Outcomes of a Public Program to Support Sustainable Livestock Farming: Evidence from Uruguay

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Abstract

As global demand for beef increases, balancing livestock productivity with environmental sustainability has become a policy priority. In response, Uruguay implemented the Sustainable Family Production Program (PFIS) between 2015 and 2017, providing targeted support for small and medium-sized cattle farmers to invest in productivity-enhancing and climate-adaptive technologies. This study provides the first causal evaluation of a national program designed to promote these dual objectives in the cattle sector. Using a regression discontinuity design based on a strict eligibility threshold and panel data from 2015 to 2020, we evaluate the program's effect on five dimensions: (i) the adoption of technology and practices, (ii) engagement in producer organizations, (iii) reported cattle health problems, and (iv) beef production per hectare, and (v) greenhouse gas emissions intensity. The intervention significantly increased the application of reproductive and herd management practices, specifically early weaning, controlled mating, and ovarian activity diagnosis, without generating shifts in the other measured outcomes by the 2020 horizon. These results highlight both the potential and the limitations of integrated technology transfer programs in promoting sustainable intensification of extensive livestock systems. They also suggest the need for longer-term evaluations to capture potential effects on productivity and emissions that may emerge as these technologies, particularly reproductive ones, influence aggregate outcomes.

Keywords: Impact Evaluation; Livestock; Technology Adoption; Rural development; Carbon Footprint

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1. Introduction[5]

Global forecasts project a 10% rise in beef consumption by 2032 (OECD & FAO, 2023). Meeting this demand is challenging as livestock grazing, the world's dominant land use (Nin et al., 2019), faces growing environmental scrutiny (Steinfeld, 2006; Gerber et al., 2013, MacLeod et al., 2018), amid accelerating climate change and rising food prices.

In this context, the transition challenge is to raise livestock productivity and climate resilience while ensuring environmental and social sustainability, goals that can support economic growth, reduce environmental pressures, strengthen farm competitiveness, and advance broader goals related to food security and climate change mitigation (Aguirre et. al, 2024). Achieving these interconnected objectives requires identifying and implementing effective livestock policies and programs, guided by robust empirical evidence.

Although appropriate technologies and practices can boost productivity and support climate adaptation, many promising technologies fail to achieve widespread adoption despite substantial research investments. This adoption gap is particularly pronounced among small-scale producers in developing countries (de Janvry et al., 2017; López et al., 2017).

Adoption occurs within complex, evolving farm systems, where fluctuating economic conditions, institutional support, market access, and environmental dynamics generate time-varying opportunities and constraints. Principal economic barriers include high capital costs relative to farm income, liquidity constraints due to limited credit access, long investment cycles, and uncertain returns. Adoption is also shaped by the technology's intrinsic attributes, such as its perceived complexity, compatibility with existing practice, trialability, and the observability of its benefits (Abadi Ghadim & Pannell, 1999; Pannell et al., 2006; Rosário et al., 2022; Montes de Oca Munguia et al., 2021; Montes de Oca Munguia & Bayne, 2025).

Ultimately, adoption depends on landholders' subjective assessments of a technology's relative advantage in relation to their goals and constraints. These perceptions are influenced by the farmer's skills, the process of learning and experience, the characteristics and circumstances of the landholder within their social environment, and the specific attributes of each practice (Pannell et al., 2006; Montes de Oca Munguia et al., 2021). Education, training, and peer knowledge sharing through producer organizations therefore facilitate the enhancement of management skills, allowing landowners to overcome the characteristic path dependency and inertia that hinder change.

To accelerate technology adoption, governments and development agencies have deployed matching grants that combine financial incentives with technical support (Lopez & Maffioli, 2008). In this type of program, mechanisms such as targeted subsidies, co-financing, and

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human-capacity development can lower first-mover costs, trigger positive spillovers, and crowd in private providers. Properly designed systems (characterized by competitive selection, clear eligibility, and strong auditing) can reduce rent-seeking and facilitate the diffusion of farm-specific innovations that the private market would otherwise underprovide.

Although these interventions primarily aim to increase productivity, they are expected to generate environmental co-benefits by improving resource efficiency and reducing emissions per unit of output.

Recent years have seen increasing interest in counterfactual-based methods to evaluate agricultural policies in general (Winters et al., 2010; de Janvry et al., 2017; Henningsen et al., 2025) and in beef cattle systems specifically (Lopez & Maffioli, 2008; Mullally & Maffioli, 2016; Durán et al., 2018; Durán & Laguna, 2021). Nevertheless, rigorous evidence of the effectiveness of livestock interventions remains limited (Mullally & Maffioli, 2016). Moreover, previous studies produced mixed results (see Table S1 in the supplementary material). To our knowledge, no study in livestock systems has simultaneously examined the causal effects of a technology support program on actual adoption, beef production, and environmental outcomes.

This study fills this gap by evaluating the effectiveness of the Sustainable Family Production Program (PFIS), a policy initiative of the Uruguayan government to enhance productivity and climate resilience among small and medium-sized livestock producers. PFIS provided targeted technical assistance and financial support for the adoption of a menu of technological and management innovations designed to improve both productivity and climate adaptation. To evaluate the program's effectiveness, we estimate its causal effect on five key dimensions: (i) the adoption of technology and practices, (ii) engagement in producer organizations, (iii) reported cattle health problems, and (iv) beef production per hectare, and (v) greenhouse gas emissions intensity.

Our identification strategy employs a regression discontinuity design (RDD) that exploits a quasi-experimental feature of the PFIS's second phase, where eligibility was determined by a strict technical scoring threshold. By leveraging this discontinuity, we are able to control for self-selection bias and rigorously isolate the program's effect.

Five years post-implementation, our analysis confirms that the PFIS successfully drove the adoption of reproductive management technologies. Specifically, the PFIS increased controlled mating by 22.4 percentage points (pp), ovarian activity diagnosis by 16.3 pp, and early weaning by 8.7 pp. Yet, this uptake has not yet translated into statistically significant gains in beef production per hectare, emissions intensity, reported cattle health problems, or the engagement of producer organizations. The discrepancy between the successful uptake of technologies and the lack of immediate effect on productivity and GHG intensity suggests that these benefits may require a longer maturation period to materialize, underscoring the critical need for continued, long-term impact evaluation. This research is timely as many countries seek to align agricultural development with commitments under their Nationally Determined Contributions. In addition, evidence from programs like PFIS can inform the design of integrated, multi-objective policies in similar agroecological and socioeconomic settings.

The paper is organized as follows. Section 2 provides background on the Uruguayan livestock sector and PFIS. Section 3 describes the data sources and empirical strategy. Section 4 presents the main findings, and Section 5 concludes with a discussion of policy implications.

. Program context and description

2.1. The livestock sector in Uruguay

Uruguay has a significant share of the global beef market. It ranked ninth among beef exporters in 2023 and contributes 4% of the global carcass weight equivalent. Domestically, the livestock sector (including meat, by-products, and dairy) accounts for about 10% of Uruguay's gross domestic product (GDP) and 19% of goods exports in 2023 (Uruguay XXI, 2024). The sector also provides around 6.5% of total employment nationwide. According to the 2011 General Agricultural Census, 74% of commercial farms specialize in meat and milk production, covering 12.6 million hectares, approximately 70% of the country's land area (DIEA-MGAP, 2014; Aguirre, 2018).

Drawing on the Río de la Plata grasslands, Uruguay's livestock production is largely extensive and pasture-based, using minimal synthetic inputs and external energy, aligning well with sustainability principles (Álvarez, 2020; Lanfranco et al., 2022; Ruggia et al., 2021). However, livestock plays a central role in the country's emissions profile. In 2020, non-dairy livestock contributed 30% of Uruguay´s gross emissions (Ministerio de Ambiente, 2021).

There is notable variability across beef production units. The top decile producers can produce up to five times more beef per hectare than the bottom decile (Aguirre, 2018, 2019, 2022c, 2022b). This heterogeneity is driven by differences in land quality, production systems, infrastructure, and technology adoption. This heterogeneity may be the reason why despite higher slaughter weights, shorter finishing periods, and the increased use of feedlots, beef production per hectare experienced modest growth over the past two decades (Peyrou, 2016; Nin et al., 2019; Aguirre, 2022a).

Adoption of improved livestock practices in Uruguay remains limited (Peyrou, 2016; Bervejillo et al., 2018; Jones et al., 2020; Aguirre, 2022b; Polcaro, 2022; Paparamborda et al., 2026) and substantial productivity gains remain to be attained within the existing technological frontier in cow calf systems (Aguirre et al., 2024a, 2024b).

In this context, the national policy has focused on productivity oriented technology transfer programs to address livestock sustainability challenges for small and medium size producers (Durán et al., 2018). To this end, the Uruguayan government has implemented several programs, including the one evaluated in this paper, which we describe in the next subsection.

2.2. The intervention and conceptual framework

The Sustainable Family Production Program (*Producción Familiar Integral y Sustentable,* PFIS) targeted small and medium producers in Uruguay from multiple sectors, including beef and dairy, horticulture, beekeeping, poultry, pig farming, fruit production, viticulture, crop farming, and forestry (Gesto et al., 2019).[6] It employed a demand driven approach. Instead of offering a fixed package of technologies, it provided a menu of eligible innovations from which producers could select, recognizing the heterogeneity of local conditions, production systems, and farmer types. This approach aimed to improve both economic outcomes and environmental sustainability through tailored, integrated strategies. Its dual focus on productivity and sustainability, combined with a flexible and participatory design, sets PFIS apart from many previous rural development initiatives. Producers could participate individually or collectively.[7] The program was implemented at the national level and promoted through radio, television, and the ministry´s website.

PFIS for the livestock sector had two primary components (Aguirre et. al, 2018a). The first aimed to enhance productivity by promoting practices and technologies related to herd management, animal health, genetic improvement, and nutrition. The second focused on increasing the resilience of production systems to climatic variability. Among others, this second component of the PFIS supported solutions to improve access to water sources, conserve soil and vegetation, improve pasture, forest management (tree planting for shade and shelter) and effluent management. The program's ultimate goal was to boost income and resilience among small and medium producers. At the same time, it was expected that the program, if effective in increasing productivity, could contribute to meet Uruguay´s mitigation pledges included in its NDC, defined as greenhouse gas emissions intensity per unit of beef in live weight.

Eligibility for the livestock program was limited to producers, managing up to 1,250 hectares with average productivity (with CONEAT index 100).[8] In 2015, this segment constituted 81% of all producers, covered 43% of the total livestock area in the country, and represented 49% of total livestock units. Producers could participate individually or collectively.[9] The program was implemented at the national level and promoted through radio, television, and the ministry´s website.

[6] The program's guidelines can be accessed at Producción Familiar integral y sustentable | MGAP.

[7] Applications were submitted online by an agronomy or veterinary technician accredited by MGAP, who had previously completed training in project formulation. Technicians received USD 409 for each approved proposal, and the program financed up to 10 technical monitoring visits per project at USD 130 each.

[8] The CONEAT index, developed by the Uruguayan government, quantifies land productivity in terms of meat and wool output. It assigns values from 0 (unsuitable for cattle production) to 250, with a national average of 100. This index plays a crucial role in fiscal policies, because it determines soil productivity for taxation purposes and serves as a standard reference in land transactions.

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Each participant could receive up to USD 16,000 in financial support, USD 8,000 per component, covering up to 80% of total project costs. Using data from the Household Continuous Survey data in the baseline year (2015), we calculate that this amount represents approximately 10 months of net income for the average small livestock producer. Another way to put the USD 16,000 in context, is to compare it to the cost of renting the land. Put it in this way, the support equals 1.1 of the yearly average land rent paid by livestock producers.

Half of the funding was disbursed at the start of the project, with the remainder provided on successful completion and compliance with the proposed activities. Although participation in each component was voluntary, the program encouraged proposals addressing both productivity and sustainability.[10] Projects were tailored based on a diagnostic assessment of farm-specific needs, with a maximum implementation period of 18 months. The total program budget was USD 13 million.

PFIS held two competitive calls, in August and October 2014 (Durán & Hernández, 2017), and received 3,611 proposals across diverse sectors. This study focuses on its effect on beef cattle producers, who submitted 1,846 proposals, accounting for 51.1% of the total.

Applications were assessed through an online evaluation system and scored from 0 to 100, based on the strength of the justification, internal coherence, comprehensiveness, technical and financial feasibility, and quality of the proposed performance indicators across economic, environmental, and social dimensions (see Annex 1 for details). In the first call, all projects that scored 60 points or higher were funded. In the second call, because of financial constraints, the cutoff was raised to 66 points. A total of 1,026 proposals from beef cattle producers received funding, representing 69.4% of their total submissions.

PFIS was implemented between 2015 and 2017 by the Rural Development Division of the Ministry of Livestock, Agriculture, and Fisheries (MGAP). Implementation began in early 2015, with the last beneficiaries entering by the end of 2016 (Table 1 outlines the program's activities). The intervention had a maximum duration of 18 months. Baseline data were collected in 2015, before implementation, and follow-up data for the impact evaluation were gathered in 2020, three years after the program concluded.

Figure 1 outlines the conceptual framework of the Sustainable Family Production Program (PFIS), mapping the hypothesized causal chain from administrative activities to long-term effects. The intervention posits that providing producers with technical assistance alongside financial incentives drives the adoption of specific technologies, which in turn leads to increased livestock productivity and farmer´s income. Beyond economic sustainability, these efficiency gains are expected to generate environmental co-benefits, specifically by reducing

[10] Although the technological component was primarily aimed at improving productivity, many of its supported actions were closely linked to environmental sustainability, particularly through their effect on emission intensity. In practice, the classification of actions by component was not always clear cut: some interventions categorized under the technological component could have been equally considered as pasture or soil management, and vice versa.

GHG emissions per unit of output. Furthermore, the shift toward sustainable land and herd management practices offers a complementary pathway to strengthen the system's resilience against climate variability.

Table 1: Timeline of the Sustainable Family Production Program (PFIS)

Activity	2015	2016	2017	2018	2019	2020
Program start	✅	✅				
Program end		✅	✅			
Baseline	✅					
Result line						✅

Note: Table 1 presents the PFIS implementation timeline. The program started in 2015, with new beneficiaries entering through late 2016; projects lasted up to 18 months, concluding by 2017. The baseline survey was collected in 2015, and the follow-up results survey in 2020, three years after completion. Source: Authors.

Figure 1. Conceptual framework of the Sustainable Family Production Program (PFIS)

Activities	⇒	Products	⇒	Results	⇒	Benefits
➔ Design of call guidelines ➔ Registration and accreditation of technicians ➔ Proposal assessment ➔ Signing of contracts by producers ➔ Project monitoring		Beneficiaries ➔ Make investments ➔ Receive technical assistance ➔ Strengthen networks and producer groups		➔ ↑ Adoption of technologies ➔ ↑ Sustainable practices ➔ ↑ Network engagement ➔ ↓ Cattle health		➔ ↑ livestock productivity ➔ ↓ GHG intensity ➔ ↑ Adaptive capacity to climate change

Note: Conceptual Framework of the Sustainable Family Production Program (PFIS). The diagram maps the progression from administrative activities (e.g., proposal assessment, technician accreditation) to beneficiary outputs (investments, technical assistance), intermediate results (adoption of technologies, network engagement, cattle health), and final benefits (increased productivity, reduced GHG intensity, and enhanced adaptive capacity). **Source**: Adapted from Durán & Hernández (2017)

The relevance of the promoted technologies is grounded in the specific ecological constraints of Uruguay's livestock sector. The country's temperate climate drives a marked seasonal cycle in forage production, characterized by a spring peak and a winter trough. This variability causes significant fluctuations in cattle body weight, which directly influences reproductive success, and overall beef production in cow-calf operations (Aguirre et al., 2024b).

In this context, increasing productivity relies on synchronizing the herd's biological cycle (gestation, lactation, and mating) with the spatiotemporal patterns of forage availability (Paparamborda et al., 2023, 2026). The optimal strategy aligns the period of highest nutritional demand (lactation) with peak forage abundance by scheduling mating for early summer. Consequently, the PFIS specifically promoted the adoption of practices and technologies that facilitate this synchronization, such as controlled mating, artificial insemination, ovarian activity diagnosis, and early weaning.

To facilitate adoption, the program facilitates targeted technical training with cost-sharing grants, addressing information asymmetries and liquidity constraints. This dual approach increases the perceived net benefits of adoption while mitigating the associated risks. While training enhances managerial capabilities and producer confidence, financial subsidies reduce upfront costs and accelerate implementation. Collectively, these instruments incentivize the uptake of reproductive and grazing management practices, along with necessary capital investments.

Among livestock producers, the majority of PFIS investments were allocated to the purchase of breeding stock or semen for genetic improvement, infrastructure upgrades (e.g., roads, pens, squeeze chutes), nutrition, animal health, technical consulting, and subdivision of pastures (Durán et al., 2018). A significant portion of the total investment was directed toward technological and productive improvements (42%), followed by water management (20%) and pasture management (16%). More than 90% of producers received technical assistance related to natural resources and productive management (see details in Annex 2).

3. Materials and methods

3.1 Data sources

To evaluate the program, we constructed a comprehensive dataset by merging administrative records with livestock survey data (Table 2). To merge these different sources of information, we used the farmers' National Livestock Information System (SNIG) identification number (known as the "DICOSE"). The SNIG registry tracks the lifecycle of every animal, including all movements and changes in ownership. By integrating these records with slaughter and auction weight data, we are able to estimate beef production at the farm level, which serves as one of our primary outcome variables (Aguirre, 2022b). Additionally, the PFIS application forms provided detailed technical and administrative data on proposed projects, allowing us to characterize the pre-treatment attributes of all applicants.

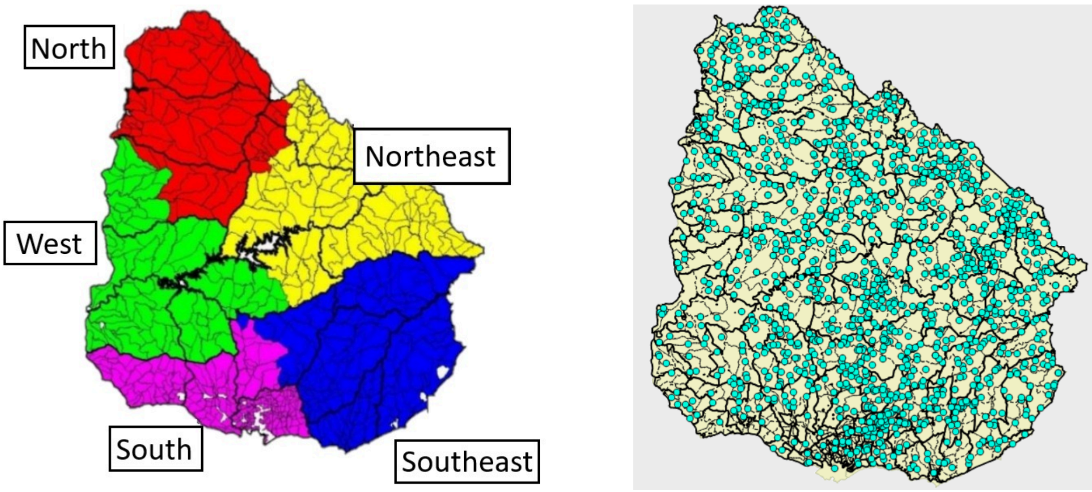
Table 2. *Main database for PFIS evaluation*

Database	Coverage	Year	Notes
PFIS application form	Applicants	2014	Technical and administrative project data
National Livestock Survey (EGN)	Applicants near threshold	2015-2016	Baseline data on livestock farms, excluding dairy
Good Practices in Natural Grassland Management Survey (EBPMCN)	Applicants near threshold	2020	Land-use and grassland management data
National Livestock Information System (SNIG)	All livestock producers	2015–2020	Livestock transaction, movement, and traceability data

The 2016 National Livestock Survey (EGN) collected economic data on Uruguay's cattle and sheep sectors. It was specifically designed to establish a baseline for evaluating PFIS.[11] Covering the 2015–2016 agricultural year, the survey includes detailed information on production systems, technology adoption, services, labor, costs, and innovation practices (Bervejillo et al., 2018). The sample excluded dairy operations and included 1,428 commercial livestock farms with at least seven livestock units (LUs), selected from the CGA 2011.

A stratified random sampling strategy was applied based on farm size, region, and PFIS participation status. The national territory was divided into five regions (Figure 2) and farms, and farms were further classified into eight categories according to size, measured in Livestock Units (Table 3). Within each category, farms were systematically selected based on the number of Livestock Units size. Farms with more than 3,500 Livestock Units or those included in the PFIS evaluation baseline, were automatically selected into the sample.

Figure 2: Agroecological areas and location of sampled Beef Production Units in National Livestock Survey 2016



Notes: The left panel displays the agroecological areas of Uruguay. The right panel shows the geolocation of livestock farmers surveyed in the 2016 National Livestock Survey . Source: Bervejillo et al. (2018).

According to Bervejillo et al. (2018), Uruguay had 25,615 farms primarily dedicated to beef production (with at least seven LUs and no dairy activity), covering 12.4 million hectares. The average size was 487 hectares, with wide variation (from 61 to 6,332 ha).

[11] The field survey was conducted by MGAP between spring 2016 and winter 2017, and collected data on the 2015/2016 agricultural season. Additional information necessary for evaluation was gathered for the two preceding seasons.

***Table 3:** Distribution of beef production units by herd size in livestock units*

Livestock Units	BPU	Land (1000 ha)	% of BPU	% of Land	CDF BPU	CDF Land
<100	10.761	651	42,0%	5,2%	42,0%	5,2%
[100,150)	2.325	345	9,1%	2,8%	51,1%	8,0%
[150,300)	3.855	1.061	15,0%	8,5%	66,1%	16,5%
[300,600)	4.232	2.220	16,5%	17,8%	82,7%	34,4%
[600,1000)	1.949	1.934	7,6%	15,5%	90,3%	49,9%
[1000,2000)	1.539	2.519	6,0%	20,2%	96,3%	70,2%
[2000,3500)	709	2.160	2,8%	17,4%	99,0%	87,5%
>3500	245	1.551	1,0%	12,5%	100,0%	100,0%
Total	**25.615**	**12.441**	**100%**	**100%**		

Note: This table presents the distribution of beef production units (BPUs) based on data from the National Livestock Survey 2016, disaggregated by herd size measured in livestock units. It reports the absolute and relative number of BPUs and total land area for each size category. The final two columns present the cumulative distribution function for BPUs and land by each successive size category. Source: Adapted from Bervejillo et al. (2018).

The Good Practices in Natural Grassland Management Survey (EBPMCN), conducted by the Ministry of Agriculture in 2020, focused on farms that had livestock as the primary activity (excluding dairy), a minimum of seven LUs, at least 100 hectares in total area, and over 50% of land covered by native grasslands.[12] Participation was mandatory for selected producers in the PFIS evaluation sample. It quantified land and livestock managed under good practices (Jones et al., 2020; Polcaro, 2022), and served as the outcome line for evaluating PFIS.

Originally, the evaluation design aimed to include all applicants within two points of the selection threshold and a random sample of interviewed treated beneficiaries for a matched comparison group (Durán et al., 2018; Durán & Hernández, 2017). The baseline was collected, but budget constraints prevented follow-up data collection for the entire sample. As a result, our evaluation on technology adoption is limited to a Regression Discontinuity Design around the cutoff of the second PFIS call, comparing applicants who scored 66 points (treated) with those who scored 65 points (control).

3.2 Variable construction

We construct the variables for our RDD guided by existing literature and data availability. The definitions and data sources for key measures are in Table 4.

We analyze two outcome sets. First, adoption of cow-calf practices and technologies: controlled mating, artificial insemination, ovarian diagnostics, and early weaning. Second, downstream outcomes potentially affected by these adoptions: (1) producer membership in an

[12] The sample frame was based on the 2016 EGN, updated with 2020 SNIG data. Stratification was done by farm size (above/below 500 ha) and region (center, north, northeast, east), yielding eight strata. A total of 500 farms were interviewed by phone, representing 11,362 producers managing 9.26 million hectares of native grasslands, roughly 83% of the total land used for livestock production in Uruguay.

organization, (2) reported cattle health problems, (3) partial productivity, and (4) GHG emissions intensity.

Our primary outcome is annual beef production per hectare.[13] It is derived from net cattle transactions (sales minus purchases), adjusted for inventory changes due to births, deaths, and reclassifications. It includes both slaughtered (fattened) and traded (lean) cattle. Expressing output per hectare facilitates meaningful comparisons across producers of different operational scales (see Annex A3 for details).

Table 4. Definitions and construction of variables

	Variable	Definition
Productivity and Emission[1]	Beef Production	Annual beef production in kg live weight per hectare (kg LW/ha)
	GHG Intensity	Total greenhouse gas emissions from beef production, expressed in kilograms of CO_2 equivalent per kilogram of beef produced (kg CO_2e/kg).
Adoption Outcomes[2]	Controlled Mating	Dummy: 1 if controlled mating practiced; 0 otherwise
	Artificial Insemination	Dummy:1 if artificial insemination used; 0 otherwise
	Ovarian Activity Diagnosis	Dummy:1 if ovarian diagnosis performed; 0 otherwise
	Early Weaning	Dummy: 1 if early weaning practiced; 0 otherwise
Other Outcomes[2]	Cattle Health Problems	Dummy:1 if reported cattle health problems; 0 otherwise
	In a Producer´s Organization	Dummy:1 if the producers is in a Producer's Organization; 0 otherwise
	Agronomist Technical Assistance	Dummy: 1 if received Technical Assistance from agronomist was received; 0 otherwise
Baseline Control Variables[3]	BLU	Standarized Bovine Livestock Units
	Land	Hectares under cattle production
	Labor	Labor input measured in full time equivalent units.
	CONEAT Index	Soil productivity index for cattle production
	Grazed Area Improved	Share of improved grazing area
	No Grazing Improvement	Dummy: 1 if no grazing improvements; 0 otherwise
	Region Group	Regional indicator variable [categories: 1=North, Northeast and Southeast, 0= South and West]. See Figure 2.
	Productive Orientation	Dummy: 1 if beef-only system (OBR<= 1)); 0 beef-sheep mixed (4>OBR>1).
	Beef Production System	Dummy: 1 if cow-calf (steers/cow-calf<=0.5); 0 full cycle or fattening (RSC>=0.5).

Notes: Data sources: [1] Computed using SNIG data and auxiliary information; [2] EBPMCN 2020; [3] EGN 2016.*

Our second outcome measures farm level GHG emissions per kilogram of beef produced (kg CO2e/kg). Using traceability data and IPCC methods, it includes methane from enteric fermentation and manure, and nitrous oxide from excreta. Emissions are converted to CO2

[13] We omitted sheep meat and wool production from our study for three reasons. First, 40.1% of BPUs that include sheep do not engage in production for commercial purposes (Bervejillo et al., 2018). Second, the contribution of ovine meat to the total combined bovine and ovine meat production is less than 7%. Third, accurate estimation of sheep meat production is significantly challenging (Aguirre, 2018).

equivalents using GWP100 factors from IPCC AR5 and aggregated annually (see Annex A4 for details).

3.3. Treatment selection mechanism

PFIS supported a total of 1,026 livestock producers through two calls for proposals. In both calls, applications were evaluated and scored on a 0–100 scale. However, approval rates differed substantially across calls: in the first call, 620 of 662 applicants were funded (93.7%), but in the second call, only 406 of 1,076 proposals received support (37.7%) because of budget constraints

In the first call, MGAP applied a strict eligibility rule: all proposals scoring 60 points or more were automatically approved. This rule was explicitly communicated to the evaluators. As shown in Table 5, this policy generated a sharp discontinuity in the probability of treatment at the 60-point threshold.

To assess the validity of using a regression discontinuity design (RDD), we tested the assumption of no manipulation around the cutoff (under the null hypothesis, the number of observations just above and just below the threshold should follow a smooth distribution). To do this, we conducted binomial tests within windows of ±1 and ±2 points around the cutoff (i.e., scores of 59–61 and 58–62), using Stata's bitest command. In both cases, the hypothesis of random assignment was rejected (p-value < 0.0001) in the case of the first call. Notably, in the first call, there were no proposals scored exactly at 59 points, suggesting upward manipulation of scores once the 60-point threshold became known. Given this strong indication of strategic behavior, data from the first call were excluded from the impact evaluation.

In contrast, for the second call, high demand and budget limitations led to an ex-post raising of the approval threshold to 66 points. Crucially, the adjustment occurred after all applications were scored and was not disclosed to evaluators during the scoring process. This minimizes the risk of strategic score manipulation and provides a more credible basis for a local randomization design.

We tested for potential manipulation at the 66-point threshold using the same binomial tests in the ±1-point window (scores of 65–66). As can be observed in Table 6, 78 applicants out of 174 obtained a 66 score, which is consistent with random assignment (p-value = 0.197). However, in the ±2-point window (scores of 64–67), the null of random assignment was rejected (p-value < 0.001), indicating potential selection at this bandwidth. Results in wider intervals (±3 and ±4) were mixed (p-value = 0.085 and p-value < 0.001, respectively), suggesting that local randomization is credible only within a very narrow range around the threshold

Table 5. Frequency of proposal of PFIS, by score, first call

Score	Treated (N) No	Treated (N) Yes	Total	
[0,30]	1	0	1	Untreated: 42 (6.3%)
[31,50]	10	0	10	
[51,56]	16	0	16	
57	0	0	0	
58	15	0	15	
59	0	0	0	
60	**0**	**64**	**64**	Treated: 620 (93.7%)
61	0	43	43	
62	0	26	26	
63	0	33	33	
64	0	51	51	
65	0	33	33	
66	0	25	25	
67	0	28	28	
[68, 100]	0	317	317	
Total	**42**	**620**	**662**	**662**

Table 6. Frequency of proposal of PFIS, by score, second call

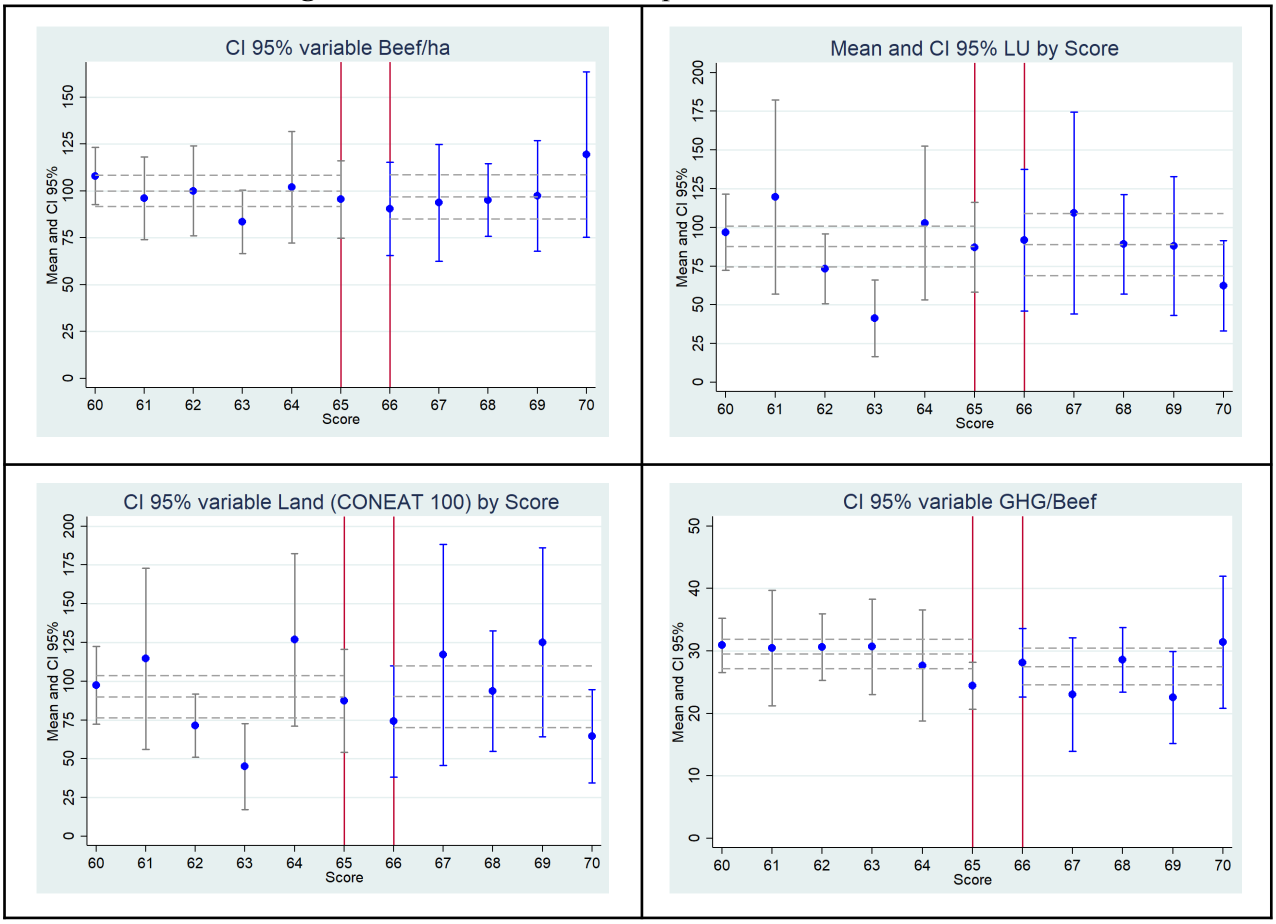
Score	Treated (N) No	Treated (N) Yes	Total	
[0,30]	61	0	61	Untreated: 670 (62.3%)
[31,58]	96	0	96	
59	4	0	4	
60	171	0	171	
61	50	0	50	
62	83	0	83	
63	49	0	49	
64	60	0	60	
65	96	0	96	
66	**0**	**78**	**78**	Treated: 406 (37.7%)
67	0	22	22	
68	0	77	77	
69	0	31	31	
70	0	49	49	
[71, 100]	0	149	149	
Total	**670**	**406**	**1076**	**1076**

Note: This table presents the frequency distribution of applicant scores for the first and second calls of the PFIS program. For each call, applicants are categorized by their eligibility status: "Treated (Yes)" denotes approved proposals scoring at or above the program cutoff, while "Untreated (No)" indicates those scoring below the threshold. Source: Authors' calculations based on administrative data from PFIS program records.

To further assess the validity of the design, we examined covariate balance in pretreatment characteristics of applicants within symmetric bandwidths (±1 to ±5 points around the 66-point cutoff). As shown in Figure 3, we find no statistically significant differences between treated and control units in the baseline variables of livestock units, land area, beef production per hectare, and GHG emissions intensity. This balance holds consistently across all bandwidths tested (see details in table S8 in Annex 5).

Taken together, those results suggest that treatment assignment near the threshold is plausibly random with respect to observable pretreatment covariates. Therefore, we adopt a local randomization framework and restrict the impact evaluation sample to applicants scoring 65 and 66 points. These observations were subsequently incorporated into the 2020 survey and used to evaluate the program's outcomes.

Figure 3. Falsification test on pre-treatment characteristic



Note. This figure presents the results of a covariate balance test for pre-treatment variables between treated and control groups, based on data from PFIS proposal forms and the SNIG at the application stage. Each panel displays the mean value and 95% confidence interval for a baseline variable: livestock units, land area, beef production per hectare, and GHG emissions intensity. Horizontal grey dotted lines indicate the group means for treated applicants (scores 66–70) and control applicants (scores 60–65). The consistent absence of statistically significant differences across all tested bandwidths supports the validity of the local randomization assumption required for the analysis.

3.4. Estimation

To estimate PFIS's causal effects, we implement a sharp regression discontinuity design (RDD). This approach is particularly well-suited to our setting because it exploits the selection rule: in the second funding call, only applicants who received a score of 66 or higher were selected for funding. The central identifying assumption of RDD is that applicants scoring just below and just above this cutoff are comparable in all observable and unobservable respects, except for their treatment status. Intuitively, assignment near the threshold can be considered as-if random, creating a localized natural experiment ideal for causal inference.

The discontinuous change in the probability of receiving treatment, from zero to one between scores of 65 and 66, supports the application of a sharp RDD under a local randomization framework. The assignment rule was exogenous, since the cutoff was determined after scoring. Moreover, the distribution of scores is balanced around the threshold, and manipulation tests confirm that applicants were unable to influence their position relative to the cutoff. Pretreatment covariates are also balanced between those scoring 65 and 66, reinforcing the plausibility of the local randomization assumption.

Because the assignment variable is discrete with mass points, it does not meet the continuity assumptions required for traditional RDD approaches.[14] To address this, we adopt the local randomization framework proposed by (Cattaneo et al., 2016), which considers treatment assignment within a narrow window around the threshold as effectively random. In this setting, potential outcomes are assumed to be independent of the treatment assignment within the window and depend only on whether the cutoff was crossed, not on the specific value of the score (Skovron & Titiunik, 2015).

Specifically, we define a randomization window of one point on either side of the cutoff, comparing applicants who scored 66 (treated) with those who scored 65 (controls). Within this window, we estimate the Local Average Treatment Effect (LATE*), defined as follows:

$$LATE^{*} = E(Y|x = 66) - E(Y|x = 65)$$

To enhance statistical power and improve precision for continuous outcome, we estimate this effect using Lin's estimator (Lin, 2013), which adjusts for pretreatment covariates and their interaction with the treatment indicator, and control for the Freedman sample bias of the ordinary least squares estimator for the treatment.[15] We incorporate baseline control variables to, and more accurately identify the treatment effect while accounting for sources of heterogeneity. Our baseline control variables are herd size (bovine livestock units, BLUs), land area, labor, improved pasture share, productive orientation (ovine to bovine ratio, OBR), production system (steers to breeding cow ratio, SBCR), and the CONEAT index (natural soil fertility).

Let Y_i represent the outcome of interest of the unit i at the farm level, T_i the treatment indicator, C_i^{Center} a vector of covariates centered at the threshold, and ε_i the error term. The estimation model is specified as follows:

$$Y_i = \tau T_i + \beta C_i^{Center} + \gamma T_i C_i^{Center} + \varepsilon_i$$

[14] When the score is discrete rather than continuous, the standard smoothness assumptions required for non-parametric estimation of conditional expectations near the cutoff become harder to justify. This challenges the validity of traditional continuity-based RDD approaches.

[15] The Freedman sample bias refers to a bias in Ordinary Least Squares (OLS) estimates that arises in small samples in the context of impact evaluation. Freedman (2008) showed that when estimating treatment effects using OLS with covariate adjustment in randomized experiments, the finite sample bias can be substantial. This occurs because OLS estimates rely on asymptotic properties that may not hold in small samples, leading to biased standard errors and confidence intervals. Although covariate adjustment can improve precision, Freedman cautioned that in small samples, it may introduce bias unless appropriate corrections, such as robust standard errors or permutation-based inference, are applied.

This specification allows for differential slopes by treatment status and improves efficiency while maintaining unbiasedness in small samples. Centering covariates reduces multicollinearity and enhances interpretability.

4. Results

This section presents the results of our analysis, which examines two sets of outcomes: (1) the adoption of key cow-calf management practices and technologies, and (2) downstream effects potentially influenced by this adoption.

The estimated effects on adoption and intermediate outcomes are presented in Table 7. We find no statistically significant effects of PFIS on the use of artificial insemination (p-value=0.587), the incidence of cattle health problems (p-value=0.345), the participation in producer organizations (p-value=0.494), or engagement with agronomic advisers (p-value=0.277). In contrast, the program had a statistically significant effect on the adoption of three practices for reproductive management practice: controlled mating (an increase of 22.4 percentage points, p-value=0.021), ovarian activity diagnosis (16.3 percentage points, p-value=0.043), and early weaning (8.7 percentage points, p-value=0.072).

Table 7: Effect of PFIS on technology adoption and management practices at resultline

Variables	Coefficient	Standard Error	p-values	R^2	N	Mean treated	Mean Control
Controlled Mating	0.224**	0.095	0.021	0.057	98	0.442	0.218
Ovarian Activity Diagnosis	0.163**	0.079	0.043	0.081	72	0.185	0.022
Early Weaning	0.087*	0.048	0.072	0.035	106	0.104	0.017
With Artificial Insemination	0.055	0.093	0.587	0.005	75	0.207	0.152
With an agronomist	0.059	0.054	0.277	0.011	119	0.118	0.059
Cattle Health Problems	-0.088	0.093	0.345	0.008	119	0.471	0.559
In a producers' organization	0.064	0.093	0.494	0.004	119	0.490	0.426

Note: This table reports the estimated local average treatment effects of participation in the PFIS program at the Resultline in 2020. Each row corresponds to a separate regression for a binary outcome. "Coefficient" denotes the estimated causal effect of PFIS on the adoption of the practice. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. "Mean Treated" and "Mean Control" report the sample means of the outcome for PFIS beneficiaries and non-beneficiaries, respectively.

With respect to the results of the PFIS on partial productivity of the treated farmers, these are presented in Table 8. As reported in its second column (Model 1), the estimated local average treatment effect at the eligibility margin on beef production per hectare is positive (approximately 5 kg/ha/year), but not statistically significant (p-value=0.766). This result is stable across model specifications. As shown in column three (Model 2) and four (Model 3) of Table 8, including pretreatment covariates does not affect the results. This consistency suggests that the lack of statistical significance is not driven by model misspecification but rather reflects a robust null effect.

Table 8. Effect of PFIS on beef production in 2020 (kg/ha/year)

VARIABLES	Model 1	Model 2	Model 3
PFIS	5.16	5.29	6.03
Standard Error	17.24	27.8	24.9
p-value	(0.766)	(0.85)	(0.81)
N	80	73	67
R^2	0.001	0.252	0.318
2020 Mean treated	106.3	110.5	114.6
2020 Mean control	101.2	100.9	98.2
2015 Controls	No	Yes	Yes
2015 Beef/ha	No	No	Yes

Note: This table reports the estimated local average treatment effects of participation in the PFIS program on beef production per hectare in the Resultline in 2020. Each column corresponds to a different model specification. Control variables and baseline beef/ha are measured using baseline data and include: BeefProductionSystem, ProductiveOrientation, RegionGroup, Land, BLU, GrazeAreaImprove, GrazeAreaImprove0, Coneat, and Labor. "Mean Treated" and "Mean Control" report the sample means of the outcome for PFIS beneficiaries and non-beneficiaries, respectively

We obtain similar results examining the effect of PFIS on greenhouse gas emissions intensity[16]. As reported in Table 9, column 2, in the most parsimonious specification (Model 1), the estimated local average treatment effect at the eligibility margin on GHG emissions per kilogram of beef is 1.534, but not statistically significant (p-value = 0.718). The result remains qualitatively similar across model specifications that sequentially introduce pretreatment covariates (Model 2) and baseline emission intensity levels (Model 3). This pattern suggests that PFIS did not generate detectable changes five years after the program began.

Table 9: Effect of PFIS on GHG intensity in 2020

VARIABLES	Model 1	Model 2	Model 3
PFIS	1.534	2.352	1.164
Standard Error	4.243	4.865	4.616
p-value	(0.718)	(0.630)	(0.802)
N	97	88	86
R^2	0.001	0.088	0.27
2020 Mean treated	26.88	26.05	26.05
2020 Mean Control	25.3	26.02	26.23
2015 Controls	No	Yes	Yes
2015 GHG Intensity	No	No	Yes

Note: This table reports the estimated local average treatment effects of participation in the PFIS program on greenhouse gas (GHG) emissions intensity, measured as kg CO2 equivalent per kg of live beef produced in the Resultline in 2020. Each column corresponds to a different model specification. Pretreatment controls and baseline GHG intensity are measured in the baseline in 2015. The set of control variables includes: BeefProductionSystem, ProductiveOrientation, RegionGroup, Land, BLU, GrazeAreaImprove, GrazeAreaImprove0, and Coneat. "Mean Treated" and "Mean Control" report the sample means of GHG intensity for PFIS beneficiaries and non-beneficiaries, respectively.

[16] An analysis of PFIS's effect on total emissions similarly yields statistically non-significant results (Annex 9)

4.1 Robustness checks

To address concerns related to the limited sample size and the narrow bandwidth around the eligibility threshold for the effect of the program on the level of beef production per hectare, we conducted several robustness checks. First, we performed a power analysis of the *t*-test used to estimate the average treatment effect (Annex 6). The results indicate a statistical power of 84.6% with a sample of 81 observations, suggesting that our analysis has a high probability of detecting a true effect if it exists. Second, we implemented exact permutation tests following (Imbens & Rubin, 2015), an approach well-suited for small samples because it does not rely on parametric assumptions and provides exact p-values. These results, presented in Annex 7, are qualitatively consistent with our main findings, further supporting their robustness. Overall, these additional analyses provide confidence that our results are not driven by sample size limitations or methodological artifacts.

In addition, we tested the sensitivity of the estimated effects on beef production and emissions intensity by progressively expanding the bandwidth around the eligibility cutoff from 1 to 5 points. These alternative specifications draw on baseline data from the PFIS application forms and outcome variables from the SNIG system. Results from these broader windows, presented in Annex 8, are directionally consistent and remain statistically insignificant, reinforcing our findings.

5. Conclusions and discussion

Using a regression discontinuity design (RDD) that exploits an exogenous discontinuous rule in its second call, we estimate the effects of a program (PFIS) implemented to support the adoption of management practices and technology by small and medium livestock producers in Uruguay.

Our results show that the PFIS did not produce statistically significant effects on beef output per hectare or on GHG intensity, in the three-year window after the end of the program. Importantly, however, the program drove behavioral changes, with statistically significant increases in the adoption of early weaning (+8.7 percentage points), controlled mating (+22.4 pp), and ovarian activity diagnosis (+16.3 pp). On the other hand, we did not find evidence consistent with the program having a similar effect on the adoption of artificial insemination, agronomical technical assistance, reported cattle health problems and the participation of beneficiaries in producer organizations.

The simultaneous adoption of early weaning, controlled mating, and ovarian activity diagnosis is meaningful because they constitute a synergistic package designed to optimize cow-calf efficiency. Controlled mating serves as the foundational step; by restricting the breeding season, it organizes the reproductive calendar to align the herd's peak nutritional demand with seasonal forage availability. Ovarian activity diagnosis functions as the essential informational mechanism of this mating schedule, by allowing producers to stratify the herd based on reproductive status. In addition, this diagnostic enables the precise application of early weaning, which acts as a targeted corrective lever to recover the body condition of anestrous cows.

On the other hand, other practices and technologies were not adopted. Failure to adopt artificial insemination may stem from the higher barriers associated with insemination: it is financially costlier, technically more complex, and demands significant management intensity.

The program also failed to induce producers to adopt agronomical technical assistance. Qualitative evidence gathered from interviews with beneficiaries and technicians, the latter were required, as part of the application process, to produce a diagnosis of the farm, many of the proposals applying for funding were produced by the producers themselves (AGEV, 2017). One possible interpretation is that since the technical direction was producer-driven. Consistent with what we know from the literature (Feder & Umali, 1993; Takahashi et al., 2020), having access to technical assistance through the PFIS was not sufficient a factor for the selected beneficiaries to adopt it. Extension impacts depend also on the perceived benefits that this assistance translates into, which in turn depends on the perceived information gap by farmers.

The absence of significant effects on the participation of beneficiaries in producer organizations could imply that the associativity promoted by the program was likely instrumental, established primarily to meet eligibility requirements for funding. Consequently, once the administrative incentive for collective action ceased, these temporary linkages likely dissolved.

In the case of cattle health incidence, the lack of effect may reflect the specific allocation of program resources. As the investment data indicates, capital and technical assistance were overwhelmingly directed toward reproductive efficiency (genetics, mating management) and infrastructure rather than specific sanitary campaigns or veterinary treatments. Furthermore, improvements in general herd health often stem from long-term nutritional gains derived from better pasture management require a longer maturation period to manifest in reported health statistics compared to the immediate binary adoption of reproductive technologies

The fact that a segment of beneficiaries did not adopt key practices, even with financial and technical support, suggests the persistence of deeper structural barriers that the intervention could not fully dismantle. Factors such as limited operational scale, labor constraints and risk aversion likely continue to inhibit technology uptake for small producers. Moreover, the heterogeneity in adoption rates implies that for certain sub-groups, the perceived transaction costs or managerial complexity of these technologies may still outweigh their expected benefits. This underscores that while removing liquidity and information constraints is necessary, it may not be sufficient to overcome the rigidities imposed by the scale and structural characteristics of family livestock systems

The absence of detectable effects on beef production and GHG emissions intensity despite the program's effectiveness in fostering the adoption of the above reproductive practices and technologies, raises the question about the necessary time lag between the adoption of these practices and their eventual effect on these outcomes. Recent reviews emphasize that adoption effects typically appear earlier than performance outcomes, especially for complex or knowledge-intensive practices (Foguesatto et al., 2020; Takahashi et al., 2020; Wokibula et al., 2024). This pattern implies that changes in management practices may precede detectable improvements in output or environmental measures, highlighting the importance of long-term evaluations.

Based on these findings, future iterations of livestock support programs may benefit from cautious redesign to improve impact, equity, and systemic efficiency. First, shifting from a uniform model to a segmented targeting approach could be considered—differentiating producers primarily constrained by liquidity, who may require some upfront support to unlock investment, from those constrained by capability, for whom initial investments in human capital and technical proficiency might be a prerequisite for effective use of financial incentives.

Second, future program designs should also explicitly analyze the appropriate subsidy percentage and its delivery method, as each model entails distinct trade-offs in costs, fiscal risks, and incentive structures. A challenge is that in livestock farming, outcomes are subject to biological, health, and market risks, and causal attribution is particularly difficult due to long production cycles and systemic complexity. This makes performance-linked payments especially difficult to design and verify. Given this, upfront funding lowers barriers to entry for small producers, but may weaken incentives for implementation. Conversely, rewards based strictly on verified outcomes strengthen performance incentives but risk unfairly excluding farmers facing exogenous risks beyond their control. A redesigned scheme could therefore consider a model combining a modest upfront component to ensure inclusion with a smaller, carefully defined variable payment contingent on achievable process indicators or outputs.

Finally, these operational changes must be supported and enriched by a robust monitoring, evaluation, and learning system. This system should track the complex, non-linear adoption pathways over time and, critically, generate evidence on the economic effects of technologies on production costs and net margins, data essential for credible extension and convincing producers of long-term benefits.

As a longer-term research agenda, for allocation and scaling of resources, it becomes necessary to generate comparative evidence on the cost-effectiveness of matching grants relative to alternative instruments (such as tax subsidies, credit guarantees, or other financial and regulatory tools) to inform resource allocation and scaling decisions in public policy.

Future impact evaluations in the livestock sector should adopt a more comprehensive lens, incorporating metrics for profitability, biodiversity, total factor productivity, and animal welfare, while using longitudinal data to discern whether initial changes lead to durable improvements. Estimating heterogeneous treatment effects across different producer groups and practices is essential to identify the most effective strategies. Integrating these granular insights into cost-benefit models will not only optimize resource allocation but also enable the design of adaptive, targeted policies.

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Supplementary material

Table S1. Impact evaluations of livestock programs for beef cattle production

	Article	Method	Output	Findings
1	**Country and period:** Uruguay: 2001-2003. **Program name:** Livestock Uruguay Program (Programa Uruguay Rural)**. Component 1:** Promote Innovation in cow-calf production. **Type of data:** Panel. **Observations:** N=990 (treated=520 and controls=470). **Universe:** Cow-calf and complete cycle up to 1250 ha CONEAT. **Analysis period**: 2001-2003			
	Lopez & Maffioli (2008)	Propensity score matching with difference in differences	Physical events record	25.3pp
			Economic events record	18.7pp
			Calves/CowBreeding	No effect
			PER=Calves/CowsOver1Year	No effect
			Degree of specialization	-5.5pp
			Dose effect (subsidy amount)	No effect
2	**Country and period:** Uruguay: 2006-2010. **Program name:** Uruguay Rural Program (Programa Uruguay Rural). **Type of data:** Panel. **Observations:** N=22020 (treated=413 and controls=21607). **Universe:** Cow-calf and complete cycle up to 1250 ha CONEAT. **Analysis period**: 2006-2010			
	Mullaly & Maffioli (2016)	Inverse probability weighting with difference in differences	Calf Births	(11.79;14.2)
			Net Calf Sales	4.59
3	**Country and period:** Uruguay: 2015-2016. **Program name:** Sustainable Family Program (PFIS, Programa Familiar Integral y Sustentable)**. Type of data:** Panel data. **Observations:** N=19,133 (treated = 648 and controls =18485). **Universe:** Cow-calf and complete cycle up to 1250 ha CONEAT. **Analysis period**: 2015-2017			
	Durán et. al (2018)	Entropy balance with difference in differences	Beef/ha	11.1 (pv=3.87%)
4	**Country and period:** Uruguay: 2014-2015. **Program name:** Inclusion of Forests in Agricultural Production Systems**. Type of data:** Panel data. **Observations:** N=18097 (treated=123 and controls=17974). **Universe:** Beef producers **Analysis period**: 2015-2017			
	Durán et. al (2018)	Entropy balance with difference in differences	sheep meat and Beef/ha	No effect
5	**Country and period:** Uruguay: 2013-2019. **Program name:** Family Livestock Farmers and Climate Change Project**. Type of data:** Panel data. **Observations:** N=344 (treated=157 and controls=190). **Universe:** Sheep meat and beef producers **Analysis period**: 2015-2017			
	Durán & Laguna (2021)	Entropy balance with difference in differences	Continuous Breeding	No effect
			Ovarian Activity Diagnosis	No effect
			Pregnancy Diagnosis	0,228 (pv <5%)
			Livestock management by body condition	No effect
			Single Herd Grazing	No effect
			Early Weaning	No effect
			Temporary Weaning	No effect
			Feed supplementation	No effect

Source: Authors.

Annexes

Annex 1. Evaluation criteria and methodological framework for evaluating PFIS proposals

The assessment framework comprised two main components: individual criteria and the overall proposal coherence.

Individual criteria	
Clarity and quality of diagnostic information	The proposal provides a clear diagnosis, outlining the main constraints and opportunities. There is internal consistency between the diagnosis, the proposed strategy, and the planned actions and objectives.
Coherence between diagnosis, actions, and budget	The proposed activities align with the identified constraints and objectives. Budget estimates are realistic, appropriate to the production context, and justified.
Application of tactical and strategic measures	The proposal includes both short and medium-term actions appropriate to the productive context and implementable with available resources.
Pertinence, feasibility and sustainability of the proposed activities	Activities are relevant, technically feasible, and economically viable. They contribute to the long-term sustainability of the system, with consideration of infrastructure, experience, cost justification, and the presence of measurable indicators.
Overall coherence	
Technical coherence and integrality	The proposal effectively integrates technological innovation, resource management, and climate adaptation strategies aligned with the program's objectives.
Technological management (closing the technology gap)	Adoption of relevant, context specific technologies that enhance productivity while sustainably reducing the technological gap.
Sustainability	The proposal promotes long-term resilience, improves productivity, and ensures environmental sustainability.
Climate change adaptation	The proposed actions are consistent with the environmental risk profile of the production system and include mitigation or adaptation strategies where necessary.

Annex 2. PFIS investments and practices among beef production unit

This annex summarizes the main practices and investments made by livestock producers who participated in the PFIS program.

Table S2. *Livestock producers, by type of practices and investments*

	Producers	Expenditure (US$)
Natural resources technical assistance	982 (94%)	1,105,175 (10%)
Technological and productive technical assistance	975 (93%)	446,593 (4%)
Water management	500 (48%)	2,158,025 (20%)
Irrigation	36 (3%)	26,397 (0.2%)
Manure management	12 (1%)	9,547 (0.1%)
Pasture management	595 (57%)	1,680,780 (16%)
Soil conservation practices	310 (30%)	874,984 (8%)
Technological and productive investments and practices	980 (94%)	4,524,978 (42%)
Total	**1046**	**10,826,479**

Table S3. *Categories and subcategories for investments and practices*

Water management	Water sources investments
	Water distribution investments
	Animal waterer infrastructure
Irrigation	Irrigation investments
Manure management	Manure management investments
Pasture and biodiversity management	Natural pastures management
	Natural forest biodiversity conservation and management
Soil conservation practices	Soil erosion minimization practices
	Crop and pasture rotation
Technological and productive investments and practices	Genetics
	Managerial capacities
	Infrastructure
	Productive processes improvements
	Nutrition
	Organizational and associative practices
	Animal health

Annex 3. Methodology for estimating beef production

The estimation of beef production in kilograms of live weight is based on categorizing cattle by sex and age, assigning each group a representative average weight, and calculating the weighted contributions across several components of the production cycle. These components include changes in herd inventory, movements of lean animals, slaughter data, and on-farm consumption.

Mathematically, total live-weight meat production for each production unit is defined for the agricultural year (spanning from July 1 of year t−1 to June 30 of year t) by aggregating the contributions from changes in animal stock, incoming and outgoing transfers of cattle, animals sent to slaughter, and animals consumed on-farm. Each term in the equation is indexed by category and production unit, with weights standardized using microdata from verified livestock sales and slaughter records. The latter are informed by annual national averages provided by INAC (Aguirre, 2022a).

$$Beef_k^{t-1,t} = \sum_{i=1}^{I} \alpha_{i,k}^{Stock} \Delta Stock_k^{t-1,t} + \sum_{i=1}^{I} \alpha_{i,k}^{Replacement} (Exit_{i,k}^{t-1,t} - Entry_{i,k}^{t-1,t}) + \sum_{i=1}^{I} \alpha_{i,k}^{Sl} Sl_{i,k}^{t-1,t} + \alpha_k^{Cons} Cons_k^{t-1,t}$$

To enable comparative analysis, total meat output is normalized by the area dedicated to cattle grazing, thus providing a measure of partial productivity expressed as kilograms of beef per hectare.

Annex 4. Methodology for estimating greenhouse gas emissions

GHG emissions from the livestock sector are calculated using annual data from DICOSE-SNIG. Emissions include methane from enteric fermentation, methane from manure management, and nitrous oxide from feces and urine deposited on pastures. The estimation framework adheres to IPCC guidelines (Calvo Buendia et al., 2019; Stocker et al., 2013; Eggleston et al., 2006) and uses global warming potential values over a 100-year horizon (GWP100-AR5), where 1 kg of CH_4 corresponds to 28 kg of CO_2 equivalent, and 1 kg of N_2O is equivalent to 265 kg of CO_2 equivalent.

Methane emissions from enteric fermentation are derived by combining IPCC default values with country-specific activity data, including animal numbers and feed characteristics. Emissions factors depend on gross energy intake, which in turn is influenced by physiological energy demands (maintenance, lactation, pregnancy, and growth) and the digestibility of consumed forage. National data on forage quality and allocation by animal category inform this calculation.

Methane emissions from manure are calculated considering the volatile solid content in feces and a methane conversion factor. In beef cattle, the methodology is simplified because manure remains in the field, without additional management. Nitrous oxide emissions, both direct and indirect, are also estimated based on Uruguay-specific data on the balance between nitrogen intake and retention by livestock, and the corresponding IPCC parameters.

Table S4. Emissions factors for CH_4 enteric fermentation, by category and year

Category	2014	2015	2016	2017	2018	2019	2020	2021	2022
Steers 3+ years	74.55	74.55	75.73	75.69	74.98	75.09	73.02	74.36	74.03
Steers 1−2 years	45.28	45.28	45.96	45.93	45.00	44.96	44.23	44.84	44.69
Steers 2−3 years	57.22	57.22	58.18	58.72	58.27	58.29	56.99	58.09	57.92
Calves	38.65	38.65	38.88	38.87	38.58	38.61	37.65	38.56	38.55
Bulls	76.89	76.89	76.87	76.87	76.85	76.87	74.81	76.84	76.83
Breeding cows	62.29	62.29	62.27	62.27	62.25	62.27	60.53	62.24	62.23
Fattening cows	65.70	65.70	66.76	66.74	65.17	65.02	63.54	64.63	64.67
Heifers 2+ years	55.62	55.62	55.34	55.94	55.52	55.39	53.84	55.28	55.29
Heifers 1−2 years	45.66	45.66	45.68	44.84	44.47	44.48	43.22	44.42	44.36

Table S5. Emissions factor for CH_4 manure management, by category and year

Category	2014	2015	2016	2017	2018	2019	2020	2021	2022
Steers 3+ years	1.41	1.41	1.45	1.45	1.42	1.42	1.35	1.40	1.39
Steers 1–2 years	0.85	0.85	0.87	0.87	0.84	0.84	0.81	0.83	0.83
Steers 2–3 years	1.08	1.08	1.11	1.12	1.09	1.09	1.05	1.09	1.08
Calves	0.76	0.76	0.77	0.77	0.76	0.76	0.73	0.76	0.76
Bulls	1.55	1.55	1.55	1.55	1.55	1.55	1.47	1.55	1.55
Breeding cows	1.25	1.25	1.25	1.25	1.25	1.25	1.19	1.25	1.25
Fattening cows	1.24	1.24	1.28	1.28	1.22	1.22	1.17	1.20	1.21
Heifers 2+ years	1.09	1.09	1.09	1.10	1.09	1.09	1.04	1.08	1.08
Heifers 1–2 years	0.90	0.90	0.90	0.88	0.87	0.87	0.83	0.87	0.87

Table S6. Emissions factor for N_2O of urine and dung by, category and year

Category	2014	2015	2016	2017	2018	2019	2020	2021	2022
Steers 3+ years	2.75	2.75	2.68	2.68	2.72	2.74	2.70	2.76	2.77
Steers 1−2 years	1.71	1.71	1.66	1.66	1.73	1.74	1.72	1.74	1.75
Steers 2−3 years	2.08	2.08	2.01	2.10	2.19	2.19	2.19	2.20	2.21
Calves	1.16	1.16	1.15	1.15	1.17	1.18	1.15	1.18	1.18
Bulls	2.08	2.08	2.08	2.08	2.08	2.08	2.02	2.08	2.08
Breeding cows	1.68	1.68	1.68	1.68	1.68	1.68	1.64	1.68	1.68
Fattening cows	2.43	2.43	2.35	2.35	2.45	2.47	2.44	2.49	2.48
Heifers 2+ years	1.68	1.68	1.65	1.67	1.71	1.71	1.68	1.71	1.71
Heifers 1−2 years	1.39	1.39	1.36	1.34	1.38	1.38	1.35	1.38	1.38

Nitrous oxide emissions from the deposition of feces and urine are estimated using equations that consider the proportion of residues deposited in pastures. The data on quantities are country specific; factors and coefficients are taken from IPCC standard tables.

Detailed annual emissions factors for each category of cattle are compiled in separate tables. These tables report methane emissions from enteric fermentation and manure, nitrous oxide emissions from dung and urine, and the aggregated emissions expressed in CO_2-equivalents by animal type and year.

Table S7. CO_2 equivalent compound emissions factors, by category and year (kg CO_2e GWP100AR5)

Category	2014	2015	2016	2017	2018	2019	2020	2021	2022
Steers +3 years	2,856	2,856	2,871	2,870	2,861	2,867	2,797	2,852	2,846
Steers 1-2 years	1,745	1,745	1,751	1,751	1,741	1,744	1,717	1,740	1,738
Steers 2-3 years	2,183	2,183	2,193	2,232	2,242	2,244	2,205	2,240	2,238
Calves	1,411	1,411	1,414	1,414	1,412	1,414	1,379	1,412	1,412
Bulls	2,747	2,747	2,746	2,746	2,746	2,746	2,672	2,745	2,745
Breeding cows	2,226	2,226	2,225	2,225	2,224	2,225	2,162	2,224	2,224
Fattening cows	2,519	2,519	2,527	2,526	2,508	2,510	2,457	2,503	2,501
Heifers +2 years	2,034	2,034	2,016	2,039	2,037	2,033	1,981	2,031	2,031
Heifers 1-2 years	1,672	1,672	1,666	1,636	1,635	1,636	1,590	1,633	1,632

Annex 5. Comparability of treated and untreated producers

This section evaluates the balance of observable characteristics between treated and untreated groups around the eligibility threshold of the second PFIS call, defined by a cutoff score of 66 points. We examine covariate balance within progressively wider score windows centered at the cutoff: ±1, ±2, ±3, ±4, and ±5 points.

Table S8. Covariate Balance Around PFIS eligibility cutoff (second Call)

Window	Score Range (Treated vs. Control)	Variable	Treated Mean	SD	Control Mean	SD	p-value
±1	66 vs. 65	Livestock Units	91.8	186.8	87.2	132.7	0.86
		Land (CONEAT 100)	74	146	87.4	151	0.58
		Beef / Land	116	82.7	91	54.2	0.18
		GHG Intensity	25.4	8.9	26.5	12	0.6
±2	66–67 vs. 64–65	Livestock Units	95.8	177	88	147.9	0.9
		Land (CONEAT 100)	83.9	149.3	101.8	168.1	0.41
		Beef / Land	117	77.4	101.2	57.9	0.29
		GHG Intensity	25	10	25.7	13.5	0.79
±3	66–68 vs. 63–65	Livestock Units	93.5	158.9	79.2	135.4	0.39
		Land (CONEAT 100)	87.8	151.4	86.7	153.7	0.96
		Beef / Land	106.4	72.8	103.2	58.3	0.76
		GHG Intensity	27.2	15	26.1	13.95	0.66
±4	66–69 vs. 62–65	Livestock Units	92.8	153	77.4	125.6	0.27
		Land (CONEAT 100)	93.9	152.1	82	137.5	0.41
		Beef / Land	106.9	71.7	102.9	57.9	0.66
		GHG Intensity	26.5	14.5	27	14.1	0.79
±5	66–70 vs. 61–65	Livestock Units	89.2	146	83	137.8	0.64
		Land (CONEAT 100)	90.5	145.2	86.4	144.8	0.76
		Beef / land	107.9	70.9	104.9	58.1	0.73
		GHG Intensity	27.2	16	26.6	13.6	0.75

Source. Authors' calculations based on PFIS proposal form and SNIG.

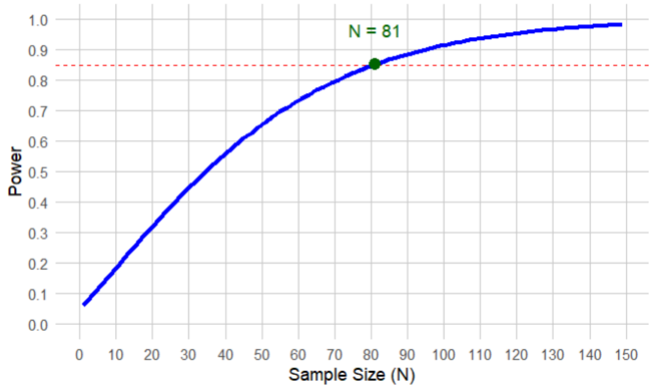
Within each window, we conduct difference-in-means tests on four baseline variables: livestock units, land area (measured in CONEAT 100-adjusted hectares), beef output per hectare, and GHG emissions intensity (see Table S6). These tests provide evidence on whether units just above and below the threshold are statistically similar in their pre-treatment characteristics, a necessary condition for the validity of a regression discontinuity design. The results show no statistically significant differences across all score windows and variables, indicating that treated and control groups near the cutoff are comparable. This supports the internal validity of the RDD strategy employed.

Annex 6. Power analysis

To assess the likelihood of rejecting the null hypothesis of no treatment effect when a true effect exists (the statistical power), we conducted a power analysis based on a two-tailed classical t-test.

We assume a treatment effect equivalent to a 10% increase in beef production per hectare, a standard deviation of 0.3, and a significance level of $\alpha = 0.05$. Given a sample size of $N = 81$, the resulting power is approximately 85%. This means there is an 85% probability of correctly rejecting the null hypothesis of no treatment effect when the effect is truly different from zero.

Figure S1: Statistical power of t-test for PFIS impact evaluation



Annex 7. Exact inference

We re-estimate the p-values of the mean comparison test statistic used to assess the effect of PFIS on beef output per hectare and GHG emissions intensity, employing the randomization inference for regression discontinuity designs under local randomization approach (Cattaneo et al., 2016). This method assumes an exact inference framework within the local randomization window. The resulting p-values are qualitatively similar to those obtained under asymptotic inference.

Table S9. p-values for selected outcome variables

Variable	Impact	asymptotic p-value	Randomized p-value	N
Beef/ha	5.156	0.766	0.73	80
GHG intensity	1.534	0.718	0.726	96

Annex 8. Sensitivity analysis of PFIS effect on beef/ha and GHG intensity

To test the robustness of our main findings, we perform a sensitivity analysis of PFIS's effect on beef production per hectare and GHG emissions intensity. We use pretreatment variables from PFIS application forms and the SNIG system to account for observable differences between treated and control groups.

We apply entropy balance to reweight the control group so that the distribution of covariates (livestock units, livestock area, soil quality [CONEAT], proportion of forage-improved area, and baseline beef output and GHG intensity) matches that of the treated group. This method minimizes the Kullback-Leibler divergence from a uniform weight distribution while ensuring covariate balance (Hainmueller, 2012).

Using these weights, we estimate treatment effects through weighted linear regression models. To assess sensitivity, we repeat the analysis in progressively wider score bandwidths around the eligibility cutoff (±1 to ±5 points).

Across all specifications, results remain qualitatively consistent and statistically nonsignificant for both beef output per hectare and GHG intensity. These findings reinforce the robustness of our main conclusions.

Figure S2: Sensibility of PFIS impact on Beef/ha with different bandwidth

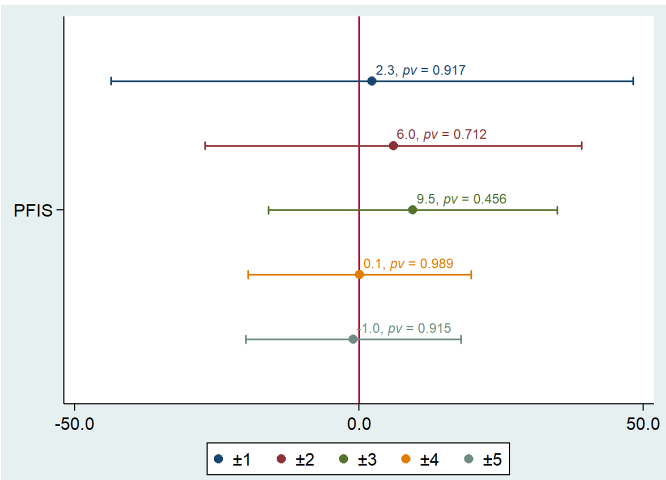
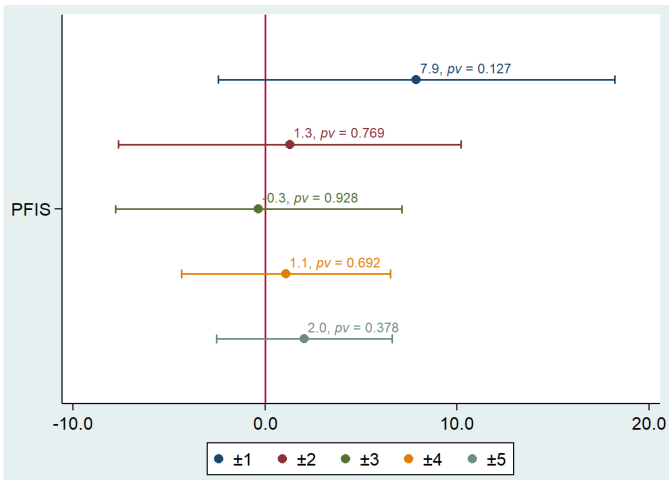


Figure S3: Sensibility of PFIS impact on GHG emissions with different bandwidth



Note: These figures present a sensitivity analysis of the PFIS program's effect on beef production per hectare and GHG emissions intensity. The analysis applies entropy balancing and weighted regressions across varying bandwidths around the eligibility score cutoff. The results show consistently non-significant treatment effects, reinforcing the robustness of the main findings.

Annex 9. Effect of PFIS on total equivalent greenhouse gas (GHG) emissions

Table S10: Effect of PFIS on GHG in 2020

VARIABLES	Model 3
PFIS	23,325
Standard Error	(75,598)
p-value	0.759
N	81
R^2	0.916
2020 Mean GHG	404,196
2015 Controls	Yes
2015 GHG	Yes

Note: The estimator is the Local Average Treatment Effect (LATE) at the eligibility margin. The outcome variable is total equivalent greenhouse gas emissions (kg CO_2 equivalent) in 2020. The model conditions on a set of pretreatment covariates and baseline (2015) GHG emissions. The covariates included are: BeefProductionSystem, ProductiveOrientation, RegionGroup, Land, BLU, GrazeAreaImprove, GrazeAreaImprove0, and Coneat.