contexts where corruption practices such as bribery are a potential approach for doing business (Asiedu and Freeman, 2009). In the same way, LFQ is positive and statistically significant. Firms that perceive an inadequately educated workforce as an obstacle invest more in both R & R&D and Research Intensity.

As for property crime, it is significant in this model specification. Its sign also puzzles since it suggests that victimized firms spent more on innovation, despite having experienced losses due to those crimes. We expect that firms that would want to continue their operations in a risky environment will be forced to invest more in R&D. A similar analysis can be derived from the specification of the research intensity model, but it has a stronger effect.

In summary, Salvadoran agribusinesses indeed had, on average, adverse reactions to the hostile environment, expressed in reductions of investments in innovation. This can be further evidenced by the fact that between 2010 and 2016, there was a statistically significant decrease in innovation expenditures in the general sample.

5.2. Determinants of innovation outputs

The next step of the CDM sequence seeks to determine the factors behind the generation of innovation outputs. In other words, what caused firms to innovate? As discussed in the methodological section, available empirical research has approached this question using the predicted values of the previous step and controlled for potential endogeneity, often using bootstrapping. However, implementing a formal test for endogeneity can be relevant to judge the econometric approach more suitable to solve the problem at hand. Thus, endogeneity between predicted research efforts and P&P innovation outputs was tested using the CFA, Control Function Approach (See Equation 2).

The residuals from the previous models were included as additional covariates in the regressions shown in Columns II and IV of Table 4. The test of endogeneity employing the CFA involves analysing the significance of the coefficients of the residuals included in the model. In this case, the null hypothesis of no endogeneity is not rejected at a significance level of 5%, implying that R&D and Research Intensity can be treated as though they were exogenous. Therefore, the estimated Probit models for P&P innovation output are presented using the innovation efforts instead of the predicted ones[18].

The dependent variable is P&P innovation output, using firms that did not report innovations as the reference value. Thus, variables with a positive regression coefficient mean that firms are more likely to generate an innovation output. Moreover, Table 4 only illustrates the direction of the effects between the explanatory variables on P&P innovations; the magnitudes are presented in Figure 1 through their marginal effects. Moreover, the model specifications shown in Table 4 differ by the measure of innovation input included as an explanatory variable, R&D expenditures, and Research Intensity, respectively.

Considering the possibility of diminishing marginal returns (i.e., non-linear relations), we included the squared terms of Firm age (transformed using arcsinh transformation) in the analysis. The argument is

[18]For the sake of clarity, R&D and Research Intensity were transformed using the inverse hyperbolic sine transform (arcsinh). Moreover, the CFA endogeneity test was performed with different specifications, including untransformed values; however, the results obtained were not different from those presented here. Furthermore, these are simpler in their interpretation through the marginal effects.

that the marginal contributions of Firm age on the probability of innovating cannot increase or decrease indefinitely after a certain threshold. The results in Table 4 seem to confirm this assertion, as the value of the variable is positive, and their quadratic form is negative. In other words, the positive effect of further years of operation will lessen as the same variable increase. Moreover, since the year control dummy was positive but not statistically significant, it can be concluded that between 2010 and 2016, there were no relevant changes in the probability of firms generating a P&P innovation outcome.

Table 4: Determinants of Innovation outputs

	P&P Innovation (I)	P&P Innovation CFA (II)	P&P Innovation (III)	P&P Innovation CFA (IV)
(Intercept)	-2.48^{***}	-2.46^{***}	-2.43^{***}	-2.35^{***}
	(0.46)	(0.56)	(0.47)	(0.56)
R&D	0.53^{***}	0.53^{***}		
	(0.11)	(0.12)		
Research intensity			0.46^{***}	0.47^{***}
			(0.10)	(0.11)
Firm-Medium	0.70^{***}	0.70^{***}	0.70^{***}	0.69^{***}
	(0.25)	(0.25)	(0.25)	(0.25)
Firm-Large	0.57^{**}	0.56^{*}	0.58^{**}	0.55^{*}
	(0.28)	(0.31)	(0.28)	(0.31)
Firm age	0.04^{**}	0.04^{**}	0.04^{**}	0.04^{**}
	(0.02)	(0.02)	(0.02)	(0.02)
Firm age^2	-0.00^{*}	-0.00^{*}	-0.00^{*}	-0.00^{*}
	(0.00)	(0.00)	(0.00)	(0.00)
Export (%)	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Foreign ownership (%)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Foreign tech. = yes	0.20	0.20	0.18	0.17
	(0.24)	(0.24)	(0.24)	(0.24)
Property crime = yes	-0.05	-0.06	-0.11	-0.13
	(0.24)	(0.26)	(0.25)	(0.27)
Insecurity- moderate	0.62^{**}	0.62^{**}	0.64^{**}	0.64^{***}
	(0.25)	(0.25)	(0.25)	(0.25)
Insecurity- major	0.53^{*}	0.54^{*}	0.52^{*}	0.55^{*}
	(0.29)	(0.30)	(0.29)	(0.31)
Corruption- moderate	0.39^{*}	0.38^{*}	0.39^{*}	0.39^{*}
	(0.23)	(0.23)	(0.23)	(0.23)
Corruption- major	0.92^{***}	0.92^{***}	0.94^{***}	0.93^{***}
	(0.29)	(0.29)	(0.30)	(0.30)
Agri-wholesale	-0.57^{**}	-0.57^{**}	-0.58^{**}	-0.56^{*}
	(0.27)	(0.29)	(0.28)	(0.29)
Agri-inputs	0.51	0.51	0.53	0.53
	(0.35)	(0.35)	(0.35)	(0.35)
Year dummy	0.25	0.25	0.19	0.20
	(0.24)	(0.25)	(0.24)	(0.25)
R&D residuals		-0.01		
		(0.15)		
Research intensity residuals				-0.04
				(0.15)
Log Likelihood	-116.64	-116.64	-114.30	-114.27
AIC	267.28	269.28	262.59	264.54
BIC	326.74	332.23	322.04	327.48
McFadden R^2	0.30	0.30	0.32	0.32
Percent correctly predicted (%)	77.46	77.87	77.87	78.28
Num. obs.	244	244	244	244

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

To check the goodness-of-fit of models in Columns I and III, we tested the joint hypothesis that all coefficients are equal to zero, using the Log-Likelihood ratio. The null hypothesis was rejected at a 5% significant level, meaning that both models fit the data better than constant-only specifications. Additionally, the McFadden pseudo-$R2$ had values of 0.30 and 0.32; and the hit rates (overall proportions of correct predictions) were around 78% in both cases, which indicates that our models correctly classify the vast majority of observations of the agribusiness sub-sample. We also checked residuals, and we found no hint of heteroskedasticity following the guidelines suggested by Fox and Weisberg (2019). Finally, the Variance Inflation Factor (VIF) analysis showed no values larger than 5; therefore, we can rule out serious multicollinearity issues.

5.2.1. Determinants of innovation outputs: marginal effects

In general, both the R&D and Research Intensity model specifications yielded similar results in coefficient significance and the direction of the effects. This result is not entirely unexpected, as the Research Intensity variable was constructed based on R&D, which -in this case- translates to consistency between both models, albeit with different magnitudes.

The partial effect of R&D was 0.14, meaning that investing 10% more in R&D increases the probability of generating a product or process innovation by 1.4 percent point. Likewise, spending 10% more on Research Intensity would increase -everything else being constant- the probability of generating a P&P innovation output by 1.2 percent point. These results would suggest that exclusive investments in R&D -on average- yield more extensive results than more broad investments in innovation.

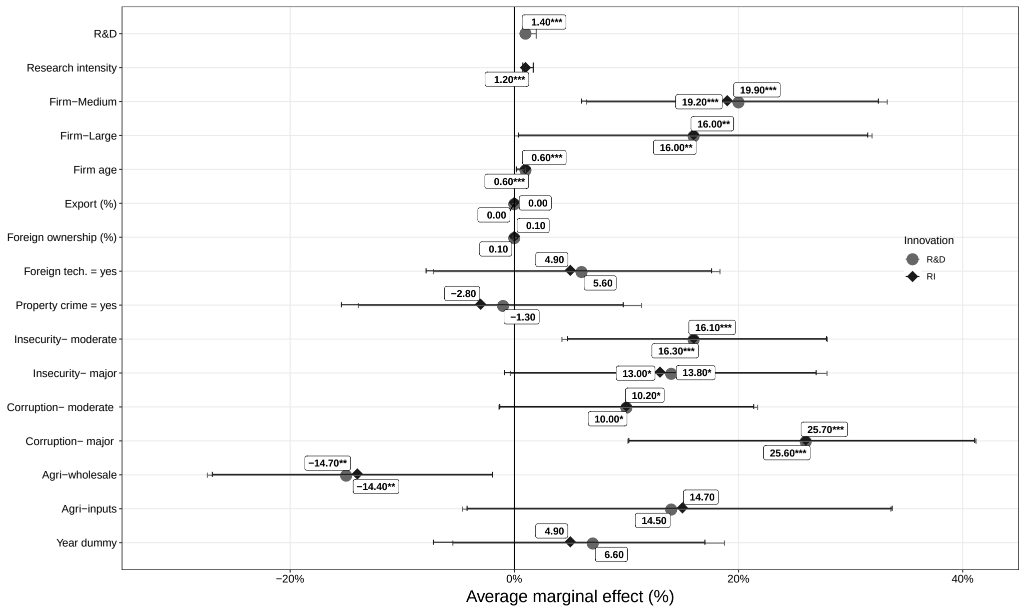

Figure 1: Marginal effects of the probit model for Innovation outputs R&D and Research Intensity (RI)

Furthermore, firm characteristics such as size[19], age and agribusiness subsector had a statistically significant effect on the probability of generating an innovation output. For example, both medium-sized and large firms invest relatively more than small firms, 19.20%, and 16.00%, respectively. Similarly, an extra year in business translates -everything else being equal- into a 0.6% probability increase of generating a P&P innovation. Moreover, agribusinesses in the wholesale and storage branch invested 14.70% less when compared to the production subsector.

[19]To separate the effects according to subgroups of firms, we recorded the number of permanent workers as a categorical variable.

Regarding the effects of the business environment, our findings indicate that firms that reported insecurity and corruption as a significant issue are more likely to generate a P&P innovation by a factor of 13.8% and 25.70%, respectively. We can argue that these otherwise unexpected results reflect a certain degree of adaptability of Salvadoran agribusinesses. Being subjected to a hostile environment has incentivised firms towards generating new products and processes, probably to avoid stopping their operations altogether. These results support the idea that in the context of developing countries, formal innovation efforts can have a comparatively lesser role than the enabling environment that fosters creating, adapting, implementing, or disseminating innovation outputs (Cirera and Maloney, 2017; Grazzi and Pietrobelli, 2016; Hall and Rosenberg, 2010; Navarro and Olivari, 2016)

5.3. Productivity equation: Innovation, Insecurity, and firm performance

As mentioned in the Methodology section, in the CDM literature, firm performance is often measured as labour productivity, and its determinants are modelled via a Cobb-Douglas function. This research expands upon this in two forms. First, it calculates the TFP (i.e. the ratio of aggregate output to aggregate input) of a firm instead of exclusively focusing on labour productivity. Second, two production-function specifications are implemented and verified. Moreover, we conducted a Wald test to check if the restricted production functional form (i.e. Cobb-Douglas) fitted the data significantly better than the unrestricted form (i.e. Translog). The null hypothesis can be rejected at a 1% significance level, meaning that a Translog specification is more suited for the data[20].

[20]The Cobb-Douglas results can be seen in Appendix A.2.

Table 5: Translog Production function

	Production function (I)	Production function P&P IV (R&D) (II)	Production function P&P IV(RI) (III)
(Intercept)	-0.45^{*}	-0.35	-0.36
	(0.25)	(0.28)	(0.28)
Capital cost	0.17^{***}	0.18^{***}	0.18^{***}
	(0.05)	(0.06)	(0.06)
Labour cost	0.35^{***}	0.36^{***}	0.36^{***}
	(0.07)	(0.07)	(0.07)
Inputs cost	0.30^{***}	0.29^{***}	0.29^{***}
	(0.07)	(0.07)	(0.07)
Security cost	0.18^{***}	0.18^{***}	0.18^{***}
	(0.06)	(0.06)	(0.06)
Capital cost^2	0.00	0.01	0.01
	(0.03)	(0.03)	(0.03)
Labour cost^2	0.06	0.06	0.06
	(0.05)	(0.05)	(0.05)
Inputs cost^2	0.03	0.03	0.03
	(0.02)	(0.03)	(0.03)
Security cost^2	-0.01	-0.02	-0.02
	(0.04)	(0.04)	(0.04)
Capital × Labour	0.07^{***}	0.08^{***}	0.08^{***}
	(0.03)	(0.03)	(0.03)
Capital × Inputs	-0.02	-0.03	-0.03
	(0.02)	(0.02)	(0.02)
Capital × Security cost	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Labour × Inputs	-0.11^{***}	-0.11^{***}	-0.11^{***}
	(0.03)	(0.03)	(0.03)
Labour × Security cost	-0.01	-0.00	-0.00
	(0.03)	(0.03)	(0.03)
Inputs × Security cost	0.04^{*}	0.04^{*}	0.04^{*}
	(0.02)	(0.02)	(0.02)
Capital-dummy	-0.10	-0.15	-0.14
	(0.15)	(0.17)	(0.17)
Inputs-dummy	-1.20^{***}	-1.25^{***}	-1.25^{***}
	(0.31)	(0.34)	(0.34)
Security cost-dummy	-0.33^{*}	-0.35^{*}	-0.35^{*}
	(0.20)	(0.20)	(0.20)
P&P Innovation = yes	-0.05	-0.19	-0.18
	(0.10)	(0.31)	(0.29)
Property crime = yes	-0.09	-0.08	-0.08
	(0.12)	(0.12)	(0.12)
Insecurity- moderate	0.05	0.05	0.05
	(0.13)	(0.13)	(0.13)
Insecurity- major	0.14	0.14	0.14
	(0.14)	(0.14)	(0.14)
Agri-wholesale	1.38^{***}	1.36^{***}	1.37^{***}
	(0.24)	(0.24)	(0.24)
Agri-inputs	0.18	0.17	0.17
	(0.12)	(0.12)	(0.12)
Firm-Medium	0.18	0.20	0.20
	(0.17)	(0.18)	(0.18)
Firm-Large	0.50^{**}	0.54^{**}	0.54^{**}
	(0.23)	(0.26)	(0.25)
Year dummy	0.15	0.13	0.13
	(0.10)	(0.11)	(0.11)
R^2	0.93	0.93	0.93
Adj. R^2	0.92	0.92	0.92
Num. obs.	202	202	202
Weak instruments		40.54	49.32
P-value		0.00	0.00
Wu-Hausman		0.27	0.26
P-value.		0.60	0.61

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

To test for endogeneity between innovation outputs and the errors of the production function (See Equation 3), we estimated two model specifications. One uses the predicted probabilities of P&P innovation outputs as an instrument (Columns II and III of Table 5), and another without the predicted probabilities.

The null hypothesis of the weak instruments test is rejected, meaning that our instruments correctly represent the probabilities of P&P innovation outputs. However, the results from the Wu-Hausmann test suggest that there is no statistical difference between the models these models. Therefore, with no strong evidence for endogeneity, the model presented in Column (I) was selected. Moreover, the adjusted R^2 value suggests that this specification explains 92% of the variations in the dependent variable.

The explanatory factors have been rescaled at their sample means so that the first-order coefficients can be interpreted as elasticities of output for the corresponding input. Moreover, the monotonicity conditions of the Translog production function is fulfilled as the estimated output elasticities of capital, labour, inputs, and security costs are positive (at the sample mean). Furthermore, the result of a Wald test suggests that the Salvadoran agribusinesses operate under constant returns of scale since the sum of the estimated partial elasticities at the sample mean is not significantly different from one. Additionally, the estimated constant rate of technological progress (15% between 2010 and 2016 or 2.5% per year within that timeframe) is not statistically different from zero, i.e. the null hypothesis of no technological change cannot be rejected. In other words, no evidence of TFP growth was found.

When comparing the partial elasticities of capital and labour, the latter (0.35) represents double the magnitude of the former (0.17) in the TFP of Salvadoran Agribusinesses. This productivity composition heavily biased towards labour is a general characteristic of the Latin American region (OECD, 2016). Moreover, following Battese (1997), three dummy variables were included to control firms that did not report their capital, inputs, or security costs. The results suggest that those firms not reporting these costs have, in general, lower outputs.

In the following, the analysis will focus on the effects related to innovation, crime, and insecurity. The coefficient of security costs was statistically significant, meaning that investments towards protection against criminality and other related disturbances play a meaningful role in a firm's level of sales. The security-cost elasticity of output (0.18) is comparatively as relevant as capital expenditures (0.17) and half that of labour or input costs (0.35 or 0.30).

A range of dummy variables is included to analyse the effects of innovation, firm characteristics, and business environment in the production function of firms. To avoid misinterpreting the coefficient of those dummy variables, the correction suggested by Kennedy (1981) was performed. Furthermore, having introduced a product or process innovation did not significantly affect the level of sales of the agribusinesses sample. In other words, any potential benefits from generating innovations do not come to bear in terms of total sales in the Salvadoran case.

Property crime and the perception of insecurity did not influence the level of output of firms. Specific experiences of property crime harm sales, while higher levels of perception of insecurity have positive effects. However, the coefficients for those effects were not statistically different to zero. In contrast, the security cost dummy was negative and statistically significant, meaning that establishments that did not incur security costs had -on average- a significantly lower level of outputs (sales) when compared to those who did. After using Kennedy's correction, the magnitude of this effect can be interpreted as 36% lower sales.

Finally, firm characteristics, such as size and subsector, are relevant to the performance of establishments. For example, those establishments listed as wholesale and storage agribusinesses have approximately 286% higher sales than processing firms. Meanwhile, the sales of large establishments are 60% greater than those of small firms.

6. Discussion and policy implications

The findings from our research reveal a problematic picture of the agribusiness sector in El Salvador. Like in the macroeconomic trends presented in the background section, firms appear to be making little progress in economic growth, as there were no substantial sales increases between 2010 and 2016. Another predominant feature of the agribusiness landscape is the importance of wholesale and storage establishments. Compared to the processing subsector, retailers and warehousing enterprises invest less in innovation, generate fewer new products or processes; but have three times the output.

In general, innovation efforts, such as R&D expenditures, are not made by most firms in the sector (at least not in a considerable amount that leads them to report it), and the practice is mainly skewed in favour of comparatively larger or export-orientated establishments. Additionally, the local business environment affects the generation of innovation outputs, but not in a form that would be expected beforehand. It is possible that when operating under a hostile environment, (e.g. perceptions of insecurity, practices of corruption), firms might be incentivised to generate innovations as a coping mechanism, and this effect is significant even after controlling for size, age or formal R&D expenditures. Arguably, these results could have different orientations or magnitudes in other industries or contexts. Nevertheless, they represent robust evidence for the determining role played by the business environment when it comes to introducing firm-level innovations in developing countries.

Despite that innovative products and processes are being introduced by a significant number of firms, our evidence suggests that they do not come to bear in terms of firm performance. In stark contrast, even after controlling for other firm characteristics, establishments that did not report or incur security costs had lower sales than those who did; and the partial contribution of security costs is comparatively as significant as capital investments.

In terms of strategies that strengthen the addition of value to agricultural products, the implications of our study are threefold. Firstly, policymakers should focus on providing incentives to small and medium-size processing agribusinesses since they are the ones who stand to gain the most from increased budgets to invest in innovation. Secondly, improving the innovation input-output system will not yield significant gains in terms of sales if the adverse effects of the business environment are not addressed simultaneously. Finally, in the specific case of El Salvador, policies that seek to promote growth through innovation should include measures to palliate the elevated costs of protection against crime, especially for smaller processing firms.

7. Conclusions and recommendations

The main objective of this paper was to determine the relationships between innovation, insecurity, and economic performance among agribusinesses in El Salvador. A CDM model was estimated using 2010 and 2016 data from the World Bank's Enterprise Survey Series. This empirical approach allows us to answer three questions sequentially: what determines the magnitude of a firm's efforts towards innovation? Do these efforts increase the probability of a new product or process being introduced? Finally, do innovation outputs translate to firm overall productivity?

Our results suggest that the level of investment in innovation activities, such as R&D expenditures, is determined by specific firm characteristics and barriers from the business environment. For example, firm size and a higher percentage of direct exports positively affected the amount spent on innovation inputs. In contrast, a more extensive proportion of foreign ownership and operating in the wholesale and storage subsector was linked to lower investments. Moreover, business environment factors such as financing obstacles and higher perceptions of insecurity lead enterprises to reduce their innovation efforts.

Regarding the generation of innovation outputs (e.g. introducing a new product or process), our evidence falls within the previous literature's conclusions with one notable exception. As expected, more expenditures on innovation inputs increase the probability of generating innovation outputs. Similarly, increments in size and age had positive effects (albeit with diminishing returns). However, a surprising finding of our analysis was that perceptions of insecurity and corruption are associated with an increased likelihood of innovating. We reason that this result reflects the dynamics of adaptability among Salvadoran agribusinesses. Arguably, firms have countered their hostile economic environment via knowledge products such as new products and processes, probably to avoid exiting the market entirely. Also, as expected and following the business model, agribusinesses in the wholesale and storage branch invested comparatively less than the processing subsector. It demonstrates that policies should support the agro-processing sector because of its importance in generating added-value products.

Furthermore, having introduced an innovation did not significantly affect the level of sales of the agribusinesses in our study. Likewise, we found no evidence of technological change in terms of Total Factor Productivity growth between 2010 and 2016. Moreover, the expenditures made towards protection against crime have a significant effect on firms' output levels. Establishments that did not incur security costs had -on average- 36% lower sales than those who did, even after controlling for other firm characteristics such as size and subsector. However, most notably, wholesale establishments had -on average- three times the amount of sales than processing agribusinesses.

Our analysis does not come without certain limitations, mainly regarding data availability and quality. As mentioned previously, changes in the core questionnaires of the Enterprise Surveys between rounds resulted in incompatible or missing indicators. Moreover, the relatively high percentages of reported innovations should be contrasted with additional questions in the surveys about the quality of the innovations (e.g. novelty to the local market, detailed description of what was introduced). Similarly, alternative measures of innovation efforts beyond R&D expenditures should be included in the questionnaire, for example, the number of hours and the expenditures dedicated to human capital training, organisational changes, or marketing strategies.

Future research on the investment-innovation-productivity could expand our results by analysing the potential complementary effects with other industries in the value chains of agricultural commodities. In addition, it would be interesting to explore how innovative practices and outputs in other sectors (i.e. agricultural production) relate to the dynamics of agribusinesses. Finally, the study on the role of an enabling business environment in firm-level and overall economic development would greatly benefit by undertaking a comparative approach, using standardised evidence from several countries and for a long enough observation period.

References

Aboal, D., Garda, P., 2016. Technological and non-technological innovation and productivity in services vis-à-vis manufacturing sectors. Economics of Innovation and New Technology 25, 435–454.

Acevedo, C., Cabrera, M., Cornia, A., 2014. Social policies or private solidarity? The equalizing role of migration and remittances in el salvador. Falling Inequality in Latin America: Policy Changes and Lessons 164.

Asiedu, E., Freeman, J., 2009. The effect of corruption on investment growth: Evidence from firms in latin america, sub-saharan africa, and transition countries. Review of Development Economics 13, 200–214.

Bank, W., 2007. World development report 2008: Agriculture for development. The World Bank.

Barasa, L., Knoben, J., Vermeulen, P., Kimuyu, P., Kinyanjui, B., 2017. Institutions, resources and innovation in East Africa: A firm level approach. Research Policy 46, 280–291. doi:10.1016/j.respol.2016.11.008

Barraza, R., Barrientos, R., Díaz, X., Pleitez, R., Tablas, V., 2020. COVID-19 y vulnerabilidad: Una mirada desde la pobreza multidimensional en el salvador. PNUD América Latina y el Caribe# COVID19| SERIE DE DOCUMENTOS DE POLÍTICA PÚBLICA. Disponible en.

Battese, G.E., 1997. A Note On The Estimation Of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values. Journal of Agricultural Economics 48, 250–252. doi:10.1111/j.1477-9552.1997.tb01149.x

Baumann, J., Kritikos, A.S., 2016. The link between r&d, innovation and productivity: Are micro firms different? Research Policy 45, 1263–1274.

BCR, 2020. Banco Central de Reserva de El Salvador.

Bellemare, M.F., Wichman, C.J., 2020. Elasticities and the inverse hyperbolic sine transformation. Oxford Bulletin of Economics and Statistics 82, 50–61.

Bogliacino, F., Perani, G., Pianta, M., Supino, S., 2012. Innovation and development: The evidence from innovation surveys. Latin American Business Review 13, 219–261. doi:10.1080/10978526.2012.730023

Calvo-González, O., López, J.H., 2015. El Salvador: Building on Strengths for a New Generation. The World Bank.

Chudnovsky, D., López, A., Pupato, G., 2006. Innovation and productivity in developing countries: A study of Argentine manufacturing firms' behavior (1992-2001). Research Policy 35, 266–288. doi:10.1016/j.respol.2005.10.002

Cirera, X., 2015. Catching Up To The Technological Frontier? Understanding Firm-Level Innovation and Productivity in Kenya. World Bank Group - Trade; Competitiveness, Nairobi.

Cirera, X., 2016. ICT Use, Innovation, and Productivity: Evidence from Sub-Saharan Africa. SSRN Electronic Journal. doi:10.2139/ssrn.2866599

Cirera, X., Cusolito, A.P., 2019. Innovation Patterns and Their Effects on Firm-Level Productivity in South Asia. Journal of Economics and Public Finance 5, p261. doi:10.22158/jepf.v5n3p261

Cirera, X., Maloney, W.F., 2017. The Innovation Paradox: Developing-Country Capabilities and the Unrealized Promise of Technological Catch-Up. The World Bank. doi:10.1596/978-1-4648-1160-9

Cirera, X., Muzi, S., 2020. Research Policy 49, 103912. doi:10.1016/j.respol.2019.103912

Cirera, X., Sabetti, L., 2019. The effects of innovation on employment in developing countries: Evidence from enterprise surveys. Industrial and Corporate Change 28, 161–176. doi:10.1093/icc/dty061

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. An introduction to efficiency and productivity analysis. springer science & business media.

Crepon, B., Duguet, E., Mairessec, J., 1998. Research, Innovation And Productivity: An Econometric Analysis At The Firm Level. Economics of Innovation and New Technology 7, 115–158. doi:10.1080/10438599800000031

Crespi, G., Zuniga, P., 2012. Innovation and Productivity: Evidence from Six Latin American Countries. World Development 40, 273–290. doi:10.1016/j.worlddev.2011.07.010

Czarnitzki, D., Hottenrott, H., 2011. R&d investment and financing constraints of small and medium-sized firms. Small business economics 36, 65–83.

De Fuentes, C., Dutrenit, G., Santiago, F., Gras, N., 2015. Determinants of Innovation and Productivity in the Service Sector in Mexico. Emerging Markets Finance and Trade 51, 578–592. doi:10.1080/1540496X.2015.1026693

Duguet, E., 2006. Innovation height, spillovers and tfp growth at the firm level: Evidence from French manufacturing. Economics of Innovation and New Technology 15, 415–442. doi:10.1080/10438590500512968

Escribano, A., Guasch, J.L., 2005. Assessing the Impact of the Investment Climate on Productivity Using Firm-Level Data: Methodology and the Cases of Guatemala, Honduras, and Nicaragua. Policy research working paper series.

Fagerberg, J., Srholec, M., Verspagen, B., 2010. Innovation and Economic Development, in: Handbook of the Economics of Innovation. Elsevier B.V., pp. 833–872. doi:10.1016/S0169-7218(10)02004-6

Fox, J., Weisberg, S., 2019. An r companion to applied regression. Sage Publications, Inc.

Frick, F., Jantke, C., Sauer, J., 2019. Innovation and productivity in the food vs. The high-tech manufacturing sector. Economics of Innovation and New Technology 28, 674–694.

FUSADES, 2019. Informe de coyuntura económica. Noviembre de 2019.

FUSADES, 2021. Competitividad y transformación digital: Claves para superar el impacto del COVID-19.

Grazzi, M., Pietrobelli, C., 2016. Firm innovation and productivity in Latin America and the Caribbean: The engine of economic development. Springer Nature.

Griffith, R., Huergo, E., Mairesse, J., Peters, B., 2006. Innovation and Productivity Across Four European Countries. Oxford Review of Economic Policy 22, 483–498. doi:10.1093/oxrep/grj028

Hall, B.H., 2011. Innovation and productivity. National Bureau of Economic Research.

Hall, B.H., Lotti, F., Mairesse, J., 2009. Innovation and productivity in SMEs: empirical evidence for Italy. Small Business Economics 33, 13–33.

Hall, B.H., Rosenberg, N., 2010. Handbook of the economics of innovation. Elsevier.

Hall, B.H., Sena, V., 2017. Appropriability mechanisms, innovation, and productivity: evidence from the UK. Economics of Innovation and New Technology 26, 42–62. doi:10.1080/10438599.2016.1202513

Hernández, X.I., Escobar, M., Dinorah, S., Meléndez, A., Alfaro, C., 2017. Diagnóstico de la situación alimentaria y nutricional en El Salvador.

Kennedy, P.E., 1981. Estimation with correctly interpreted dummy variables in semilogarithmic equations. The American Economic Review 71, 801–801.

Mairesse, J., Mohnen, P., 2010. Using innovation surveys for econometric analysis, in: Handbook of the Economics of Innovation. Elsevier, pp. 1129–1155.

Mairesse, J., Mohnen, P., Kremp, E., Kremp, E., 2005. The Importance of R&D and Innovation for Productivity: A Reexamination in Light of the French Innovation Survey. Annales d'Economie et de Statistique 487–527.

Martins, F.G.D., Silva, F.G.F. da, Rocha, C.H., Queiroz, M., Araújo, C.E.F., 2012. Analysis of efficiency of the regulated transportation coach operator by stochastic frontier of Cobb-Douglas and translog functions: the case of the interstate passenger coach transportation in Brazil. Journal of Transport Literature 6, 08–33. doi:10.1590/s2238-10312012000300002

Mohnen, P., Hall, B.H., 2013. Innovation and Productivity: An Update. Eurasian Business Review 3, 47–65. doi:10.14208/BF03353817

Musolesi, A., Huiban, J.P., 2010. Innovation and productivity in knowledge intensive business services. Journal of Productivity Analysis 34, 63–81. doi:10.1007/s11123-009-0163-5

Navarro, J.C., Olivari, J., 2016. Nuevos caminos. Washington DCB: Banco Interamericano de Desarrollo.

Oddone, N., 2018. Promoción de la transformación productiva en el sector alimentos y bebidas en El Salvador.

OECD, 2016. Boosting Productivity and Inclusive Growth in Latin America. Organisation for Economic Co-Operation and Development.

OIT, 2020. Diagnóstico sobre economía informal. Énfasis en el sector comercio de los países del norte de centroamérica: El salvador, honduras y guatemala.

Peñate, M., De Escobar, K., Quintanilla, A., Alvarado, C., 2016. Estimación del Costo Económico de la Violencia en El Salvador 2014. Banco Central de Reserva de El Salvador.

Ramaschiello, V., 2015. Defining agro-industry a statistical classification perspective valentina ramaschiello -ESS FAO-UNIDO expert group meeting on agro-industry measurement (AIM) FAO, rome, 24-25 november 2015.

Reardon, T., Echeverria, R., Berdegué, J., Minten, B., Liverpool-Tasie, S., Tschirley, D., Zilberman, D., 2019. Rapid transformation of food systems in developing regions: Highlighting the role of agricultural research & innovations. Agricultural systems 172, 47–59.

Reardon, T., Tschirley, D., Dolislager, M., Snyder, J., Hu, C., White, S., 2014. Urbanization, diet change, and transformation of food supply chains in asia. Michigan: Global Center for Food Systems Innovation 46.

Rivers, D., Vuong, Q.H., 1988. Limited information estimators and exogeneity tests for simultaneous probit models. Journal of Econometrics 39, 347–366. doi:10.1016/0304-4076(88)90063-2

Salguero, J., 2016. Extorsión o apalancamiento operativo? Aproximación a la Economía Pandilleril en El Salvador. FES América Central 13.

Santacoloma, P., Riveros, H., 2007. Strengthening agribusiness linkages with smalescale farmers. Case studies in latin america and the caribbean. Food & Agriculture Org.

Santacoloma, P., SuC!rez, R., Riveros, H., 2005. Strengthening agribusiness linkages with small-scale farmers.

The World Bank, 2021b. El Salvador Overview.

The World Bank, 2021a. The World Bank's Open Data.

The World Bank, 2021c. Enterprise Surveys Indicators Data - World Bank Group.

UN, 2002. International Standard Industrial Classification of All Economic Activities (ISIC).

UNIDO, 2013. Agribusiness development - transforming rural life to create wealth.

UNIDO, 2021. 3ADI+: Accelerator for Agriculture and Agroindustry Development and Innovation | UNIDO.

United Nations, 2008. International Standard Industrial Classification of All Economic Activities. Statistical papers Series M No. 4/Rev.4. Statistical papers series m.

UNODC, 2019. Global study on homicide 2019. United Nations Office on Drugs and Crime.

UNODC, 2020. Desempleo, economía informal y crimen organizado.

USDA, 2018. El Salvador - Food Processing Ingredients Annual.

WFP, 2019. El Salvador - Country Brief 2019.

WFP, 2020. El Salvador - Country Brief 2020.

WFP, 2021. El Salvador.

Wollni, M., Brümmer, B., 2012. Productive efficiency of specialty and conventional coffee farmers in costa rica: Accounting for technological heterogeneity and self-selection. Food Policy 37, 67–76. doi:10.1016/j.foodpol.2011.11.004

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge; London.

Wooldridge, J.M., 2012. Introductory Econometrics - A Modern Approach, 5th ed.

Zhang, J., Islam, M.S., 2020. The Heterogeneous Impacts of R&D on Innovation in Services Sector: A Firm-Level Study of Developing ASEAN. Sustainability 12, 1643.

Zylbersztajn, D., 2017. Agribusiness systems analysis: Origin, evolution and research perspectives. Revista de AdministraC'C#o 52, 114–117. doi:10.1016/j.rausp.2016.10.004

Appendix

A.1. Agribusiness sample selection notes

The selected firms according to their main product were:

Agribusiness inputs

- Textiles (Manufacture of textiles)
  Firms with codes 1723, 1711 and 1712
- Chemicals (Manufacture of chemicals and chemical products)
  Firms with codes 2412, 2421
- Machinery (Manufacture of machinery and equipment n.e.c.)
  Firms with codes 2921, 2925

Agribusiness wholesale and storage

- Wholesale trade
  Firms with codes 5121, 5122
- Warehousing (Supporting and auxiliary transport activities; activities of travel agencies)
  Firms with codes 6302

Agribusiness processing

- Food (Manufacture of food products and beverages)
  All firms with codes with first two digits 15
- Tobacco (Manufacture of tobacco products)
  All firms with codes with first two digits 16
- Leather (Tanning and dressing of leather, manufacture of luggage, handbags, saddlery, harness and footwear)
  Firms with codes 1911
- Wood (Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials)
  All firms with codes with first two digits 20

A.2. Cobb Douglas production function

Table A1: Cobb Douglas Production function

	Production function (I)	Production function P&P IV (R&D) (II)	Production function P&P IV(RI) (III)
(Intercept)	-0.40	-0.23	-0.23
	(0.27)	(0.29)	(0.29)
Capital cost	0.05	0.06^{*}	0.06^{*}
	(0.03)	(0.03)	(0.03)
Labour cost	0.49^{***}	0.50^{***}	0.50^{***}
	(0.09)	(0.09)	(0.09)
Inputs cost	0.42^{***}	0.42^{***}	0.42^{***}
	(0.05)	(0.05)	(0.05)
Security cost	0.08^{*}	0.08	0.08
	(0.05)	(0.05)	(0.05)
Capital-dummy	-0.18	-0.25	-0.25
	(0.15)	(0.16)	(0.16)
Inputs-dummy	-1.00^{***}	-1.12^{***}	-1.12^{***}
	(0.34)	(0.38)	(0.38)
Security cost-dummy	-0.49^{**}	-0.54^{**}	-0.54^{**}
	(0.21)	(0.22)	(0.22)
P&P Innovation = yes	0.05	-0.25	-0.25
	(0.11)	(0.32)	(0.30)
Property crime = yes	-0.13	-0.12	-0.12
	(0.12)	(0.13)	(0.13)
Insecurity- moderate	0.18	0.19	0.19
	(0.14)	(0.14)	(0.14)
Insecurity- major	0.27^{*}	0.28^{*}	0.28^{*}
	(0.14)	(0.15)	(0.15)
Agri-wholesale	1.77^{***}	1.76^{***}	1.76^{***}
	(0.24)	(0.24)	(0.24)
Agri-inputs	0.15	0.14	0.14
	(0.12)	(0.12)	(0.12)
Firm-Medium	0.27	0.31^{*}	0.31^{*}
	(0.17)	(0.18)	(0.18)
Firm-Large	0.38	0.45	0.45
	(0.28)	(0.31)	(0.31)
Year dummy	0.33^{***}	0.32^{***}	0.32^{***}
	(0.11)	(0.12)	(0.12)
R^2	0.92	0.91	0.91
Adj. R^2	0.91	0.91	0.91
Num. obs.	202	202	202
Weak instruments		39.01	47.54
P-value		0.00	0.00
Wu-Hausman		1.09	1.23
P-value.		0.30	0.27

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$