RIDGE
RESEARCH INSTITUTE FOR DEVELOPMENT, GROWTH AND ECONOMICS
SINCE 2014

Outcomes of Livestock Sustainable Technology Transfer: Evidence from Uruguay

Emilio Aguirre, Juan Baraldo, Marcelo Caffera, Hugo Laguna

RIDGE Working Paper 016

This paper was presented at the 2025 RIDGE December Forum

RIDGE Working Papers are not formal publications. They are preliminary versions of research presented at the RIDGE Forum and posted on the RIDGE website with the author's permission. They remain the intellectual property of the authors and may be submitted for publication in academic journals.

Outcomes of Livestock Sustainable Technology Transfer: Evidence from Uruguay

Emilio Aguirre[1]
Juan Baraldo[2]
Marcelo Caffera[3]
Hugo Laguna[4]

Draft. Last modified on August 5, 2025. [Link to the latest version]

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, this program provided support to small and medium-sized cattle farmers to invest in technologies and management practices aimed at enhancing both productivity and climate resilience. This study provides the first causal evaluation of a national program designed to promote these dual objectives in the cattle sector. We assess the effect of PFIS on three outcomes: (i) technology adoption, (ii) productivity, and (iii) greenhouse gas emissions intensity. To identify causal effects, we use a regression discontinuity design based on a strict eligibility threshold, using panel data from producers between 2015 and 2020. Although we found no statistically significant effects on beef productivity per hectare or greenhouse gas emissions intensity during the study period, the program significantly increased adoption of good reproductive and herd management practices, including early weaning, controlled mating, and ovarian activity diagnosis. 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 impacts on productivity and emissions that may emerge as these technologies, particularly reproductive ones, influence aggregate outcomes.

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

JEL: Q12; Q16; D24; Q57

---

[1] Facultad de Ciencias Sociales de la Universidad de la República, Uruguay. emilioaguirreimbriaco@gmail.com, https://orcid.org/0000-0002-6004-1918
[2] Ministerio de Ganadería, Agricultura y Pesca, Uruguay. jbaraldo@mgap.gub.uy, https://orcid.org/0000-0002-6855-4670
[3] Departamento de Economía, Universidad de Montevideo, Uruguay. marcaffera@um.edu.uy, https://orcid.org/0000-0001-7508-4067
[4] Ministerio de Ganadería, Agricultura y Pesca, Uruguay. hlaguna@mgap.gub.uy, https://orcid.org/0000-0003-3644-1046

1. Introduction[5]

Global projections forecast a 10% increase in beef consumption by 2032 (OECD & FAO, 2023). Meeting this growing demand poses a significant challenge, especially as livestock grazing, the dominant land use worldwide (Nin et al., 2019), comes under increasing environmental scrutiny (Steinfeld, 2006; Gerber et al., 2013, MacLeod et al., 2018). Concerns are exacerbated by the accelerating effects of climate change and rising food prices.

The transition challenge is therefore to improve livestock productivity and climate resilience while simultaneously ensuring environmental and social sustainability. Enhancing productivity 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.

The adoption of appropriate technologies can drive both productivity improvements and climate adaptation. However, in many developing countries, particularly among small-scale producers in low and middle-income regions, the uptake and effective use of new technologies remain limited (de Janvry et al., 2017; López et al., 2017). In the livestock sector, barriers to investment and adoption include producers' restricted access to financial markets and limited access to reliable information about available technologies and their potential economic benefits. These obstacles often stem from broader structural issues, such as market failures, information asymmetries, and a misalignment between technological solutions and the actual needs and constraints faced by farmers.

In response, governments and development agencies have implemented technology transfer programs that combine financial incentives with technical assistance. Although these interventions primarily aim to increase productivity, they are increasingly expected to generate environmental co-benefits by improving resource efficiency and reducing emissions per unit of output. Nevertheless, in spite of the role of cattle farming in deforestation and methane emissions, rigorous evidence of their effectiveness remains limited. To our knowledge, no studies in livestock systems have simultaneously examined technology adoption, productivity, and environmental outcomes within a unified empirical framework using causal identification strategies.

Recent years have seen increasing interest in counterfactual-based methods to evaluate agricultural policies (Winters et al., 2010; de Janvry et al., 2017). Uruguay stands out, still uniquely so, for its rigorous application of these methods in the livestock sector. Previous

[5] The opinions expressed in this document are solely those of the authors and do not reflect or represent the official positions of the Inter-American Development Bank (IDB) or the Ministry of Livestock, Agriculture, and Fisheries. This research was supported by funding from the IDB through the call for proposals "Speeding the Adoption of Sustainable Cattle Production Technologies in Latin America and the Caribbean." We especially acknowledge the valuable suggestions and feedback provided by Paul Winter, Allen Blackman, and other colleagues at the IDB sustainable cattle technology workshop. Any errors or omissions are the responsibility of the authors.

studies on livestock interventions, particularly those focused on beef production units (BPUs), have used matching techniques combined with difference-in-differences estimators, producing mixed results (see Table S1 in the supplementary material). For example, Lopez & Maffioli (2008) found that the pilot Uruguayan Livestock Program, which subsidized up to 50% of extension service costs for small and medium-sized producers, encouraged technology adoption but had no effect on calf production. Conversely, Mullally & Maffioli (2016) reported that a revised version of the program led to increased output and net sales.

More recent evaluations have examined programs with explicit sustainability objectives. The Family Farmers and Climate Change Project (2013–2019), aimed at strengthening climate resilience among drought-prone producers, found no significant changes in most sustainable practices (Durán & Laguna, 2021).[6] Similarly, Durán et al. (2018) analyzed four interventions in the Rural Productive Development Program (*Plan Ovino*, *Llamado Lechero*, and *Programa Agroforestal*, as well as PFIS) and reported mixed effects on the partial productivity of meat and milk production.

This study aims to fill the evidence 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 financial support for the adoption of a menu of technological and management innovations designed to improve both productivity and climate adaptation. To assess its effect, we estimate the causal effects of the program on (i) beef productivity per hectare, (ii) adoption of good management practices, and (iii) greenhouse gas (GHG) emissions intensity. Our approach employs a regression discontinuity design that leverages a natural experiment arising from the second phase of PFIS, where program assignment followed a discontinuous rule based on a technical scoring system, providing robust estimates while mitigating self-selection bias.

To our knowledge, this is the first study to evaluate the effect of a livestock technology transfer program on GHG emissions intensity within a causal framework, using a regression discontinuity design approach. This research is timely, as many countries seek to align agricultural development efforts with their commitments under their National Development Contribution. Evidence from programs like PFIS can inform the design of integrated, multi-objective policies in similar agroecological and socioeconomic settings.

Our results indicate that although PFIS did not produce statistically significant changes in beef productivity or emissions intensity by 2020, it significantly increased the adoption of reproductive technologies: early weaning increased by 8.7 percentage points, controlled mating by 22.4 percentage points, and ovarian activity diagnosis by 16.3 percentage points. These findings suggest that, although immediate impacts on productivity and emissions were

[6] The eight practices analyzed in this study included: (1) continuous breeding, (2) ovarian activity diagnosis, (3) pregnancy diagnosis, (4) livestock management based on body condition, (5) single herd grazing, (6) early weaning, (7) temporary weaning, and (8) supplementation. Among these, a statistically significant impact of 22.8% was observed exclusively for practice pregnancy diagnosis, when comparing treated groups to the control group.

not observed, the adoption of reproductive technologies might set the stage for future improvements. Given that such technologies are tied to breeding and herd management cycles, their effects may manifest over a longer horizon, underscoring the importance of ongoing, long-term evaluations to capture the eventual benefits in productivity and environmental sustainability.

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.

2. Program context and description

2.1. The livestock sector in Uruguay

Uruguay has a significant share of global beef markets, ranking ninth among beef exporters in 2023 and contributing 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).

Uruguay's livestock production is predominantly extensive and pasture-based, relying on the *Río de la Plata* grasslands. These systems use minimal synthetic inputs and external energy, aligning well with sustainability principles (Álvarez, 2020; Lanfranco et al., 2022; Ruggia et al., 2021). However, sustainability challenges exist. In 2020, agriculture, forestry, and land-use activities accounted for 57% of Uruguay's total net GHG emissions, with non-dairy livestock contributing 30% of gross emissions (Ministerio de Ambiente, 2021). Improving productivity is therefore a critical strategy to attain the mitigation objectives included in the Uruguayan National Development Contribution, which are defined in terms of emissions intensity per unit of meat production.

Despite higher slaughter weights, shorter finishing periods, and the increased use of feedlots, overall beef production per hectare has experienced only modest growth over the past two decades (Peyrou, 2016; Nin et al., 2019; Aguirre, 2022c). There is notable variability across beef production units: the top decile 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. However, substantial productivity gains remain attainable through improved technical management, even within the existing technological frontier (Aguirre et al., 2024a, 2024b).

Nevertheless, the adoption of improved livestock practices in Uruguay remains limited (Peyrou, 2016; Paparamborda, 2017; Bervejillo et al., 2018; Aguirre, 2022; Jones et al., 2020; Polcaro, 2022) and empirical evidence on the effectiveness of technology transfer programs is scarce (Mullally & Maffioli, 2016).

2.2. The intervention and conceptual framework

The Sustainable Family Production Program (*Producción Familiar Integral y Sustentable,* PFIS) had two primary components (Aguirre et. al, 2018a).[7] The first aimed to enhance productivity by promoting technologies related to herd management, animal health, genetic improvement, and nutrition. The second focused on increasing the resilience of production systems to climatic variability by supporting sustainable natural resources management (improving water access, soil and vegetation conservation, sustainable pasture and 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 livestock producers while contributing to national objectives of low emission agriculture.

PFIS targeted multiple sectors, including beef and dairy, horticulture, beekeeping, poultry, pig farming, fruit production, viticulture, crop farming, and forestry (Gesto et al., 2019). 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.

Eligibility for the livestock program was limited to family and small to medium-scale, those producers managing up to 1,250 hectares with average productivity (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.

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. Half of the funding was disbursed at the start of the project, with the remainder provided on successful completion and compliance

[7] The program's guidelines can be accessed at Producción Familiar integral y sustentable | MGAP.
[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.
[9] 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.

with the proposed activities. Although participation in each component was voluntary, the program encouraged integrated 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.

Figure 1 illustrates the program's procedures and its hypothesis that livestock producers who adopted the promoted technologies and received technical assistance would increase their productivity and income. These gains were expected to enhance economic sustainability, while reducing GHG emissions per unit of output. In addition to efficiency improvements, the adoption of more sustainable land and herd management practices offers a complementary pathway to strengthen climate resilience and environmental sustainability.

Figure 1. Conceptual framework of 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	⇒	➔ ↑ livestock productivity ➔ ↓ GHG intensity ➔ ↑ Adaptive capacity to climate change

Source: Adapted from Durán & Hernández (2017)

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 point was raised to 66 points. A total of 1,026 proposals from beef cattle producers received funding, representing 69.4% of their total submissions.

[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.

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). 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.

Table 1: *Gantt diagram for PFIS*

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

Source: Authors.

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). More than 90% of producers received technical assistance related to natural resources and productive management (see details in Annex 2). A significant portion of the total investment (42%) was directed toward technological and productive improvements, followed by water management (20%) and pasture management (16%).

3. Materials and methods

3.1 Data sources

Our evaluation of PFIS uses multiple data sources from the Uruguayan Ministry of Livestock, which implemented the program. These include administrative records, nationally representative surveys, and livestock traceability data. These databases are summarized in Table 2.

Table 2. *Main database for PFIS evaluation*

Database	Coverage	Year	Notes
PFIS application form	Applicants	2014	Technical and administrative project data
General Agricultural Census (CGA)	All agricultural producers	2011	Sampling frame for subsequent surveys
National Livestock Survey (EGN)	Applicants near threshold	2016	Baseline data on livestock farms (>7 LU), 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	2011–2020	Livestock transaction, movement, and traceability data

Source: Authors. Note: LU = livestock unit.

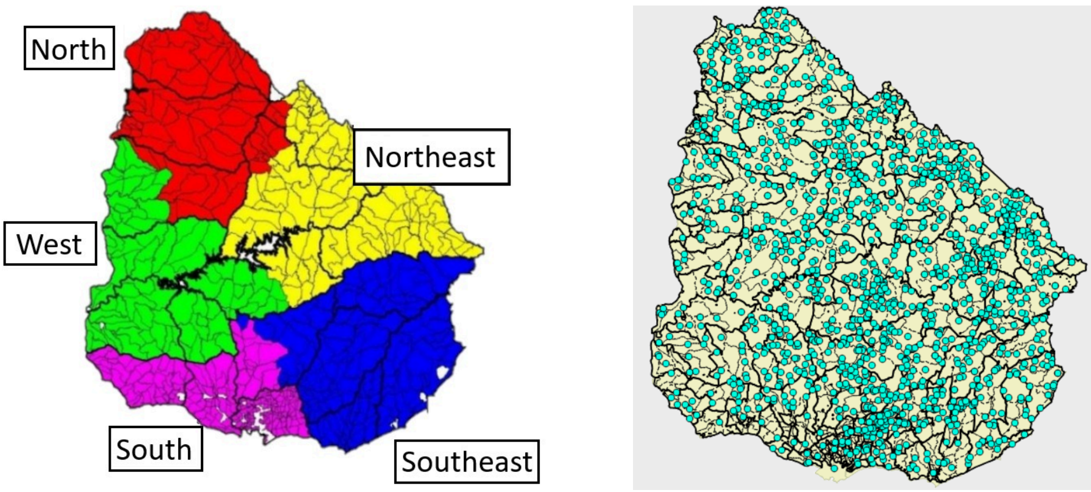
The PFIS application form collected technical and administrative data on proposed projects, allowing for the characterization of applicants and the construction of control variables for impact evaluation in the baseline.

Agricultural Censuses are part of Uruguay's statistical system, and served as the sampling frame for subsequent surveys. The latest available census is the 2011 CGA.

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 LUs (Table 3). Within each category, farms were systematically selected based on LU size. Farms with more than 3,500 LUs 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



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 size, in livestock units*

Livestock Units	BPU	Land (miles 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%**		

Source: Adapted from Bervejillo et al. (2018).

Note: BPU: beef production unit; CDF: cumulative distribution function

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).

The National Livestock Information System (SNIG) is a comprehensive administrative registry that ensures traceability of all major livestock species in Uruguay. It records the lifecycle of each animal, including movements and changes in ownership. By integrating data on slaughter weights and auctions, SNIG allows for estimating beef production at the farm (BPU) level, one of our outcome variables (Aguirre, 2022b).

3.2 Variable construction

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

[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.

We have two outcome variables. The first one is $BEEF_i$, is defined as annual beef production per hectare in farm i.[13] This variable is derived from net cattle transactions (sales minus purchases), adjusted for inventory changes stemming from 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). Our second outcome variable is $GHGIntensity_i$, measures GHG emissions per kilogram of beef (kg CO2e/kg) produced at the farm level. These emissions, calculated using SNIG data and IPCC methods, encompass methane emissions from enteric fermentation and manure, as well as nitrous oxide from excreta. Emissions are expressed in CO2 equivalents using GWP100 factors from IPCC AR5 and aggregated annually (Annex A4).

Table 4. Definitions and construction of variables

Variable	Definition
Outputs (y) (derived from SNIG)	
BEEF	Annual beef production (kg live weight per hectare)
GHGIntensity	GHG emissions per kg of beef produced (kg CO_2e/kg)
Cow-calf technologies (from EBPCMN 2020)	
ControlledMating	1 if controlled mating practiced; 0 otherwise
RevisedBulls	1 if bulls evaluated before mating; 0 otherwise
ArtifInsemination	1 if artificial insemination used; 0 otherwise
OvActivityDiagnosis	1 if ovarian diagnosis performed; 0 otherwise
EarlyWeaning	1 if early weaning practiced; 0 otherwise
TemporaryWeaning	1 if temporary weaning practiced; 0 otherwise
Other outputs (from EBPCMN 2020)	
Cattle Health Problems	1 if reported cattle health problems; 0 otherwise
Producer Organization	1 if part of producer organization; 0 otherwise
AgronTA	1 if received TA from agronomist; 0 otherwise
Baseline control variables (from EGN 2016)	
BLU	Standarized Bovine Livestock Units
Land	Hectares under cattle production
Labor	Full-time-equivalent labor input
CONEAT	Soil productivity index for cattle production
GrazeAreaImprove	Share of improved grazing area
GrazeAreaImprove0	1 if no grazing improvements; 0 otherwise
RegionGroup	Regional indicator variable [categories: 1=North, Northeast and Southeast, 0= South and West]. See Figure 1.
ProductiveOrientation	1 if beef-only system (OBR<= 1)); 0 beef-sheep mixed (4>OBR>1).
BeefProductionSystem	1 if cow-calf (steers/cow-calf<=0.5); 0 full cycle or fattening (RSC>=0.5).

Source: Authors.

[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).

To evaluate the effects of PFIS, we focus on the adoption of specific cow-calf management practices and technologies, including: controlled mating, bull evaluation, artificial insemination, ovarian diagnostics, and various weaning practices.

Finally, we also assess the effect of the program on other outcomes: cattle health, participation in producer groups, and access to technical assistance.

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	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

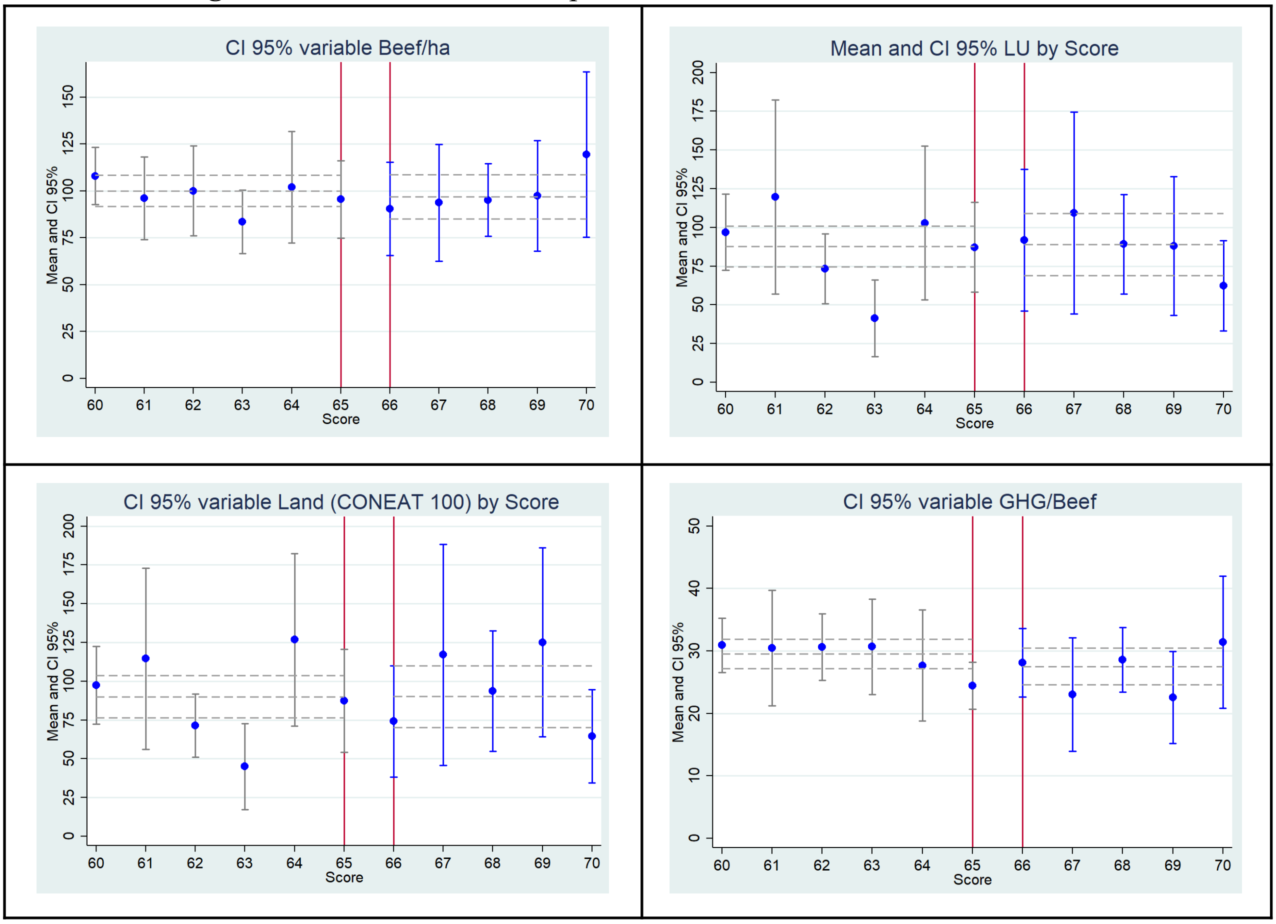
Score	Treated (N) No	Yes	Total	
[0,30]	61	0	61	Untreated: 670 (62.3%)
[31,58]	96	0	96	
59	4	0	4	
60	171	0	171	
61	50	0	50	
62	83	0	83	
63	49	0	49	
64	60	0	60	
65	96	0	96	
66	**0**	**78**	**78**	Treated: 406 (37.7%)
67	0	22	22	
68	0	77	77	
69	0	31	31	
70	0	49	49	
[71, 100]	0	149	149	
Total	**670**	**406**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

Source: Authors.

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 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 included in the resultline survey used for the evaluation.

Figure 3. Falsification test on pre-treatment variables, under second call



Note. Graphs show mean values and 95% confidence intervals for baseline outcomes by score. Horizontal lines indicate group means for treated and control units.
Source. Authors' calculations based on PFIS proposal forms and SNIG data.

3.4. Method

Our primary unit of analysis is the agricultural production unit, defined as a commercial operation larger than one hectare that shares labor, capital, and inputs. To estimate the causal effect of PFIS on technology adoption and production outcomes at this level, we implement a regression discontinuity design (RDD). This approach exploits the sharp eligibility rule applied during the second PFIS call, under which only producers that scored 66 or higher were selected. The central assumption of the RDD framework is that applicants who scored just above and just below the threshold are comparable in all respects other than treatment status.

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.

We incorporate baseline control variables to enhance statistical power, improve precision, 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).

Because the assignment variable is discrete, 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 improve precision and reduce bias in small samples, we estimate this effect using Lin's estimator (Lin, 2013), which adjusts for 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] Let Y_i represent the outcome of interest, 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:

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

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.

[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.

4. Results

We begin by analyzing the effect of PFIS on beef production per hectare. As reported in Table 7, the estimated local average treatment effect at the margin of eligibility is positive, approximately 5 kg/ha/year, but not statistically significant. The result remains stable across model specifications, including those that control for a range of pretreatment covariates and baseline production levels. This consistency suggests that the lack of statistical significance is not due to model misspecification but rather reflects the robustness of the null finding.

Table 7. 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
	(0.766)	(0.85)	(0.81)
N	80	73	67
R^2	0.001	0.252	0.318
Mean(y)	103.2	104.6	105.2
Controls	No	Yes	Yes
Beef/ha	No	No	Yes

Note: p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
The controls variables are: BeefProductionSystem, ProductiveOrientation, RegionGroup, Land, BLU, GrazeAreaImprove, GrazeAreaImprove0, Coneat, Labor.
Source: Authors' calculations based on EGN, EBPMCN, and SNIG data.

We then examine the program's effect on emissions intensity, measured as GHG emissions per kilogram of beef produced. Results are presented in Table 8. The estimated effect is again not statistically significant, and remains so across models with and without covariates or baseline GHG intensity.

Table 8: Effect of PFIS on GHG intensity

VARIABLES	Model 1	Model 2	Model 3
PFIS	2.93	2.74	1.7
	(0.464)	(0.465)	(0.651)
N	96	94	90
R^2	0.006	0.03	0.106
Y mean	25.2	25.4	25.2
Controls	No	Yes	Yes
2016 GHG Intensity	No	No	Yes

Note: The outcome variable is kg CO2-equivalent emitted per kg of meat produced.
The controls variables are: BeefProductionSystem, ProductiveOrientation, RegionGroup, Land, BLU, GrazeAreaImprove, GrazeAreaImprove0, Coneat, Labor. p-values in parentheses.
*** pv<0.01, ** pv<0.05, * pv<0.1
Source: authors' estimation based on EGN, EBPMCN and SNIG data.

To address concerns related to the limited sample size and the narrow bandwidth around the eligibility threshold, we conducted several robustness checks. First, we performed a power analysis of the *t*-test used to estimate the average treatment effect for the beef 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 significant, reinforcing our findings.

Like in the case of productivity and emissions intensity, we find no statistically significant effects of the PFIS on the use of artificial insemination, incidence of cattle health problems, participation in producer organizations, or engagement with agronomic advisers. However, the program did have a statistically significant impact on the adoption of three good practices for reproductive management and herd efficiency (Table 9): controlled mating (an increase of 22.4 percentage points, p-value = 0.018), ovarian activity diagnosis (16.3 percentage points, p-value = 0.015), and early weaning (8.7 percentage points, p-value = 0.055).

Table 9: Effect of PFIS on technology adoption on Resultline

Variables	Coefficient	p-values	R^2	N	Mean
Controlled Mating	0.2237**	0.018	0.057	98	0.442
Ovarian Activity Diagnosis	0.163**	0.015	0.082	72	0.185
Early Weaning	0.0869*	0.055	0.035	106	0.104
With Artificial Insemination	0.055	0.548	0.005	75	0.207
Cattle Health Problems	-0.088	0.345	0.008	119	0.471
In a producers' organization	0.064	0.494	0.004	119	0.490
With an agronomist	0.059	0.256	0.011	119	0.118

Note: p-values in parentheses. *** pv<0.01, ** pv<0.05, * pv<0.1

5. Conclusions and discussion

Technology transfer programs are widely employed to enhance livestock productivity and promote sustainability. However, robust empirical evidence on their effectiveness remains limited. Rigorous evaluation is crucial not only for ensuring transparency and accountability but also for informing the design of cost-effective policies.

This study contributes to bridging this evidence gap by assessing the effect of Uruguay's PFIS on small and medium-sized beef producers on productivity, emissions intensity, and the adoption of specific technology and management practices. Leveraging a natural experiment from the second PFIS call, where treatment assignment followed a discontinuous rule, we estimate causal effects using an RDD.

Our results show that PFIS did not produce statistically significant effects on beef output per hectare or on GHG intensity, indicating that it did not achieve productivity or sustainability gains 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).

The absence of detectable effects on beef production and GHG emissions intensity despite the program's effectiveness in fostering the adoption of the above technology and management practices, raises the question of the necessary length of time between when a farmer adopts these technologies and they materialize in productivity and emissions intensity gains. It may be the case that there is a necessary time lag between the adoption of these practices and their eventual impact on productivity and emissions reduction. On the other hand, three years may be a sufficient time for these effects to materialize in part, at least, and the behavioral change fostered by the program is not enough to lay a foundation for future productivity improvements.

In any case, our findings reinforce the value of carefully designed, evidence-based public interventions and underscore the importance of embedding rigorous impact evaluation into policy design and implementation cycles.

Future impact evaluations could adopt a wider perspective by including metrics for profitability, biodiversity, animal health, and other sustainability dimensions. Additionally, assessing heterogeneous effects across different producer segments can help identify which support strategies yield the most durable benefits across diverse beef systems. Understanding whether early behavioral changes translate into long-term improvements will also require longitudinal data and follow-up studies.

6. References

Aguirre, E. (2018). Evolución reciente de la productividad ganadera en Uruguay (2010-17). Metodología y primeros resultados. In *Anuario OPYPA* (pp. 457–470). Ministerio de Ganadería Agricultura y Pesca.

Aguirre, E. (2019). Productividad ganadera de los establecimientos de carne bovina del Censo General Agropecuario. In *Anuario OPYPA* (pp. 497–510). Ministerio de Ganadería Agricultura y Pesca.

Aguirre, E. (2022a). *Evolución de la productividad ganadera en Uruguay (2005-2021)*. https://www.researchgate.net/publication/368839939_Evolucion_de_la_productividad_ganadera_pastoril_en_Uruguay_2005-2021

Aguirre, E. (2022b). La asociación entre adopción de tecnologías y productividad en la ganadería de carne vacuna en Uruguay. In *Anuario OPYPA* (pp. 559–570). Ministerio de Ganadería Agricultura y Pesca.

Aguirre, E. (2022c). La variabilidad de la producción ganadera pastoril en Uruguay entre 2005 y 2021. In *Anuario OPYPA* (pp. 549–558). Ministerio de Ganadería Agricultura y Pesca.

Aguirre, E. (2022d). *Productividad y adopción de tecnologías en la ganadería de carne vacuna en Uruguay*. https://www.researchgate.net/publication/368839950_Productividad_y_adopcion_de_tecnologias_en_la_ganaderia_de_carne_vacuna_en_Uruguay/stats

Aguirre, E., García Suárez, F., & Sicilia, G. (2024a). Technical efficiency in beef cattle farming in Uruguay: Insights from census data. *Agrociencia Uruguay*, *28*, e1237–e1237. https://doi.org/10.31285/AGRO.28.1237

Aguirre, E., García Suárez, F., & Sicilia, G. (2024b). Technological frontier in Uruguay's beef cattle production: An analysis of technical efficiency and its main drivers. *Agribusiness*. https://doi.org/10.1002/agr.21944

Álvarez, J. (2020). Desempeño relativo de la productividad física de la ganadería de Nueva Zelanda y Uruguay, 1870-2010. *Historia Agraria: Revista de Agricultura e Historia Rural*, *80*, 107–144.

Bervejillo, J. E., Campoy, D., Gonzalez, C., & Ortiz, A. (2018). Resultados de la Encuesta Ganadera Nacional 2016. *Anuario OPYPA 2018*, 443–455.

Calvo Buendia, E., Tanabe, K., Kranjc, A., Baasansuren, J., Fukuda, Ngarize, S., Osako, A., Pyrozhenko, Y., Shermanau, P., & Federici. (2019). 2019 Refinement to the 2006 IPCC guidelines for national greenhouse gas inventories. In *Agriculture, forestry and other land use* (Vol. 4, p. 824). IPCC Geneva, Switzerland:

Cattaneo, M. D., Titiunik, R., & Vazquez-Bare, G. (2016). Inference in Regression Discontinuity Designs under Local Randomization. *The Stata Journal*. https://doi.org/10.1177/1536867X1601600205

de Janvry, A., Sadoulet, E., & Suri, T. (2017). Chapter 5—Field Experiments in Developing Country Agriculture. In A. V. Banerjee & E. Duflo (Eds.), *Handbook of Economic Field Experiments* (Vol. 2, pp. 427–466). North-Holland. https://doi.org/10.1016/bs.hefe.2016.08.002

DIEA-MGAP. (2014). *Censo general agropecuario 2011: Resultados definitivos*.

Durán, V., Aguirre, E., Baraldo, J., Fuletti, D., & Hernández, E. (2018). Primera evaluación del Programa de Desarrollo Productivo Rural. In *Anuario OPYPA* (pp. 583–597). Ministerio de Ganadería Agricultura y Pesca.

Durán, V., & Hernández, E. (2017). Estrategia de evaluación del Programa Producción Familiar Integral y Sustentable (PFIS). In *Anuario OPYPA 2017*. Ministerio de Ganadería Agricultura y Pesca.

Durán, V., & Laguna, H. (2021). Evaluación de Impacto del Proyecto Ganaderos Familiares y Cambio Climático. In *Anuario OPYPA 2021*. Ministerio de Ganadería Agricultura y Pesca.

Eggleston, H., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K. (2006). *2006 IPCC guidelines for national greenhouse gas inventories*.

Gerber, P. J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., & Tempio, G. (2013). *Tackling climate change through livestock: A global assessment of emissions and mitigation opportunities.*

Gesto, N., Lado, A., & Laguna, H. (2019). Informe de caracterización de la población potencial ganadera del Programa Familiar Integral y Sustentable. In *Anuario OPYPA*. Ministerio de Ganadería Agricultura y Pesca.

Hainmueller, J. (2012). Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Political Analysis*, *20*(1), 25–46.

Imbens, G. W., & Rubin, D. B. (2015). *Causal Inference in Statistics, Social, and Biomedical Sciences*. Cambridge University Press.

Jones, C., Costa, N., Gonzalez, C., Risso, S., Baraldo, J., Aguirre, E., Laguna, H., Durán, V., & Oyhantcabal, W. (2020). Fortalecimiento del sistema de reporte y verificación de la Contribución Determinada Nacional al Acuerdo de París: Indicador de ganadería en campo natural. In *Anuario OPYPA 2022*. Ministerio de Ganadería Agricultura y Pesca.

Lanfranco, B., Soares de Lima, J. M., Fernández, E., & Ferraro, B. (Eds.). (2022). Bioma Pampa: Una historia de sinergias entre pastizales, ganado y humanos. *Revista INIA*. https://doi.org/10.22004/ag.econ.336991

Lin, W. (2013). Agnostic notes on regression adjustments to experimental data: Reexamining Freedman's critique. *The Annals of Applied Statistics*, *7*(1), 295–318. https://doi.org/10.1214/12-AOAS583

López, C. A., Salazar, L., & De Salvo, C. P. (2017). *Public Expenditures, Impact Evaluations and Agricultural Productivity: Summary of the Evidence from Latin America and the Caribbean*. IDB. http://dx.doi.org/10.18235/0000627

Lopez, F., & Maffioli, A. (2008). *Technology adoption, productivity and specialization of uruguayan breeders: Evidence from an impact evaluation*. https://webimages.iadb.org/publications/english/document/Technology-Adoption-Productivity-and-Specialization-of-Uruguayan-Breeders-Evidence-from-an-Impact-Evaluation.pdf

MacLeod, M., Vellinga, T., Opio, C., Falcucci, A., Tempio, G., Henderson, B., Makkar, H., Mottet, A., Robinson, T., & Steinfeld, H. (2018). Invited review: A position on the global livestock environmental assessment model (GLEAM). *Animal*, *12*(2), 383–397.

Ministerio de Ambiente. (2021). *Uruguay presentó su cuarto Informe bienal de actualización y el*

Reporte nacional de Inventario de GEI 1990—2019. Ministerio de Ambiente. https://www.gub.uy/ministerio-ambiente/comunicacion/noticias/uruguay-presento-su-cuarto-informe-bienal-actualizacion-reporte-nacional

Mullally, C., & Maffioli, A. (2016). Extension and Matching Grants for Improved Management: An Evaluation of the Uruguayan Livestock Program. *American Journal of Agricultural Economics*, *98*(1), 333–350. https://doi.org/10.1093/ajae/aav050

Nin, A., Freiría, H., & Muñoz, G. (2019). *Productivity and efficiency in grassland-based livestock production in Latin America: The cases of Uruguay and Paraguay* (Working Paper IDB-WP-1024; p. 69). IDB Working Paper Series. https://doi.org/10.18235/0001924

OECD, & FAO. (2023). *OECD-FAO Agricultural Outlook 2023-2032*. https://www.oecd-ilibrary.org/content/publication/08801ab7-en

Paparamborda, I. A. (2017). *¿ Qué nos dicen las prácticas de gestión del pastoreo en los predios ganaderos familiares sobre su funcionamiento y resultado productivo?*

Peyrou, J. (2016). *La cadena de la carne vacuna*. Universidad Católica del Uruguay.

Polcaro, S. (2022). Análisis de resultados de la Encuesta de Buenas Prácticas de Manejo de Campo Natural. In *Anuario OPYPA 2022*. Ministerio de Ganadería Agricultura y Pesca.

Ruggia, A., Dogliotti, S., Aguerre, V., Albicette, M. M., Albin, A., Blumetto, O., Cardozo, G., Leoni, C., Quintans, G., Scarlato, S., Tittonell, P., & Rossing, W. A. H. (2021). The application of ecologically intensive principles to the systemic redesign of livestock farms on native grasslands: A case of co-innovation in Rocha, Uruguay. *Agricultural Systems*, *191*, 103148. https://doi.org/10.1016/j.agsy.2021.103148

Skovron, C., & Titiunik, R. (2015). A practical guide to regression discontinuity designs in political science. *American Journal of Political Science*, *2015*, 1–36.

Steinfeld, H. (2006). *Livestock's long shadow: Environmental issues and options*. FAO.

Stocker, Qin, Plattner, Tignor, Allen, Boschung, Nauels, Xia, Bex, & Midgley. (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Uruguay XXI. (2024). *Informe sector Ganadero—2024*. https://www.uruguayxxi.gub.uy/es/centro-informacion/articulo/informe-sector-ganadero-2024/

Winters, P., Salazar, L., & Maffioli, A. (2010). *Designing Impact Evaluations for Agricultural Projects*. IDB. http://dx.doi.org/10.18235/0008595

Supplementary material

Table S. 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=19133 (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
			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.

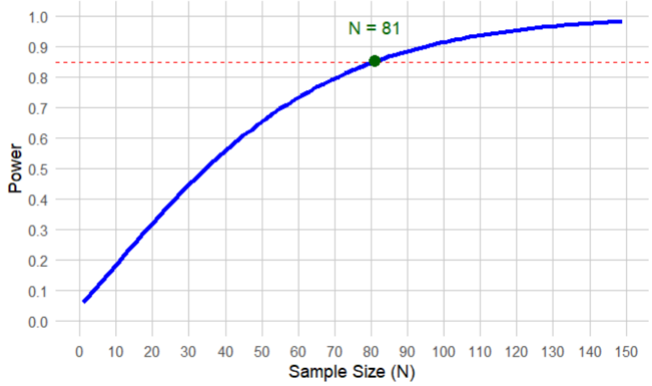
Within each window, we conduct difference-in-means tests on four baseline variables: livestock units, land area (measured in CONEAT 100-adjusted hectares), beef output per hectare, and GHG emissions intensity (see Table S6). These tests provide evidence on whether units just above and below the threshold 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 S 1 : 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	0.76	0.73	80
GHG intensity	2.928	0.47	0.46	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.

Sensibility of PFIS impact on Beef/ha with different bandwidth	Sensibility of PFIS impact on GHG emissions with different bandwidth