The Impact of Cash Transfers on the Use of Health Services During the COVID-19 Pandemic: Evidence from Peru*

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Abstract

This study examines the effects of unconditional cash transfers on the utilization of medical and pharmaceutical services. At the height of the COVID-19 crisis, the Peruvian government introduced cash transfers to alleviate the socioeconomic burden on the most vulnerable households. Using data from the 2021 Peruvian Household Survey, we apply a causal inference approach based on propensity score matching, which allows for the identification of households with comparable observable characteristics. Our findings suggest that the cash transfers did not significantly influence spending patterns. These results provide valuable insights into the effectiveness of cash transfer policies during periods of adversity, with implications for the design of social and economic protection policies in crisis contexts.

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1 Introduction

The COVID-19 pandemic severely impacted countries, prompting governments to adopt exceptional policy measures to alleviate its effects on the population. Non-pharmaceutical interventions (NPIs) were implemented widely to (i) slow the spread of contagion and (ii) reduce infections (Ferguson et al., 2020). In Peru, NPIs were among the most stringent in the region and the strictest globally (Gruber, 2021).

Peru was one of the countries most affected by the pandemic, recording the highest COVID-19 mortality rate in the world (Dong et al., 2020) and suffering significantly from the recession. The crisis was intensified by structural issues such as informality and inadequate infrastructure (Gruber, 2021). In 2021, the labor informality rate reached 76.8%, one of the highest in the region (INEI, 2021). Limitations in the social security system hindered the effectiveness of NPIs. In this context, cash and in-kind transfer programs were implemented to mitigate the negative impact of the pandemic on the incomes and food security of vulnerable households.

In Latin America and the Caribbean (LAC), existing cash transfer programs were expanded, and new programs were created, resulting in nearly universal coverage. In Peru, cash transfer programs reached 52% of the total population, with 38% covered by the Bono Yo me quedo en casa, Bono independiente, Bono rural, and Bono Familiar Universal (Ullmann et al., 2021). These cash transfers aimed to reduce the negative impact of the strict quarantine and COVID-19.

The Bono Familiar Universal (BFU), which had the widest coverage, benefited 8.4 million households, covering 78% of the population (Rubio et al., 2021). A one-time exceptional payment of 760 PEN[1] was made to those who met the following criteria: (i) households in poverty according to the Household Targeting System (SISFOH), (ii) households with members receiving benefits from the Juntos Program, Pensión 65, or Contigo, (iii) households whose members were not registered in the Registro Centralizado de Planillas y de Datos de los Recursos Humanos del Sector Público (AIRHSP)[2] or private payrolls, excluding pensioners and those in training programs. Additionally, eligible households could not have members with an income exceeding 3000 PEN.

Our research aims to find the impact of the BFU on non-explicit objectives that are relevant in the pandemic context, such as the use of health services. It addresses the question: Did the BFU impact the use of medical care during COVID-19? In the Peruvian context, the discussion on the impact of unconditional

[1]This amount represents approximately 74 percent of the minimum wage.
[2]This registry encompasses all formal workers in the country.

cash transfers (UCTs) is limited. Most studies on transfers focus on conditional cash transfers (CCTs), given the extensive reach of the Juntos program[3]. In Latin America, CCT programs are cost-effective, which is why the literature tends to focus on these types of policies. In contrast, in Africa, where high poverty levels make UCT programs more suitable, short-term effects are positive on well-being indicators (Baird et al. (2013), Gaarder (2012)). However, due to the recent establishment of UCTs as policy responses, there is room in the literature to address their effects on the use of health services.

We analyze the relationship between UCTs and the use of health services, referencing the neoclassical theory of consumer utility maximization and health production theory. In these models[4], consumer demand for good health is categorized as both a consumption good and an investment good. As a consumption good, individuals derive satisfaction and show a strong preference for good health based on their preferences. As an investment good, good health determines the total amount of time available for market and non-market activities.

Grossman (1972) develops a human capital model in which the stock of health depreciates over time and can be increased through investment. An increase in the stock of health enhances efficiency in production. Doroh et al. (2013) note that the utilization of health services is a significant determinant of health. The accessibility of health services for vulnerable and disadvantaged populations has been recommended by the World Health Organization as a fundamental concept of primary health care. However, access to health services remains a challenge in Peru due to the deficient health system. The pandemic exacerbated issues of fragmentation and inequity within this system, reducing the government's capacity to respond to the crisis (Gianella et al., 2021).

It is reasonable to think that households receiving cash transfers will, on average, have more available resources (income effect) that can be used to consume healthcare, medications, or associated expenses for accessing health services (fees at medical centers, transportation). Given the vulnerable situation of households that received cash transfers, there is a higher likelihood of an increase in their food spending, which also has a positive indirect impact on health. Poverty is understood as a social determinant of health, as it can generate or intensify issues directly related to lower health quality due to restricted access to drinking water and sanitation, education, and housing (Pega et al., 2017). Utilizing health services can lead to better health, translating into higher levels of well-being. The decision to use these services may depend on

[3]Studies by Perova and Vakis (2009); Pérez-Lu et al. (2017); Gahlaut (2011); Sanchez et al. (2016)

[4]Both theories have been documented in textbooks and articles on health economics, such as: Santerre and Neun (2013), Feldstein (2012), Grossman (1972), Gertler et al. (1987), Fenny et al. (2015), Asmah et al. (2013), and Asmah and Orkoh (2015).

various factors, such as the cost of medical care, income, education, genetic characteristics, environmental factors, ethnicity, cultural beliefs, among other variables. Therefore, the objective is to evaluate whether UCTs increased the use of health services through self-reported visits to health facilities.

Given the context of the pandemic, the cash transfers were widely promoted by the government as a tool to mitigate the negative effects on income resulting from the crisis. As a result, recent databases from INEI contain information on these programs. A Propensity Score Matching approach will be implemented to find comparable individuals and determine the program's effect among different groups with similar characteristics. Thus, the contribution of this research lies in enhancing the economic literature on UCTs for both Peru and Latin America. Furthermore, our focus on access to medical services is underexplored in the Peruvian context.

This document is organized as follows: Section 2 presents the literature review; Section 3 contains information about the data sources; Section 4 shows the empirical strategy that will evaluate the program's impact on access to health services and health spending; Section 5 presents the results of the matching and the impact; Section 6 discusses our results; and Section 7 provides the conclusions.

2 Literature Review

Cash transfer programs can improve health outcomes through pathways of poverty reduction, food security, and productive capacity (Novignon et al., 2022). Ranganathan and Lagarde (2012) identified 13 CCT programs evaluated in countries across Latin America, Asia, and Africa, with results suggesting that CCTs have been effective in increasing the use of preventive services, improving immunization coverage, certain health outcomes, and promoting healthy behaviors. Owusu-Addo and Cross (2014) examined 16 publications from 6 studies and concluded that CCT programs had positive impacts on the utilization of health services. Similarly, Owusu-Addo et al. (2018) reviewed eight CCTs and found that two out of three studies indicated positive impacts on the use of health facilities. Conversely, Pega et al. (2017) found insufficient evidence of impacts on health service utilization, although some evidence suggested increases in medical care spending.

The BFU was granted in response to an emergency that can be considered a "epidemiological disaster," sharing characteristics with UCTs in humanitarian disaster contexts. Pega et al. (2015) evaluate the effects of UCTs on improving the use of health services in disaster contexts in low- and middle-income countries, including 3 studies in Nicaragua and Niger for households that received cash donations as part of disaster response; the included studies did not report evidence that UCTs affected the use of health services. On the other hand, Reyes et al. (2018) found that the UCT provided by UNICEF to victims of Typhoon Yolanda allowed beneficiary families to purchase multivitamins, which are useful for adequate food intake and thus improve their health. According to Luseno et al. (2013), UCTs improve health outcomes for all vulnerable children aged 6 to 17, who, compared to children from non-beneficiary households, have higher chances of utilizing health services for severe illnesses.

In the context of the pandemic, Pilkauskas et al. (2022) conducted a randomized controlled trial in the United States where the treatment was an unconditional transfer to vulnerable households, finding no effect on health outcomes. In Togo, Tossou (2021) find a positive impact of cash transfers on the demand for health services for beneficiary households. In Colombia, Alvarez et al. (2022) study the effect of UCTs on mobility patterns as a measure for social distancing, finding that the effectiveness of cash transfers depends on factors related to civic capital. In Peru, Curi-Quinto et al. (2021) study the effect of the BFU on food security, finding that government support was insufficient in reducing food insecurity.

3 Data

The data source for this study comes from the Peruvian Household Survey (ENAHO) for 2021. ENAHO includes various modules that provide information about household characteristics and their members concerning social, economic, health, education, and employment aspects. The indicator for the use of medical services and pharmacies was constructed based on the question of whether respondents sought care at a health facility or visited pharmacies for their ailments. The treatment variable was obtained from the Social Programs Module[5].

To identify comparable groups, the survey provides variables such as age, gender, education level of the head of the household, whether they are native speakers, household size, rural residence, access to services (water, sanitation, and electricity), and the department of residence. The sample was restricted to heads of households reporting chronic illness and/or having been ill in the past 4 weeks, yielding a total of 52,355 observations, of which 11,900 received the BFU. Table 1 presents the descriptive statistics for the main variables in the study.

[5]Household's heads were asked the following question: ”In the last 3 years, have you or any member of your household benefited from any of the following programs?”, where BFU was one of the options

Table 1: Descriptive statistics

Variables	BFU Households	Control
Age of Household Head (Mean)	54.64	53.13
Number of Household Members (Mean)	3.37	3.40
Access to Services (Mean)	0.46	0.52
Household Head: Female	34.29%	35.64%
Education of Household Head		
None or Incomplete Primary	33.53%	28.16%
Complete Primary or Incomplete Secondary	32.87%	30.59%
Complete Secondary or Incomplete Tertiary	25.88%	29.06%
Complete Tertiary	7.71%	12.19%
Rural Area	50.77%	43.59%
Use of Medical Services	17.34%	17.45%
Use of Pharmacies	13.47%	14.25%
Health Expenditure (Mean in annual PEN)	1,180.13	1,317.60
Food Expenditure (Mean in annual PEN)	5,496.54	5,919.17
Number of Observations (N)	11,900	40,455

4 Identification Strategy

To evaluate the impact of the BFU on the use of health services, we rely on non-experimental methods applicable to the available data. One of the main challenges in estimating this impact lies in identifying an appropriate control group. The estimation of the BFU's effect is based on the question: what would have happened to head of household i if they had not received the program? The difference between what actually occurred and the counterfactual estimate defines the program's impact. As noted by Mata and Hernández (2015), those who benefited from the program and those who did not may differ, so it is necessary to remove these differences to avoid bias. This allows us to extract the causal effect between the variables of interest. To eliminate differences between the treatment and control groups, we will implement the matching method or Propensity Score Matching (PSM).

Let $Y_i(1)$ represent the outcome if individual i received the treatment (BFU), and $Y_i(0)$ represent the outcome if the individual did not receive the BFU. T is a binary variable, where $T = 1$ indicates the treated group and $T = 0$ the control group. The objective is to estimate the Average Treatment Effect (ATE) by comparing the outcomes between the treated and control groups:

$$ATE = E[Y_i(1)] - E[Y_i(0)]$$

If the treatment were randomly assigned, the ATE would equal the Average Treatment Effect on the Treated

(ATT). However, since we are using non-experimental data, there is a risk of selection bias. To estimate the ATT, we employ PSM, relying on two assumptions: ignorability and common support.

PSM identifies individuals in the treatment and control groups with similar observable characteristics X, where the only difference is whether or not they received the BFU. The probability of participating in the treatment, $P(X) = Pr(T = 1|X)$, is used for matching, ensuring that estimation occurs within the common support region where both groups are comparable. This assumption guarantees that individuals with the same characteristics have a positive probability of being in either group. We also rely on the conditional independence assumption, which posits that observable differences are the sole source of selection bias, enabling valid outcome comparisons.

Before applying PSM, we conduct a comparison of means between the treatment and control groups for observable characteristics to assess similarity among household heads. If significant differences are detected, we proceed with PSM to mitigate these disparities. We estimate the participation model using a logit model, which requires careful selection of variables that simultaneously affect participation decisions and outcomes. As shown by Heckman et al. (1998), PSM estimates are sensitive to the variables included in the propensity score $P(X)$. The logit model is represented as:

$$P(T_i = 1|x_i) = F(x_i'\beta + \mu_i)$$

where T_i is a binary variable indicating whether the household head is a beneficiary of the BFU, and X_i is the vector of characteristics such as age of the household and the household head such as gender, education, age, size of the household, rural, access to services, native language and location of the household (region).

With the obtained scores, we match treated and control units using the nearest neighbor method, where each treated unit pairs with a control unit with the closest propensity score. It is crucial to define the common support region, ensuring that matched units have comparable characteristics. Observations outside this region are excluded from the analysis. The balance of covariates between treatment and control groups is verified by comparing means post-matching. According to Bernal and Peña (2011), for PSM to be effective, the treatment and control groups must be similar after conditioning on the propensity score:

$$P(X|T = 1) = P(X|T = 0) \tag{1}$$

Finally, we compute standard errors to establish confidence intervals for the Average Treatment Effect on the Treated (ATT), which can be calculated analytically for nearest neighbor matching. For kernel matching, bootstrapping may be required, though Abadie and Imbens (2008) argue that it is ineffective for nearest neighbor estimators. PSM has limitations, as highlighted by Gertler et al. (2011), including the necessity of large datasets and the inability to incorporate unobservable characteristics in propensity score calculations.

4.1 Descriptive Analysis of the Difference Test

The difference test compares the averages of the two groups to infer a relationship between the treatment and control groups. An analysis of the observable socioeconomic characteristics was conducted to assess the similarity among household heads in both groups. From table 2, we observe that the two groups are identical in observed characteristics such as household size and healthcare utilization. However, significant differences are evident in other variables, including age, sex, education, ethnicity, rural area status, pharmacy use, healthcare spending, and food expenditure. The results indicate a relatively similar frequency in the use of medical services between the two groups.

Regarding healthcare spending, the results show a higher frequency in favor of the control group. While the analysis reflects only averages, it does not capture the actual effect of cash transfers on healthcare utilization. The existence of differences in observable characteristics between the two groups biases this outcome. Therefore, propensity score matching is essential, as it provides more robust results by neutralizing these biases.

Table 2: Comparison of Control and Treatment Groups

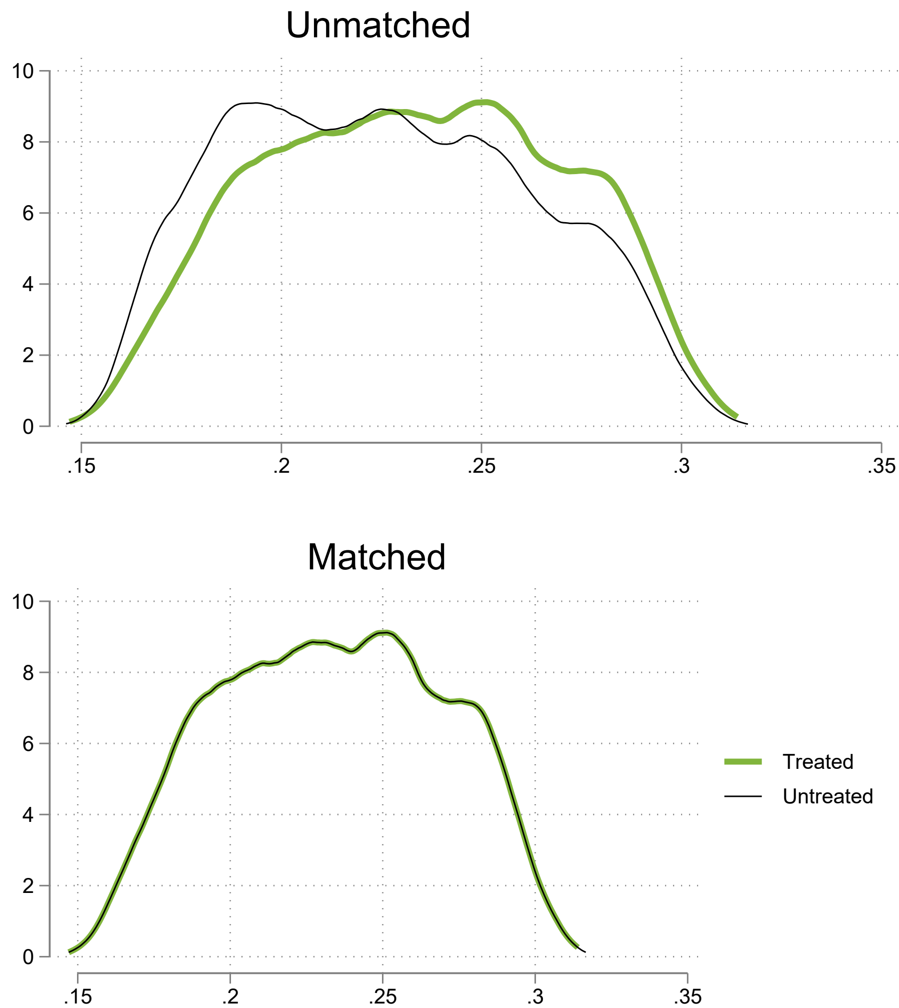
Variables	Control	Treatment	Difference (t-student)
Age of Household Head	53.13	54.64	-9.38
Sex of Household Head	0.36	0.34	2.73
Education of Household Head	2.25	2.08	16.99
Native	0.36	0.38	-3.83
Household Size	3.40	3.37	1.70
Rural Area	0.44	0.51	-13.86
Access to Services (Water, Sanitation, and Electricity)	0.52	0.46	11.30
Department	12.27	12.08	2.52
Use of Medical Services	0.17	0.17	0.29
Use of Pharmacies	0.14	0.13	2.16
Health Expenditure	1,317.60	1,180.13	5.30
Food Expenditure	5,919.17	5,496.54	9.05

4.2 Matching

With the estimated coefficients, we predict the probability of receiving the BFU for both the treated and control groups. It is useful to visualize the predicted probability distributions for both groups using histograms, as shown in figure A1. Figure A2 illustrates the results of the common average propensity score distributions defined within the interval [0.10; 0.35]. The analysis of this graph indicates that the propensity scores exhibit overlapping distributions in the common support region for both treatment and control groups. This overlap shows that each treated individual (BFU recipient) can match with at least one control individual (non-recipient). The values with the highest scores and the best overlap are found between 0.15 and 0.30.

Figure 1 presents a Kernel density plot estimating the underlying distributions of the propensity scores before and after matching. Before matching, there is a significant difference in the distributions of the two groups. After matching, the propensity score distributions are nearly identical. This analysis reflects the evolution of household heads receiving or not receiving the BFU. Prior to matching, the curve for households receiving the BFU due to COVID-19 (treatment group) extends to the right compared to the control group, indicating that these households likely utilize cash transfers to increase the frequency of health service use during the pandemic. After matching, there is little difference between the treatment and control groups; the two curves are similar across the common support. This suggests that the matching between BFU recipients and non-recipients was successful.

Figure 1: Non-parametric estimation before and after the matching



In Figure 2, the black dots illustrate the success of the propensity scores, averaging across 8 key covariates for the matching analysis in a basic model. These dots represent the average difference between the unpaired treatment and control groups at baseline, while the crosses indicate the average difference between the paired treatment and control groups. The large initial differences are reduced to nearly zero after matching the propensity scores between the two groups. The matching results based on socioeconomic characteristics reveal that before matching, several variables such as education, access to basic services, rural area, and age are dispersed between the treatment and control groups. After matching, the differences diminish, with the crosses centering around zero. This demonstrates that the treatment was successful, confirming the analysis from figure 1. We conclude that after matching, the individuals are comparable due to their similar characteristics.

Figure 2: Propensity score distribution before and after the matching

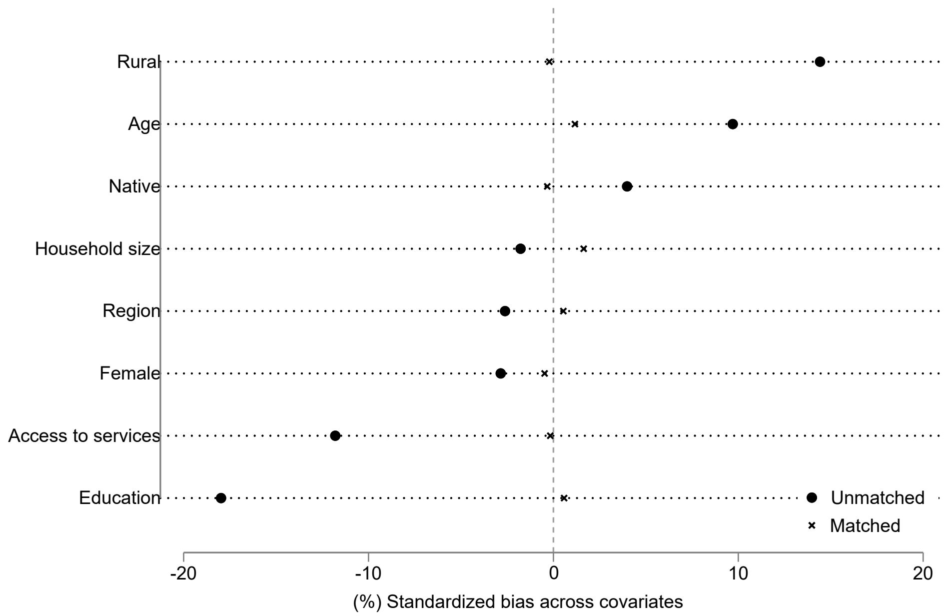


Table A1 presents the t-tests and the bias percentage that occurs when matching the variables. Before matching, the differences are significant, whereas after matching, the variables have p-values exceeding 5%. This indicates successful matching, with individuals being similar in terms of socioeconomic characteristics. We can conclude that households without access to the BFU during the pandemic have comparable probabilities of being BFU recipients. Furthermore, the percentage of bias reduction through variable matching is notably high for certain variables, such as being native, education level, rural area, and access to services. This confirms the success of matching socioeconomic variables.

5 Results

The findings of our analysis raise important questions about the effectiveness of the BFU in addressing health-related challenges during the COVID-19 pandemic. Despite expectations that the cash transfer program would enhance access to medical services and alleviate financial burdens associated with healthcare and food expenditures, our results indicate a lack of statistically significant impacts on these critical outcomes. Table 3 shows that the average usage of medical services for the treatment group was 0.1734 compared to 0.1762 for the control group, resulting in a difference of -0.0028 (S.E. = 0.0049, T-stat = -0.56), which is not statistically significant. Similarly, the spending on healthcare shows a slight increase of 20.4828 (S.E. = 30.3017, T-stat = 0.68) for the treated group compared to the control group, but this result is also statistically insignificant, suggesting that the BFU may not have meaningfully influenced healthcare expenditure. Although there was a notable difference in pharmacy usage before matching (0.1347 for treated vs. 0.1425 for controls, with a difference of -0.0078, S.E. = 0.0036, T-stat = -2.16), the ATT results show no significant impact after matching, indicating that the program did not lead to an increase in pharmacy utilization. These results highlight that while the BFU may have provided some financial relief, it was inadequate in fundamentally altering healthcare behaviors or expenditures in a meaningful way. The observed variations suggest that cash transfers alone may not effectively address systemic barriers to healthcare access and utilization, especially in a pandemic context.

Table 3: Effect of BFU on relevant outcomes

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Use of medical services	Unmatched	0.1734	0.1744	-0.0010	0.0040	-0.28
	ATT	0.1734	0.1762	-0.0028	0.0049	-0.56
Use of pharmacies	Unmatched	0.1347	0.1425	-0.0078	0.0036	-2.16
	ATT	0.1347	0.1344	0.0003	0.0044	0.08
Health expenditure	Unmatched	1180.6232	1318.0346	-137.4114	25.9649	-5.29
	ATT	1180.6232	1160.1404	20.4828	30.3017	0.68
Food expenditure	Unmatched	5496.6690	5918.8334	-422.1644	46.7280	-9.03
	ATT	5496.6690	5473.2107	23.4583	55.2364	0.42

6 Discussion

We study the effect of the most extensive unconditional cash transfer program in Peru, which provides one-time assistance to vulnerable households during the pandemic. Our results indicate that there are no significant differences in the use of medical services, and, conversely, receiving the treatment may be associated with a slight reduction in their utilization. This finding aligns with Pega et al. (2017), which concludes that UCTs do not affect this variable of interest.

We believe that the deficiencies in the health system, exacerbated by the pandemic, prevented access to these services, despite having additional resources. Regarding the use of pharmacies, the sign of the difference suggests that access to them for treating illnesses was possible. The collapse of the health system and a culture of self-medication may have led beneficiaries to choose this option.

As for health expenditure, while no significant effect is found, the difference indicates an increase, which may be attributed to the pandemic's distortion of the medicine market. In terms of food expenditure, the difference suggests an increase, consistent with literature indicating that poorer households tend to spend more in this area (Banerjee and Duflo, 2007), as well as findings by Londoño-Vélez and Querubin (2022), which report modest positive effects of UCTs on access to food. Curi-Quinto et al. (2021) note that the financial support provided by the government during this initial phase did not alleviate or protect families from food insecurity. The reduction in income during COVID-19 and inefficiencies in cash transfer distribution—such as delivery delays and inadequate targeting of the most vulnerable populations—may explain the ineffectiveness of this government support.

Moreover, the structure of the cash transfer program warrants scrutiny, as the amount allocated per household proved insufficient to meet their basic needs. According to Jaque et al. (2020), 65.8% of respondents reported that state subsidies were inadequate for acquiring essentials such as food and medicine during the pandemic. Furthermore, the socioeconomic situation of households in 2021 was severely impacted by the effects of the pandemic in 2020, resulting in a significant decline in well-being, with the poverty rate increasing by 9.9 percentage points that year (BCRP, 2021).

Finally, the institutional framework in our country has often been questioned regarding program implementation. Hauchecorne (2020) notes that from the beginning of payments, there were issues of leakage and undercoverage among beneficiaries in the distribution of these cash transfers.

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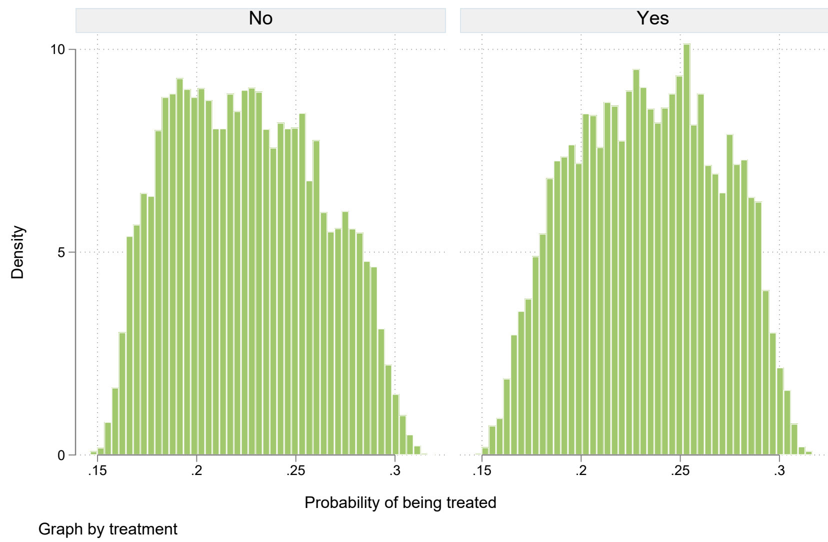
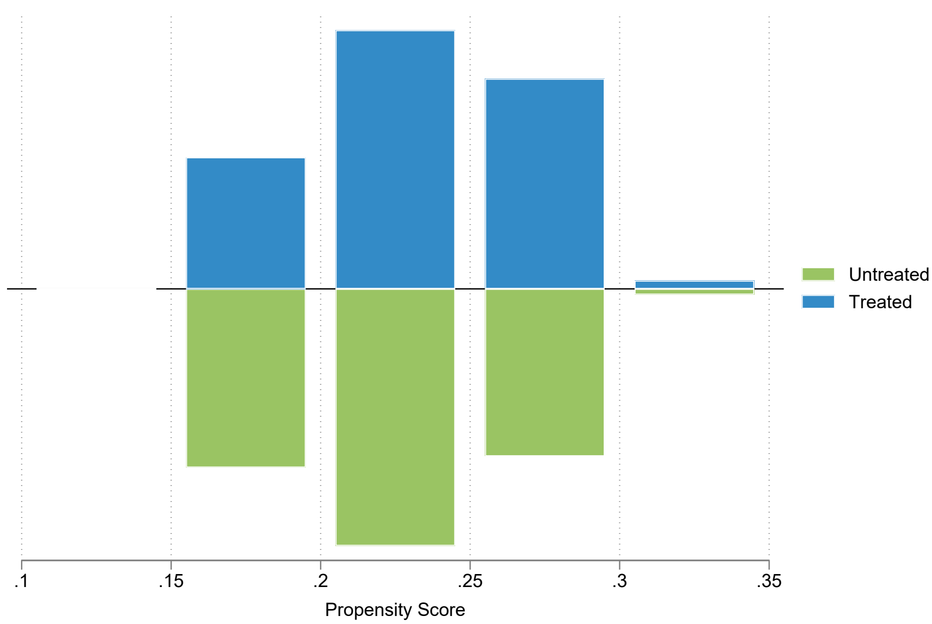
A Appendix

Appendix Figure A1: Histogram of the scores



Appendix Figure A2: PSM in the common support



Appendix Table A1: Bias reduction and T-test

Variables		Average		% of bias	% reduction of bias	t-test		V(T)/V(C)
		Treated	Control			t	p ¿ —t—	
Age of household head	Unmatched	54.638	53.132	9.2		9.38	0.000	1.06*
	Matched	54.632	54.451	1.2	88.0	0.89	0.375	1.01
Gender of household head	Unmatched	0.3428	0.3564	-2.8		-2.73	0.006	-
	Matched	0.3429	0.3419	-0.5	83.3	-0.37	0.712	-
Education level	Unmatched	2.0778	2.2527	-18.0		-17.00	0.000	0.90*
	Matched	2.0783	2.0727	0.6	96.8	0.46	0.646	1.00
Native	Unmatched	0.3768	0.3576	4.0		3.83	0.000	-
	Matched	0.3768	0.3784	-0.3	91.7	-0.25	0.799	-
Household size	Unmatched	3.3677	3.4001	-1.8		-1.70	0.088	1.01
	Matched	3.368	3.3381	1.6	7.8	1.26	0.206	1.02
Rural area	Unmatched	0.5077	0.4359	14.4		13.86	0.000	-
	Matched	0.5077	0.5088	-0.2	98.6	-0.17	0.866	-
Access to services	Unmatched	0.4574	0.5163	-11.8		-11.30	0.000	-
	Matched	0.4575	0.4583	-0.2	98.6	-0.13	0.896	-
Department	Unmatched	12.08	12.271	-2.6		-2.52	0.012	1.03
	Matched	12.08	12.041	0.5	79.4	0.41	0.680	1.01

* if variance ratio outside [0.96; 1.04] for U and [0.96; 1.04] for M.