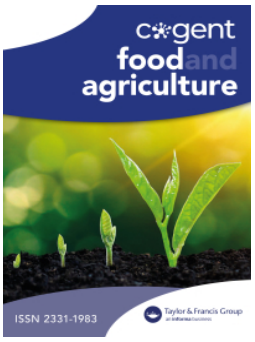


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# Technology access without impact? An evaluation of Ecuador's input subsidy program for rice

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**ABSTRACT**
In many developing economies, agricultural input subsidies are increasingly delivered through public-private partnerships (PPPs), yet rigorous impact evaluations remain scarce, especially in Latin America. This study assesses Ecuador's Agricultural Input Kit (KIA) program, which distributed over 1 million subsidized packages of certified seeds, fertilizers, and agrochemicals to improve rice productivity and reduce production costs. The analysis draws on household survey data collected in two waves (2014/2015 and 2019/2020), conducted under institutional ethical approval, with written informed consent obtained in person from all participants. We estimate causal effects on adoption, yields, and costs using a Difference-in-Differences (DiD) approach with Propensity Score Matching (PSM). Results show a 37% increase in improved variety adoption among large farms, but no significant yield effects and an 18% decline in adoption among smallholders. These heterogeneous impacts reflect persistent constraints, including credit inaccessibility, a lack of irrigation, and weak extension systems. This study contributes to the limited evidence on input subsidy programs in Latin America's rice sector and offers two key insights: first, PPPs require better targeting and integration with financial tools like microcredit; second, support services must be tailored to the structural barriers facing smallholder farmers to achieve equitable productivity gains.

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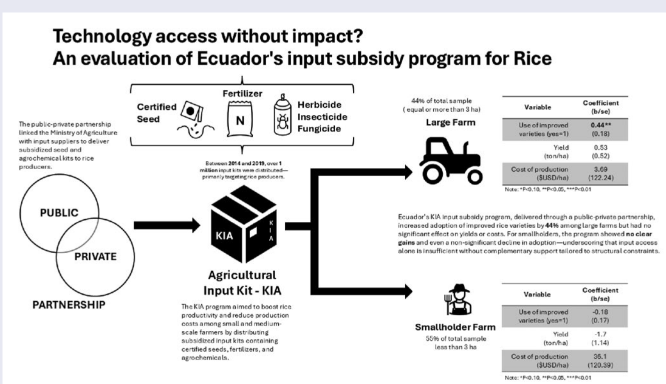
Agriculture & Environmental Sciences; Agricultural Economics; Economics and Development

**GRAPHICAL ABSTRACT**




## 1. Introduction

The effectiveness of agricultural public policies hinges on their capacity to balance economic efficiency with equity. Public-private partnerships (PPPs), increasingly promoted as vehicles for agricultural innovation, often face challenges in aligning private commercial incentives with public development goals

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(Barrett et al., 2022; Klerkx et al., 2019). These misalignments can lead to suboptimal resource allocation that favors large-scale producers, exacerbating inequalities and leaving smallholder farmers underserved (Domínguez et al., 2025; Liverpool-Tasie et al., 2020; Reardon et al., 2020; Spielman et al., 2025). Weak oversight mechanisms and inadequate targeting strategies often reinforce these disparities, particularly in contexts where governance structures lack transparency and accountability (Jayne et al., 2019).

A key area where such inefficiencies manifest is in the adoption of agricultural technologies. While technological innovation is vital to improving productivity, resilience, and rural welfare, the literature identifies persistent barriers to adoption, especially among smallholders. These include high upfront costs, liquidity constraints, limited access to credit and extension services, and risk aversion (Feder, Just & Zilberman, 1985; Glover et al., 2019). Structural challenges such as asymmetric information and underdeveloped input markets further hinder the diffusion of improved technologies (Anderson & Feder, 2004; Doss, 2006). Although these constraints are well documented, empirical evidence on how to overcome them through well-designed policy interventions, particularly in specific commodity contexts, remains limited (Liu et al., 2024).

The rice sector illustrates these challenges acutely. Rice is a staple and policy priority, vulnerable to climate shocks (e.g. El Niño floods) and shaped by stabilizing interventions (FAO, 2024; USDA FAS, 2025). In Ecuador, rice provides 15% of daily caloric intake and sustains around 65% of smallholder households (FAO, 2019a; Marin et al., 2021). Production is concentrated in the coastal provinces of Guayas, Los Ríos, and Manabí, yet average yields have stagnated at 4.3 t/ha, well below neighbouring countries like Peru (7.7 t/ha), and are increasingly vulnerable to climate shocks (Banco Central del Ecuador, 2021).

Despite the availability of improved seed varieties and production technologies, adoption remains uneven and particularly low among smallholders due to structural barriers, including limited access to finance and weak institutional support (Martínez et al., 2023; Minten & Barrett, 2008).

In response, the Ecuadorian Ministry of Agriculture launched the Kit de Insumos Agrícolas (KIA) program, a large-scale PPP aimed at enhancing rice productivity through the distribution of subsidized technological packages, consisting of certified seeds, fertilizers, and agrochemicals, delivered via a network of Integrated Technological Systems. Between 2014 and 2019, over one million kits were distributed. The program's stated objective was to reduce production costs and improve yields among small and medium-scale rice farmers. While initial assessments suggest some positive results, they largely rely on descriptive statistics (e.g. Pino et al., 2018) or implementation reports without controlling for selection bias. Other policy evaluations in the Ecuadorian rice sector, such as Bonilla Bolaños and Singaña Tapia (2019) on PSAR, Díaz González and Morales-Opazo (2020) on Plan Semillas and Plaza et al. (2022) on intensive systems, offer useful context but do not focus on KIA, leaving its causal effects untested.

The KIA program targeted registered small and medium-scale rice producers, and kits were allocated on a per-farm basis rather than per household. Each kit was designed to cover the input requirements for one hectare of rice cultivation. Farmers cultivating less than one hectare could still receive a kit; however, the package was not proportionally downsized, suggesting a potential over-provision of inputs for smaller plots. Eligibility required registration in the National Agricultural Registry, possession of a valid national identification card, and formal acceptance of MAG program conditions, including in certain phases mandatory commercialization through the National Storage Unit (UNA EP). As a result, KIA primarily reached formally registered producers and may have excluded more informal or subsistence-oriented smallholders.

This study addresses this gap by conducting an impact evaluation of the KIA program using a Difference-in-Differences (DiD) estimator combined with Propensity Score Matching (PSM). This quasi-experimental strategy allows us to estimate the association between program participation and key outcomes, including technology adoption, productivity, and production costs, by comparing beneficiary and non-beneficiary farmers before and after program implementation, while mitigating confounding due to selection bias. While this approach improves internal validity, the results should be interpreted as suggestive rather than definitive causal effects, given the observational nature of the data.

Our contribution is threefold. First, we expand the empirical literature on agricultural input subsidies in Latin America, where rigorous impact evaluations, particularly in the rice sector, remain sparse relative to those in Africa and Asia (Martínez et al., 2023; Mishra et al., 2022; Yerovi & De Salvo, 2018). Second, we illustrate the usefulness of combining DiD with PSM to generate policy-relevant insights under non-experimental conditions (Abadie & Cattaneo, 2018; Heckman et al., 1997; Imbens & Wooldridge, 2009). Third, we shed light on the performance of PPPs in promoting inclusive agricultural transformation, showing that without tailored design and implementation, such programs may reinforce rather than alleviate existing inequalities in access and outcomes.

## 2. Context and background

### 2.1. Rice production in Ecuador

Rice is one of the world's most widely consumed staple foods, playing a fundamental role in food security and rural economies (Calpe, 2006; FAO, 2004). In Ecuador, it is the most consumed plant-based food, contributing 15% of the average caloric intake per capita and serving as a dietary staple for approximately 17 million people (Espinosa, 2021; FAO, 2019a). The coastal region relies particularly on rice, making it an essential component of local diets.

From an agricultural perspective, rice is a key economic driver. In 2018, rice cultivation accounted for 12.7% of Ecuador's total agricultural land, and when considering only temporary crops, it represented 37% of the cultivated area (Andrade et al., 2021). Production is highly concentrated in the coastal provinces of Guayas, Los Ríos, and Manabí, which together account for 98% of the national output (Andrade et al., 2021; Orrego-Varón et al., 2016).

Despite its significance, rice productivity has stagnated over the past two decades. While historical improvements saw yields increase from 2.2 tons per hectare (t/ha) in the 1960s to 4.1 t/ha in recent years, the national average has remained at approximately 4.3 t/ha since the early 2000s (ESPAC, 2019; MAG, 2022; Orrego-Varón et al., 2016). This figure is below the global average of 4.7 t/ha and the regional average of 4.9 t/ha. Moreover, the gap is wider when compared to Colombia (5.7 t/ha) and Peru (7.7 t/ha) in 2019 (FAO, 2019b).

Ecuador's rice sector faces multiple structural challenges that hinder productivity growth. Limited access to credit restricts farmers from investing in quality inputs and mechanization, while weak extension services hinder the dissemination of best agronomic practices. Market inefficiencies, including price volatility and inadequate storage and distribution infrastructure, further discourage investment and reduce profitability. Additionally, climate variability and environmental concerns, such as greenhouse gas emissions from rice paddies, pose long-term sustainability risks (FAO, 2015; Vinci et al, 2023).

The total area under rice cultivation has declined significantly in recent years. Between 2015 and 2019, the planted area shrank by nearly one-third, as farmers shifted to hard maize, a crop perceived as more resilient to climate variability (Banco Central del Ecuador, 2019). Extreme weather events, such as El Niño and La Niña, have exacerbated this decline by causing floods and prolonged droughts, directly impacting yields. Additionally, falling rice prices in 2018 discouraged farmers from planting rice, further accelerating this transition (Banco Central del Ecuador, 2019).

Despite these challenges, technological advancements and sustainable practices offer potential solutions. Between 2013 and 2019, rice productivity increased by 43.5% in certain regions, driven by optimized planting densities, reduced environmentally harmful practices, and the adoption of high-yielding rice varieties (FAO, 2018). Research suggests that certified seeds and modern agrochemicals can further push yields to 4.8 t/ha. However, adoption remains uneven, as 65% of Ecuador's rice producers are smallholders with limited financial resources and restricted access to innovation (Alarcón & Lema, 2023; Marin et al., 2021).

### 2.2. Public-private partnerships and agricultural innovation

Overcoming productivity constraints in Ecuador's rice sector requires coordinated efforts between public and private sector actors. Public-private partnerships (PPPs) have emerged as a mechanism for developing and disseminating improved rice varieties, strengthening market links, and enhancing agronomic management practices. These collaborations are critical in addressing barriers such as limited credit access, weak extension services, and climate-induced risks, which continue to hinder growth in the sector.

A transformation in Ecuador's rice sector has been the rapid adoption of improved rice varieties. Marín et al. (2021) document a shift from SENACA FL 09 (SFL 09) to SENACA FL 11 (SFL 11) between 2014 and 2019. Initially, SFL 09 covered 31% of the cultivated area, but by 2019, SFL 11 dominated with 61% due to its superior grain quality and higher market demand. The adoption of these varieties has been influenced by farm size, household characteristics, and gender dynamics in decision-making (Orrego-Varón et al., 2016).

Several actors have driven these advancements. The Latin American Fund for Irrigated Rice (FLAR) collaborated with PRONACA[1], a private agribusiness, to develop SFL 09 and SFL 11. Although PRONACA is no longer affiliated with FLAR, it retains royalties from certified seed sales. More recently, FLAR renewed its partnership with Ecuador's National Agricultural Research Institute (INIAP for its acronym in Spanish) to expand beyond varietal development and promote agronomic management and sustainable farming practices. AGRIPAC[2], a leading agribusiness firm, has also joined these efforts, securing exclusive access to FLAR germplasm for further seed development and commercialization.

### 2.3. The Kit de Insumos Agrícolas – KIA

The Agricultural Input Kit (KIA) program in Ecuador was implemented by the Ministry of Agriculture and Livestock (MAG for its acronym in Spanish) to support small-scale farmers, with a focus on rice producers. The program aimed to distribute one million subsidized farming kits to enhance productivity and sustainability among these farmers (MAG, 2020). By addressing input accessibility constraints, the KIA program sought to strengthen rice production and other selected crops like maize to improve farmer livelihoods.

Each KIA package was designed to provide a comprehensive set of inputs tailored to rice cultivation. The kits typically included certified high-yield rice seeds, various fertilizer types (DAP, muriate of potash, urea, and ammonium sulfate), herbicides, insecticides, and fungicides. These inputs were calibrated to meet the production requirements of one hectare of rice, ensuring that participating farmers had access to essential resources for optimal crop management. However, kits were designed between private firms and MAG representatives, without considering INIAP's researchers missing a piece of the puzzle to align kits objectives to be profitable and technically research efficient.

Also, distribution was facilitated through MAG's national programs, and the implementation process included technical assistance and follow-up support to help farmers correctly apply the inputs and adopt best agronomic practices. This support was essential to support farmers into using and applying correctly the subsidized inputs. Nonetheless, to be eligible for the KIA program, farmers had to meet specific requirements, including registration in the National Agricultural Registry, the presentation of a valid national identification card, and acceptance of the program's terms as defined by MAG. Additionally, in certain phases of the program, beneficiaries were required to sell their harvested rice to the National Storage Unit (UNA EP), a government entity responsible for input distribution and post-harvest commercialization (MAG, 2022). This has made it difficult to track KIA kits dissemination and biased farmers eligibility.

The KIA initiative was part of broader national strategies to improve food security, boost agricultural productivity, and strengthen farmer resilience against market fluctuations and climate variability. However, like many agricultural subsidy programs, it faced challenges related to logistical coordination, farmer participation, and long-term financial sustainability (MAG, 2022). While no specific impact evaluations of KIA have been identified, studies on similar programs in Latin America suggest mixed results. For instance, research on Argentina's Rural Development and Family Farming Program (PRODAF) found that targeted agricultural subsidies can enhance farm productivity when combined with adequate technical assistance (Schling & Pazos, 2022). These findings highlight that the success of initiatives like KIA largely depends on their design, implementation, and ability to address structural challenges.

## 3. Materials and methods

### 3.1. Study design and data collection

This study employs a quasi-experimental panel data design to evaluate the impact of the Kit de Insumos Agrícolas (KIA) program on the adoption of improved rice varieties and agronomic practices in Ecuador.

The analysis is based on household survey data collected in two phases, corresponding to the 2014/2015 and 2019/2020 agricultural campaigns with their corresponding ethical review and farmers informed consent provided in person by each farmer interviewed.

The first phase (2014/2015) was conducted in collaboration between International Center for Tropical Agriculture (currently Alliance Bioversity-CIAT) and the National Institute of Agricultural Research (INIAP) (Marin et al., 2018). The sample consisted of 1,028 rice producers from Guayas, Los Ríos, Manabí, and El Oro, selected through a random sampling method. Data were collected in two production cycles: November–December 2014 (second cycle) and March–April 2015 (third cycle). This baseline dataset provided a detailed characterization of rice production practices, input use, and household characteristics.

The sampling strategy was designed to ensure representativeness across the main rice-producing regions of Ecuador. The sampling frame was defined using official agricultural statistics and expert knowledge from INIAP to identify the primary rice-producing provinces (Guayas, Los Ríos, Manabí, and El Oro). Within each province, cantons were selected to capture the diversity of production systems, and farmers were randomly selected within these strata.

Rice production in Ecuador is geographically concentrated d in coastal provinces, with Guayas and Los Ríos as the main producing regions and Manabí and El Oro consistently among the country's core rice-growing areas (Marin et al., 2018; Portalanza et al., 2022). Official ESPAC statistics confirm that these provinces account for most of the national rice production and harvested areas (ESPAC, 2024), supporting the external validity of the sampling frame.

The second phase (2019/2020) aimed to assess changes in cultivation practices, technology adoption, and productivity, leveraging the Ministry of Agriculture and Livestock (MAG)'s quarterly yield estimation surveys. While the sampling methodology remained consistent, satellite imagery replaced traditional statistical reports to define primary rice-producing areas, improving geographic precision but limiting the construction of a fully comparable panel dataset.

In the follow-up survey, the sampling strategy maintained consistency in geographic coverage, but satellite imagery and updated administrative data were used to identify active rice-producing areas, improving spatial targeting. Enumerators followed a structured sampling protocol to locate and re-interview baseline households when possible, and to identify additional farmers within the same production zones when necessary. This approach ensured continuity of the sample while adapting to changes in production patterns.

In both survey rounds (2014/2015 and 2019/2020), enumerators obtained verbal informed consent from all participants prior to conducting the interviews. A standardized script, explaining the voluntary nature of the study, confidentiality, and the right to withdraw at any time, was read aloud and programmed directly into the CSEntry CSPro application. Once participants confirmed their understanding and willingness to participate, enumerators recorded written consent within the software. This verbal consent procedure was approved by the Institutional Review Board (IRB) of the International Center for Tropical Agriculture (CIAT), under approval number #2019-IRB15, and adhered to ethical standards for research involving human participants, this research fully complies with the ethical principles outlined in the Declaration of Helsinki.

The questionnaire was administered digitally using CSEntry CSPro, and structured into three main sections covering 17 modules to ensure comparability with the 2014–2015 survey while integrating necessary adjustments for impact assessment. The survey collected socio-demographic information, including household composition, education, employment, and income. Additionally, it gathered detailed data on agricultural production, covering land use, crop management, input use, and adoption of improved rice varieties and agronomic practices.

A total of 612 households were surveyed across 25 cantons in five provinces (Guayas, Los Ríos, Manabí, El Oro, and Loja), covering 99% of Ecuador's harvested rice area (ESPAC, 2019). To ensure panel data consistency, only farmers who cultivated rice during the second production cycle (July–December 2019)[3] were included, reducing the 2014/2015 sample from 1,028 to 439 panel producers. The final panel dataset comprised 312 farmers, while households from the 2014 sample lost in 2019 were classified as attrition cases (Table 1).

Of the 1,028 farmers surveyed in 2014/2015, 439 were eligible for panel construction in 2019 based on continued rice cultivation. Among these, 312 farmers were successfully re-interviewed in 2019/2020,

**Table 1.** Distribution of surveyed households in 2014–2015 and 2019.

| Province | Baseline households (2014–2015) | Data-2019 | |
|---|---|---|---|
| | | Panel households | New households |
| Guayas | 735 | 198 | 185 |
| Los Ríos | 221 | 56 | 56 |
| Manabí | 48 | 45 | 1 |
| El Oro | 24 | 13 | 0 |
| Loja | 0 | 0 | 57 |
| **Total** | **1,028** | **312** | **299** |
| **Total cultivated area (Ha)** | **3,548** | **3,151** | |

yielding a panel retention rate of 71.1% and an attrition rate of 28.9%. Attrition was primarily driven by crop switching, permanent migration out of rice production, and temporary unavailability during fieldwork.

### 3.2. Estimation strategy

Given the non-random assignment of the KIA program, direct comparisons between beneficiaries and non-beneficiaries are likely to yield biased estimates due to selection effects. Farmers who participate in the program may differ systematically from those who do not, both in observable and unobservable characteristics, such as farm size, access to inputs, or managerial ability.

To address this challenge, this study adopts a combined Propensity Score Matching (PSM) and Difference-in-Differences (DiD) approach. This quasi-experimental strategy is particularly suited for observational panel data settings where treatment is not randomly assigned, but longitudinal information is available. Rather than estimating a purely causal effect, this approach aims to identify the association between program participation and key production outcomes under a set of identifying assumptions.

The use of PSM allows the construction of a comparison group that is similar to treated farmers in terms of observable baseline characteristics, thereby reducing selection bias arising from observable differences (Caliendo & Kopeinig, 2008; Khandker et al., 2010; White & Raitzer, 2017). In turn, the DiD estimator exploits within-farmer variation over time to control for time-invariant unobserved heterogeneity between treated and control groups, under the assumption of parallel trends.

The combination of matching and DiD follows a two-step semi-parametric identification strategy widely used in non-experimental impact evaluations. In the first step, matching is used to restrict the sample to a region of common support, improving comparability between treated and control units. In the second step, DiD differences out time-invariant unobserved factors that may affect both treatment participation and outcomes. This approach is consistent with the framework proposed by Heckman et al. (1997) and further developed by Abadie (2005) and Abadie and Imbens (2006), and has been widely adopted in agricultural and development economics (Imbens and Wooldridge, 2009; Stuart, 2010; Wooldridge, 2010). While this strategy cannot fully eliminate bias arising from time-varying unobservables, it substantially improves the credibility of the estimates relative to simple cross-sectional comparisons. The estimation process follows three key steps. First, a binary logit model is estimated to determine the probability of program participation, where the dependent variable equals 1 for KIA beneficiaries (treated group) and 0 for non-beneficiaries (control group). This model is specified as a function of relevant baseline covariates and is used to generate propensity scores (PSs).

Second, PSM procedures are applied to construct a matched sample where treatment and control units have similar observable characteristics at baseline, ensuring comparability (except for program participation), and satisfying the common support and balancing conditions. Observations outside the region of common support are excluded and trimming procedures are applied to reduce potential extrapolation bias.

Third, the matched treatment and control samples are used to estimate a DiD model using panel data from the 2014/2015 baseline and 2019/2020 endline surveys. The DiD framework exploits temporal variation by comparing changes over time in key outcomes (e.g. yield, production costs) between farmers who participated in the KIA program (treatment group) and those who did not (control group). The model specification is as follows:

$$Y_{it} = \alpha + \delta\left(KIT_i * Post_{it}\right) + \gamma\, Post_{it} + X_{it}^{'}\theta + \mu_i + \epsilon_{it} \qquad \text{(equation 1)}$$

$Y_{it}$ represents the outcome variable for the farmer $i$ at time $t$, which captures the key indicators affected by the KIA program. $KIT_i$ is a binary treatment indicator, taking the value 1 if the farmer participated in the KIA program (treatment group) and 0 otherwise (control group), and $Post_{it}$ is a time dummy equal to one for the post-intervention period (2019/2020). The coefficient $\delta$ on the interaction term $KIT_i * Post_{it}$ identifies the average treatment effect on the treated. $t$.

The model includes farmer fixed effects, which control for time-invariant unobserved heterogeneity, and a common post-period effect capturing aggregate shocks affecting all farmers. We additionally allow for time-varying controls ($X_{it}$) when available (e.g. changes in access to services or farm-level shocks) to improve estimation precision. Baseline covariates ($X_{i0}$) are used to construct propensity scores for matching, but they are not included separately in the fixed-effects DiD specification because time-invariant regressors are absorbed by the farmer fixed effects. Finally, $\epsilon_{it}$ is the idiosyncratic error term, capturing unobserved factors affecting the outcome variable.

## 4. Results

To support causal identification, we first describe baseline comparability and matching quality, then report average program impacts, and finally present heterogeneity by farm size. To construct the counterfactual, we estimate a logit participation model at baseline (beneficiary = 1; non-beneficiary = 0) to generate propensity scores (PS), which are then used for matching.

Table 2 presents the logit model estimates. The results indicate that farmers using certified seeds were significantly more likely to participate in the KIA program, underscoring the program's emphasis on promoting improved seed adoption. Access to agricultural training also exhibited a strong positive association with participation, suggesting that prior exposure to extension services increased the likelihood of enrollment. Other factors, such as household head gender and membership in social organizations, showed positive but statistically insignificant correlations with participation. Notably, access to credit was not a significant determinant, indicating that financial constraints alone did not drive enrollment decisions. Additionally, regional disparities in participation suggest differences in program outreach and accessibility. These findings underscore the need to control baseline differences when estimating program impacts.

To assess the validity of the constructed counterfactual, we examine covariate balance before and after matching. Table 3 reports the standardized differences and variance ratios for key baseline variables.

**Table 2.** Logit model estimates for KIA sample selection using baseline DATA.

| Variable definition | Logit coefficients (b/se) | Marginal effects (b/se) |
|---|---|---|
| Own rice area (Ha) | −0.013 (0.028) | −0.002 (0.004) |
| HH head gender (Male = 1) | 0.767 (0.54) | 0.098 (0.068) |
| Social organizations (producer association, cooperative, etc.) (Yes = 1) | 0.55 (0.39) | 0.07 (0.049) |
| Irrigation system (Yes = 1) | 0.621 (0.744) | 0.079 (0.095) |
| Land tenure (Own = 1) | 0.206 (0.367) | 0.026 (0.047) |
| Certified seed (Yes = 1) | **3.121*** (0.386) | **0.400*** (0.025) |
| Sown density (kg/ha) | −0.004 (0.005) | 0 (0.001) |
| Yield (Ton/ha) | 0.012 (0.093) | 0.002 (0.012) |
| Access to credit (Yes = 1) | −0.19 (0.352) | −0.024 (0.045) |
| Access to training (Yes = 1) | **1.150*** (0.354) | **0.147*** (0.044) |
| Rice Cost Production ($USD/Ha) | −0.001 (0.001) | 0 (0) |
| Number of household members older than 15 years | −0.069 (0.123) | −0.009 (0.016) |
| Province_GUAYAS (Yes = 1) | 0 (.) | 0 (.) |
| Province_LOS RIOS (Yes = 1) | 0.143 (0.427) | 0.019 (0.058) |
| Province_MANABI (Yes = 1) | 0.970 (0.551) | 0.130 (0.078) |
| Province_EL ORO (Yes = 1) | 0.102 (0.958) | 0.014 (0.131) |
| Use of Improved Modern Varieties (Yes = 1) | −0.085 (0.351) | −0.011 (0.045) |
| **Observations** | **299** | |

*Note.* $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

**Table 3.** Covariate balance summary before and after matching.

| Covariate | Standardized difference (raw) | Standardized difference (matched) | Variance ratio (raw) | Variance ratio (matched) |
|---|---|---|---|---|
| Gender (Male = 1) | 0.361 | 0.000 | 0.933 | 1.000 |
| Land Tenure (Own = 1) | −0.092 | −0.132 | 1.071 | 1.106 |
| Member of Organization | 0.357 | −0.020 | 0.821 | 1.020 |
| Uses Certified Seeds | 1.596 | 0.000 | 0.676 | 1.000 |
| Received Training | 0.614 | 0.000 | 0.983 | 1.000 |

*Note*. Standardized differences above 0.25 or variance ratios outside [0.8, 1.25] indicate imbalance (Rosenbaum & Rubin, 1985). After matching, all covariates show acceptable balance.

**Table 4.** Impact estimates of the KIA program: difference-in-differences with Propensity Score matching.

| Variable | Coefficients (b/se) |
|---|---|
| **Adoption of Improved varieties** | |
| Use of Improved Modern Varieties (Yes = 1) | 0.15 (0.11) |
| Use of Improved Modern Varieties _FLAR (Yes = 1) | 0.17 (0.12) |
| Use of Improved Modern Varieties _FLAR _only with SFL09 (Yes = 1) | 0.01 (0.08) |
| Use of Improved Modern Varieties _FLAR _only with SFL011 (Yes = 1) | **0.18**** (0.09) |
| Use of Improved Modern Varieties _INIAP _only with INIAP14 (Yes = 1) | −0.17 (0.11) |
| Observations | 312 |
| **Yield and Production Costs** | |
| Yield (Ton/ha) | −0.82 (0.55) |
| Observations | 254 |
| Rice Cost Production ($USD/Ha) | 63.27 (90.87) |
| Observations | 309 |

*Note*. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Before matching, imbalances were observed, particularly in institutional and technology-related variables, particularly certified seed use and access to training. Matching substantially improves balance for these key access-related covariates, reducing standardized differences to near zero and bringing variance ratios close to unity. Some baseline productivity and regional variables, however, remain partially imbalanced after matching. These residual differences are explicitly addressed in the impact analysis using farmer fixed effects within the difference-in-differences framework, which controls for time-invariant unobserved heterogeneity and helps strengthen the credibility of the identification strategy.

To estimate the program's impact, we implement a Difference-in-Differences (DiD) model with Propensity Score Matching (PSM) to account for selection bias. Table 4 presents the DiD-PSM estimates, which suggest heterogeneous associations with the adoption of improved rice varieties. The use of modern varieties (VPP) showed a positive change in some specifications and a negative change in others (reported as percentage-point differences), indicating heterogeneous adoption patterns. Similarly, the adoption of FLAR varieties followed a comparable trend, with a positive effect in some instances but also a negative association, suggesting that some farmers faced adoption barriers. Among specific varieties, SFL011 is associated with a statistically significant increase in adoption, whereas INIAP14 is associated with a negative change in adoption.

The program's effect on productivity and costs was also assessed using the Difference-in-Differences (DiD) and Propensity Score Matching (PSM) frameworks. Table 4 shows that, on average, the yield are estimated to decline, with some cases experiencing a slightly less negative effect. This pattern may reflect that, despite adopting improved varieties, farmers may face constraints in achieving expected yield gains due to inadequate complementary inputs, environmental constraints, or suboptimal agronomic practices. Regarding production costs, Table 4 reveals an estimated increase in total cost per hectare to $63.27, with substantial variability. While improved varieties may offer potential productivity benefits, their adoption appears to require higher input requirements, which could impose financial burdens on some farmers.

To validate the baseline DiD–PSM results, we conducted a comprehensive set of robustness checks varying both the identification strategy and matching assumptions. Specifically, we estimated: (i) DiD models in changes without controls, (ii) DiD models controlling for baseline covariates, (iii) PSM–DiD using nearest-neighbor matching (NN = 1 and NN = 2), and (iv) PSM–DiD with caliper restrictions (0.05 and 0.10). Across all specifications, the main program effect remains remarkably stable: participation in KIA consistently increases adoption of the FLAR SFL011 improved variety by approximately 17–19 percentage points, while no statistically significant effects are detected for yields or total production costs. These results, reported in Supplementary Appendix Tables A1–A6, are robust to alternative matching algorithms and model specifications, providing a consistent basis for the subsequent heterogeneity analysis.

### 4.1. Heterogeneous effects by farm size

The impact of the KIA program varied significantly by farm size (Table 5). The adoption of modern varieties (VPP) was higher among large farms, while small farms are associated with a negative change (−0.18), suggesting that larger producers may be better positioned to integrate new technologies. A similar pattern was observed for FLAR varieties, with positive adoption among large farms but a negative effect for small farms, indicating that economies of scale may facilitateadoption. The pattern is consistent with differences in input complementarity and scale.

Regarding productivity and costs, Table 5 shows that small farms experience a significant decline in yield, whereas large farms exhibit a slight but statistically insignificant increase in yield. This pattern is consistent with the hypothesis that small farms face greater constraints in optimizing productivity gains, possibly due to limited access to fertilizers, irrigation, or mechanization. In terms of costs, Table 4 indicates that production costs are higher for small farms compared to large farms, reinforcing the presence of economies of scale. Cost variability was also notable, reflecting differences in production structures and input cost fluctuations. The higher cost burden for small farms may limit their ability to fully capitalize on the benefits of improved varieties, underscoring the need for targeted support mechanisms.

Overall, these findings highlight that while the KIA program facilitated access to improved rice varieties, the results suggest that its effects are heterogeneous across farm sizes. Larger farms appear to be better positioned to adopt and benefit from modern varieties, whereas small farms may face significant constraints, particularly in terms of production costs and yield performance.

## 5. Discussion, policy implications and future directions

This study assessed the effectiveness of Ecuador's Agricultural Input Kit (KIA) program, a large-scale public-private partnership designed to improve productivity through subsidized input packages. While the program achieved high rates of improved seed adoption among large-scale producers, its overall impact on productivity and cost reduction was limited. Yield gains were statistically insignificant, and smallholder farmers, who represent a critical target group, saw declines in adoption. These results suggest potential structural limitations of input subsidy programs when implemented in isolation from complementary services and institutional support.

**Table 5.** Impact estimates of the KIA program: difference-in-differences with Propensity Score matching by farm size.

| Variable | Coefficients (b/se) | |
|---|---|---|
| | Small farms | Large farms |
| **Adoption of Improved varieties** | | |
| Use of Improved Modern Varieties (Yes = 1) | −0.18 (0.17) | **0.44**** (0.18) |
| Use of Improved Modern Varieties _FLAR (Yes = 1) | −0.15 (0.14) | **0.40**** (0.17) |
| Use of Improved Modern Varieties _FLAR _only with SFL09 (Yes = 1) | −0.01 (0.07) | 0.04 (0.14) |
| Use of Improved Modern Varieties _FLAR _only with SFL011 (Yes = 1) | −0.13 (0.14) | **0.37***** (0.14) |
| Use of Improved Modern Varieties _INIAP _only with INIAP14 (Yes = 1) | 0.19 (0.17) | **−0.36**** (0.15) |
| Observations | 139 | 173 |
| **Yield and Production Costs** | | |
| Yield (Ton/ha) | −1.7 (1.14) | 0.53 (0.52) |
| Observations | 124 | 130 |
| Rice Cost Production ($USD/Ha) | 36.1 (120.39) | 3.69 (122.24) |
| Observations | 137 | 172 |

*Note.* *$p<0.10$; **$p<0.05$; ***$p<0.01$, small farms are those with less than 3 ha of rice planted, while large farms are those with more or equal than 3 ha planted.

The findings resonate with a broad body of literature that cautions against overreliance on input subsidies as a mechanism for agricultural transformation. Feder et al. (1985) and subsequent evaluations across Sub-Saharan Africa and Latin America (Jayne & Rashid, 2013; Ricker-Gilbert et al., 2013) demonstrate that input use efficiency, and the returns to adoption, depend critically on access to irrigation, technical assistance, input markets, and finance. In Ecuador's case, while high-quality seeds were made available through the KIA program, many smallholders lacked the complementary infrastructure and institutional support required to achieve productivity gains. This underscores a potential limitation in the program's design: the assumption that input access alone is sufficient to catalyze technology adoption and generate impact across heterogeneous farming systems.

Moreover, the study reveals pronounced heterogeneity by farm size. Larger farms were significantly more likely to adopt the promoted seed varieties and report benefits. These producers typically have greater access to working capital, information, and physical assets, which allow them to complement the subsidized packages with necessary inputs and practices. In contrast, smaller farms, often operate under credit constraints and without access to extension services, struggled to use the inputs effectively, resulting in both lower adoption rates and limited productivity improvements. This pattern is consistent with long-standing critiques of untargeted agricultural subsidy schemes, which tend to reinforce structural inequalities unless accompanied by specific design features that prioritize equity (Mason et al., 2017; Morris, 2007).

Recent evidence indicates that input-subsidy initiatives often succeed in raising adoption but produce uneven productivity gains where complementary constraints persist (Arouna et al., 2021; Mason & Ricker-Gilbert, 2013). Larger farms typically capture more benefits because they can pair improved seed with fertilizer, irrigation, and advisory services (Han et al., 2023; Ragasa & Mazunda, 2018); smallholders are more likely to face binding liquidity and information constraints, limiting returns to adoption (Sheahan & Barrett, 2017; van Asseldonk et al., 2023). These patterns are consistent with studies showing that adoption alone rarely translates into yield gains without access to full support bundles, and with evaluations of 'smart' subsidy programs that document mixed productivity effects when complements are weak (Karata, 2024). Overall, scale and organizational advantages may help explain farm-size heterogeneity in outcomes, thereby strengthening the case for bundling subsidies with finance, extension, and more targeted approaches.

Interestingly, credit access did not emerge as a significant predictor of program participation in our econometric models. However, this may reflect a deeper problem of liquidity constraints and financial exclusion rather than the irrelevance of credit per se. Prior research demonstrates that access to financial services, such as microcredit, input financing, or crop insurance, is crucial for enabling smallholders to take advantage of subsidized input programs (Hess et al., 2016; Karlan et al., 2014). Without access to working capital or mechanisms to mitigate production risk, smallholders are unable to invest in the full set of complementary inputs needed to make improved seeds productive.

These findings suggest several implications for policy and program design. First, input subsidies should be complemented with agronomic support services, including extension, irrigation infrastructure, and timely input delivery. Studies consistently show that the productivity impact of subsidized seeds tends to increase when paired with these supports (Glover et al., 2019; Ricker-Gilbert et al., 2013). Second, improving financial inclusion must be a core component of public-private agricultural interventions. Bundling input packages with tailored financial instruments, such as weather-indexed insurance, value-chain financing, or digital microcredit, could enable smallholders to overcome liquidity constraints and de-risk technology adoption (Castro et al., 2023; Karlan et al., 2014). Third, more precise targeting mechanisms are needed to ensure that programming resources reach the most constrained and vulnerable farmers. The use of geospatial targeting, digital beneficiary registries, and eligibility criteria based on need rather than convenience would enhance both equity and efficiency (Chirwa & Dorward, 2013; Mason et al., 2017).

Finally, this study contributes to the broader literature on the evaluation of agricultural public-private partnerships by applying a quasi-experimental design in a Latin American context, where rigorous evaluations remain relatively scarce compared to Africa or Asia. Despite its contributions, the study faces several limitations that merit discussion. First, while propensity score matching reduces observable bias, it cannot control unobserved heterogeneity such as farmer motivation, risk preferences, or localized climatic shocks. Therefore, the results should be interpreted as suggestive associations rather than definitive causal effects. Second, between baseline and endline, the balanced panel declined from 1,028 to 312 farmers due to migration, farm exit, and non-response, raising concerns about potential selection bias, especially in underrepresented provinces.

To address these limitations, future research should aim to construct larger panel datasets across multiple agricultural cycles and integrate objective biophysical measurements, such as NDVI data from satellite imagery, for yield validation. Moreover, incorporating qualitative research methods could help uncover sociocultural and institutional factors that influence adoption decisions, which are not captured by quantitative survey instruments alone. Mixed-methods approaches would be particularly valuable in disentangling the mechanisms behind observed heterogeneity and in tailoring policy recommendations to diverse farming contexts.

In conclusion, Ecuador's KIA program exemplifies the potential and the limits of input-focused public-private partnerships. While the program appears to have succeeded in expanding access to improved technologies among better-resourced farmers, it shows limited evidence of inclusive and sustained productivity gains. For subsidy programs to deliver equitable agricultural transformation, they may need to be embedded in broader support systems that address farmers' financial, informational, and infrastructural constraints. Only then can such programs move from short-term input delivery to long-term development impact.

## Notes

1. PRONACA (Procesadora Nacional de Alimentos) is a leading Ecuadorian agribusiness company focused on food production, processing and distribution.
2. AGRIPAC is a major agricultural input supplier in Ecuador, specializing in seeds, fertilizers and agrochemicals.
3. A key limitation of the 2019 survey was the lack of harvest data during field visits, as data collection occurred before harvesting. To address this, telephone interviews reached 44% of surveyed farmers (138 producers). While this helped fill data gaps, it introduced constraints in yield analysis.

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## Ethical approval

All procedures involving human participants were conducted in accordance with the ethical standards of the institutional and national research committees and with the 1964 Declaration of Helsinki and its later amendments. The study protocol received ethical approval from the Institutional Review Board (IRB) of the International Center for Tropical Agriculture (CIAT), Palmira, Colombia (Approval No. 2019-IRB15). Enumerators obtained informed written consent within the software in person from each participant prior to data collection, following the procedures outlined and approved by the IRB. Participants were informed about the study objectives, the voluntary nature of participation, confidentiality of their responses, and their right to withdraw at any time without consequence.

## Author contributions

CRediT: **Alexander Buritica Casanova**: Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft; **Diego Armando Marin Salazar**: Data curation, Formal analysis, Investigation, Software, Visualization, Writing – review & editing; **Nicolas Fajardo Reyes**: Writing – review & editing; **Robert Andrade**: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

## Disclosure statement

The authors declare that there is no conflict of interest with respect to the research, authorship, and/or publication of this article. While the authors have collaborated with the Ministry of Agriculture and the National Institute of Agricultural and Livestock Research of Ecuador, they are employed by separate entities and have no financial or personal relationships that could have influenced the work reported in this paper.

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## Data availability statement

The data that support the findings of this study are publicly available and complementary information will be made available on reasonable request. The 2014 database was published in Data in Brief (https://doi.org/10.1016/j.dib.2018.04.019) and is available in Dataverse (https://doi.org/10.7910/DVN/DX3F4T) for download and access. The second database is available in Mendeley Data (https://doi.org/10.17632/xzycyvmks2.4) with the option to download. These repositories provide all necessary data for replication of our analysis and if complementary data is requested, we will make it available.

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