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Show Me the Money! The Effects of a Conditional Cash-Transfer Program on the Labor Market in Ecuador

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Abstract
Do cash transfers discourage work and incentivize leisure? Or do cash transfers help beneficiaries escape the poverty trap, acquire more capital, and raise their income in the future? I conduct a difference-in-differences analysis of panel data from 2018 and 2019 for Ecuador's cash-transfer program, Bono de Desarrollo Humano. The estimated effects on earnings, hours worked, and capital accumulation are negative. I use propensity score matching and exact matching to create a better control group for the difference-in-differences analysis. I find negative effects, but the statistical significance varies depending on the specification. On balance, Bono de Desarrollo Humano has discouraged work in Ecuador.

JEL Codes: D04; J08
Keywords: economic development, labor economics, cash-transfer programs

I. Introduction

Cash-transfer programs have become a worldwide tool for welfare assistance (Gentilini, Honorati, and Yemtsov 2014). For instance, cash transfers were the main policy response to the COVID-19 crisis implemented by governments globally (Jerving 2020). Previous research has shown that cash-transfer programs can alleviate poverty (Fiszbein and Schady 2009), improve educational outcomes (Schultz 2004), and improve health conditions (Gertler 2004).

Moreover, many studies have been conducted to assess the impact of cash transfers on the labor market. In a comprehensive survey using randomized control trials for programs in different developing countries, Banerjee et al. (2017) find mixed evidence that cash-transfer programs disincentivize work. Other research, specifically in Latin America, finds no significant results using quasi-experimental methods or randomized control trials. Some examples are Attanasio and Gómez (2004) on Colombia's Familias en Acción program, Galiani and McEwan (2013) on Honduras's Programa de

Acción Familiar (PRAF II), and Alzúa, Cruces and Ripani (2013) on Mexico's Progresa program. Other works find that cash transfers reallocate labor from the formal sector to the informal sector in Argentina (Garganta and Gasparini 2015) and Brazil (De Brauw et al. 2015). Few studies point out that cash transfers might reduce labor income. For instance, Fernández and Saldarriaga (2014) report that recipients in the Peruvian program Juntos work from six to ten hours less per week.

Particularly in the case of Ecuador, research on its conditional cash-transfer program, Bono de Desarrollo Humano (BDH), shows mixed results. BDH was established in 1998 and continues to be one of the main tools used to fight the poverty trap in the South American country. Some studies report positive outcomes from implementing BDH. For example, Mideros and Gassmann (2021) point out that BDH can foster social mobility in the long run. Also, evidence suggests that BDH improves child development and school enrollment (Schady and Araujo 2006; Paxson and Schady 2010; Fernald and Hidrobo 2011). However, another strand of the literature posits null or negative results. Ponce and Bedi (2010) find no effect on human capital, and Samaniego and Tejerina (2010) report no improvement in financial inclusion for BDH's recipients.

In the same way, there is still no consensus in the literature on BDH's effects on the Ecuadorian labor market. One branch of the literature finds no behavior change among BDH recipients in the labor market. For example, Bosch and Schady (2019) observe no effect on the labor supply using a regression-discontinuity method in a recent study. Yet Gonzalez-Rozada and Pinto (2011), applying the same method, find that BDH recipients spend more time unemployed. On middle ground, using a unitary discrete-choice model, Mideros and O'Donoghue (2015) find that household heads are not discouraged from working but that BDH's transfers might be used for housework and childcare by single recipients.

Theoretically, conditional cash transfers can have different effects on the labor supply. On the one hand, they may discourage work and incentivize leisure. On the other hand, cash transfers may help beneficiaries get out of the poverty trap, acquire more capital, and raise their income in the future. Thus, these competing theoretical implications should be addressed empirically.

For this purpose, this paper studies the effect of BDH on the Ecuadorian labor market. Using panel data from 2018 and 2019 and applying a difference-in-differences method, I find that the estimated effects on earnings, hours worked, and capital accumulation are negative. In addition, I use propensity score matching and exact matching to create a better control group for the difference-in-differences analysis. I find negative effects, but the statistical significance varies depending on the specification. On balance, the BDH program has discouraged work in Ecuador.

This paper contributes to the literature on BDH and conditional cash-transfer programs by applying a quasi-experimental method in a middle-income country. The difference-in-differences analysis can potentially study the effects on an average recipient of BDH unlike a regression-discontinuity analysis, in which only recipients and nonrecipients at the cutoff are considered. Additionally, the regression-discontinuity specification uses binomial outcome variables (yes or no answers), such as whether the recipient worked last week. My specification can potentially measure the behavior of BDH recipients at the margin—that is, how much BDH's cash transfer affects the earnings, hours worked, and capital accumulation of the marginal recipient. Finally, the paper takes advantage of the most recent prepandemic data in a panel-data format that is publicly available.

The paper proceeds as follows. Section 2 describes the theory regarding the cash-transfer effect. Section 3 explains how BDH works. Section 4 contains the empirical analysis. Finally, section 5 discusses the implications of the findings.

II. Theory

In order to study the effect of cash transfers on the labor supply, the paper applies the basic orthodox neoclassical model of labor-leisure choice (Borjas 2019, chap. 2). This model follows the standard microeconomic theory and shows how the labor supply is derived and what variables can affect it. It also provides the fundamentals of the equations used in the empirical section to estimate the effects of BDH on the labor supply.

In this model, a representative agent has to choose how to allocate their time between labor and leisure to maximize their utility function, which is subject to a budget constraint. Assuming an interior solution, the optimal solution is when the agent's marginal rate of substitution equals the wage rate. That means the rate at which the agent is willing to give up leisure hours in exchange for additional consumption is equal to the wage rate. Formally, we can represent this model as follows:

$$\max_{C,L} U = f(C,L)$$
$$s.t.$$
$$C = wh + V$$
$$T = h + L$$

The variables are defined as follows:

C: consumption

L: hours of leisure

w: wage rate per hour

h: number of hours working

V: nonlabor income

T: total hours available

By solving this optimization problem, we can get the labor-supply function, which shows the optimal allocation of h^* given different levels of w. Formally, the labor-supply function is $h = f(w,V)$. Once we know h^*, we can find L^* via the time constraint $L^* = T - h^*$. We are interested in knowing what happens to the optimal number of working hours h^*, and consequently the optimal number of hours of leisure, L^*, when an individual receives a cash transfer. Cash transfers can be considered nonlabor income. What is the effect of an increase of V, caused by a cash-transfer program such as BDH, on $h^*$and L^*? Formally we can express this effect as $\frac{\partial L^*}{\partial V}$. This comparative static depends on whether L is a normal good ($\frac{\partial L^*}{\partial V} > 0$) or an inferior good ($\frac{\partial L^*}{\partial V} < 0$). If leisure is a normal good, an increase of nonlabor income will discourage more hours of work, whereas if leisure is an inferior good, nonlabor income will foster more hours of work. Importantly, an increase of V is a pure income effect and the substitution effect is zero.

Ideally, we would estimate the labor-supply function $h = f(w,V)$ to determine $\frac{\partial L^*}{\partial V}$ using econometric analysis. That is, we would estimate how the recipients' allocation of hours to work responds to an increase of their nonlabor income V via BDH. More importantly, we want to estimate the sign and magnitude of the income effect caused by BDH. In this way, we can empirically test whether BDH encourages leisure or work.

In empirical studies, a variation of the labor-supply function is often used (Gujarati 2002, chap. 13). For example, a version of the wage-determination model developed by (Mincer 1974) has been often applied in labor economics. In this model, a type of inverse supply function is used in the form of $\frac{w}{h} = g(V, x_1, .., x_n)$, where x_n

are other covariates that might affect the wage rate. These covariates are called compensating differentials and include education, occupation, geographic location, and other sociodemographic characteristics. In addition, studies show there is a wage premium for formal workers in relation to informal workers that should be accounted for (Ohnsorge and Yu 2022).

Besides affecting the optimal allocation of labor and leisure, another mechanism through which BDH might help recipients is helping them escape the poverty trap. Kraay and McKenzie (2014) survey different types of poverty traps such as the savings trap, the nutritional trap, and borrowing constraints. The saving-based poverty trap applies to individuals who are too poor to save. If they cannot save, they cannot accumulate capital, and thus, their income can stagnate. In nutritional poverty traps, individuals cannot get enough nutrients to do physical work or produce sufficient food to stay healthy. Finally, individuals might face borrowing constraints and thus cannot access the financial system and make investments with potentially higher returns.

Given the short time frame of the period of analysis of this paper, we are most interested in the savings poverty trap. Formally, the Solow growth model is the simplest way to illustrate this kind of trap. If we have a per capita production function that depends on the capital per worker $y_t = f(k_t)$ with positive but decreasing marginal returns to k, a savings rate s, and a rate of depreciation δ, then the steady-state equilibrium k^* occurs when the amount of savings covers the depreciation of capital $sf(k_t) = \delta k_t$. A higher s would mean higher capital accumulation and in turn higher output per worker and presumably a higher standard of living.

A savings poverty trap is a situation in which s is really low because almost all the output is being allocated to consumption and there is no room for savings and capital accumulation that would lead to higher output in the future. As a consequence, a savings poverty trap might be avoided with a big push such as a cash transfer that can potentially encourage higher savings rates, which would lead to higher output in the future without compromising present consumption. Incorporating the nonlabor income V into the per capita production function, we get $y_t = f(k_t, V)$. Empirically, we should expect $\frac{\partial y^*}{\partial V} > 0$ if the poverty-savings-trap hypothesis is true.

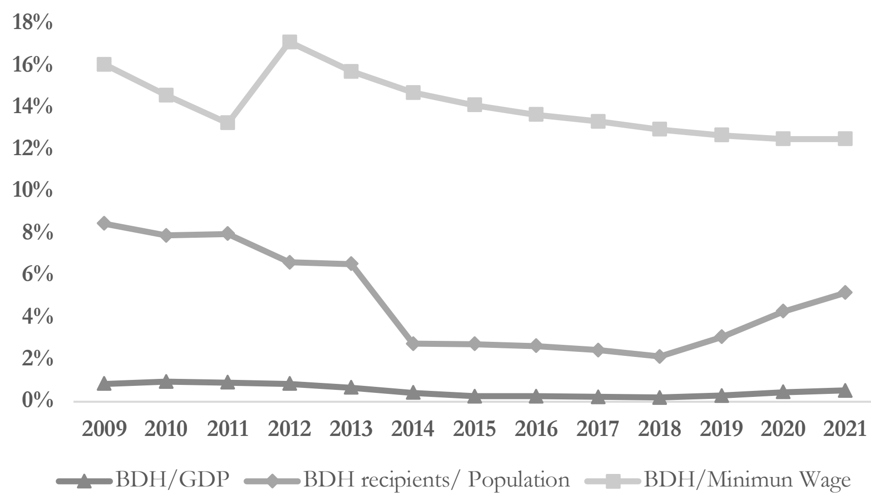
III. Description of BDH

For over two decades, BDH has been used as a policy tool by governments with different ideologies. According to the Economic Commission for Latin America and the Caribbean, USD 250 million was spent covering more than four hundred thousand recipients representing 2.64 percent of the total population in 2016. Recently, the number of beneficiaries doubled to more than eight hundred thousand recipients in 2021 because of the COVID-19 crisis.

BDH is the successor of the Bono Solidario program, which started in 1998. De jure, BDH can be categorized as a conditional cash-transfer program. BDH is currently housed under the Ministry of Economic and Social Inclusion. According to the ministry, the goal of BDH is to sustain a minimum basic consumption level for households in or vulnerable to poverty.

As figure 1 shows, spending and the number of recipients have fallen over the years. Spending is less than 1 percent of GDP, and the ratio of the number of recipients to the total population is below 3 percent. However, the minimum amount of BDH transfers has roughly been maintained throughout the years. The USD 50 transfer represented more than 13 percent of the minimum wage in 2017. BDH's total spending has been procyclical: expansion and contraction of the program has followed the Ecuadorian business cycle.

Figure 1. Evolution of BDH



Source: Instituto Nacional de Estadisticas y Censo, Ministry of Economic and Social Inclusion, Banco Central del Ecuador

The amount of BDH transfers varies depending on the number of children under sixteen years old in a household. The transfers range from USD 50 to USD 100 and are received monthly. The minimum transfer represented 12.5 percent of the minimum wage in Ecuador for 2021. The cash transfers are delivered via the private bank network.

The conditions of eligibility for the program are mainly education and health care requirements. In terms of education, children between five and seventeen years of age must achieve 75 percent attendance in public schools. In addition, children under fifteen years of age must not perform any type of formal or informal work. They must only assign their time to education and development activities. In terms of health care, pregnant women must have five prenatal checkups in the public health care system. Similarly, children under the age of one and children between one and five years of age must have at least six and two medical checkups, respectively. Young adults must attend the family-planning talk organized by the public health care system at least once a year. Finally, recipients of BDH must not build their houses in flood zones or near mudslides or be squatters.

The penalty for noncompliance is a reduction of the cash transfer. For instance, half of the transfer is withdrawn if children do not enroll in the public school system. If the attendance requirement is not satisfied, BDH transfers can be permanently suspended. Moreover, a warning is issued the first time that recipients fail to fulfill the health care requirements. If there is a second or third breach, BDH transfers are reduced by 20 or 40 percent, respectively. Finally, the transfer is suspended if there is a fourth breach. The de jure conditions of eligibility (Ministerio de Bienestar Social del Ecuador 2003) are sporadically enforced de facto (Rinehart and McGuire 2017). For example, with a small sample of urban recipients, the Ministry of Economic and Social Inclusion suspended payments for noncompliance only in 2011 (Miorelli 2014, p. 8).

The eligibility criteria have two stages. The first stage identifies geographic areas where poverty is prevalent based on Instituto Nacional de Estadisitica y Censos's information and following the Comunidad Andina de Naciones's Indice de Necesidades Insatisfechas index. The index is based on residential characteristics and access to services, levels of education, and the number of people dependent on household income. The second stage involves surveying the identified areas to examine, by direct observation, the sociodemographic characteristics of each household. Once all the information is collected, a composite measure is constructed that is called the poverty score. Like the Indice de Necesidades Insatisfechas, the poverty score focuses on household composition, levels of education, working conditions, dwelling environment, and access to general services. After the information on the main components is processed, a single eligibility cutoff point for the score is chosen based on the Ministry of Economic and Social Inclusion's target population and available budget. The sample for this study comes from the 2014 census (Registro Social). Any citizen can bypass this procedure and request to be considered a beneficiary of BDH by going directly to the ministry's office.

IV. Empirical Analysis

The sample is a balanced panel data set of fifteen thousand individuals taken from household data from the Survey of National Employment, Unemployment and Subemployment (Encuesta Nacional de Empleo, Desempleo y Subempleo) from Instituto Nacional de Estadisticas y Censo in Ecuador. The data set consists of only two periods: December 2018 and December 2019.

The dependent variables are monthly net income, number of hours worked in a month, and monthly decapitalization. Net income is the sum of income obtained from hired labor and self-employment work minus the cost incurred for such activities. Monthly decapitalization is the amount of money taken from self-employment income for present consumption. Self-employment activities include any microenterprise that individuals might engage in to obtain a monthly income. I do not consider hourly wages given that workers are not usually paid by the hour and in this setting the number of hours might be misrepresented (Borjas 2019, chap. 2).

Sociodemographic variables are used as covariates to control for compensating differentials such as education, occupation, informal sector, and geographic location. For education, I use a dummy variable indicating whether a person has at least finished high school. For occupation, I constructed dummy variables for self-employment and unemployment status. To control for the wage premium in the formal sector, I added a dummy variable to indicate whether the individual works in the informal economy. The informal-economy dummy is defined as 1 for an individual who does not possess an ID with the Ecuadorian tax agency (Servicio de Rentas Internas) and hence does not pay income taxes. For geography, I use a variable that indicates whether the person lives in an urban or rural area. Finally, other sociodemographic variables are considered, such as age, marital status, and gender. I also constructed the *Other Subsidies* variable by summing up other subsidies the person might receive, such as a handicap subsidy.

Table 1 shows the summary statistics. I only consider individuals who are part of the labor force by dropping individuals older than sixty-five. According to the World Bank, GDP per capita for Ecuador is USD 519, which is close to the representative income in my sample (USD 473). Similarly, the mean number of hours worked corresponds to Ecuador's regular workweek of forty hours. The variable *BDH Amount* is the cash transfer received through BDH. In the sample, 105 individuals received BDH transfers in 2019 and did not receive them before. The minimum and maximum amounts of cash transfers are USD 50 and USD 100, respectively. The average age of the sample is forty-one years old, 40 percent are married, 66 percent completed high school, and 65 percent are men.

Table 1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Net Income	27,696	472.86	961.01	(58,000.00)	82,000.00
Hours Worked	27,696	40.47	12.72	1.00	119.00
Decapitalization	4,691	(63.24)	96.60	(4,000.00)	-
BDH Amount	105	52.40	10.00	50.00	100.00
Age	27,696	41.21	11.66	12.00	64.00
Married	27,696	0.40	0.49	-	1.00
High school	27,696	0.66	0.47	-	1.00
Male	27,696	0.65	0.48	-	1.00
Urban	27,696	0.66	0.47	-	1.00
Other Subsidies	27,695	22.71	90.21	-	2,162.00
Self Employed	27,696	0.35	0.48	-	1.00
Unemployed	27,696	0.02	0.15	-	1.00
Informal	19,051	0.52	0.50	-	1.00

Table 2 compares the means of the variables described before for the recipients of BDH transfers (treated units) and the nonrecipients in the whole sample. The treatment variable *Treated* indicates any person who received the transfer in 2019 but not in 2018. The untreated group consists of individuals who did not receive BDH transfers either in 2018 or 2019. Those who received a transfer in 2018 are not considered.

Table 2. Treated-group comparison

Variable	Treated Mean	Non-Treated Mean
Net Income	159.07	475.25
Hours Worked	31.98	40.54
Decapitalization	(45.35)	(63.62)
BDH Amount	52.40	-
Age	42.78	41.19
Married	0.27	0.40
High school	0.21	0.67
Male	0.38	0.65
Urban	0.26	0.66
Other Subsidies	21.45	22.72
Self Employed	0.69	0.35
Unemployed	0.04	0.02
Informal	0.94	0.52

As we might expect, the treated group earns a lower income, works fewer hours, is less educated, is more likely to live in rural areas, and, most importantly, engages in more self-employment activity. The mean income for the treated group is USD 159.07, which means that the lowest BDH transfer (USD 50) represents 31 percent of the average income and the highest BDH transfer (USD 100) represents 63 percent of the average income. I first run a difference-in-differences regression on the whole sample. The model is as follows:

$$y_i = \beta_0 + \beta_1 t + \beta_2 treated + \beta_3 (t * treated) + X_i{}'\alpha + \mu_i$$

Here, y_i is monthly income or number of hours worked in a week or monthly decapitalization; $treated$ is any person who received a BDH transfer in 2019 but not in 2018; $X_i{}'$ are other covariates, such as sociodemographic characteristics and compensating differentials; and μ_i is the error term.

The parameter of interest is β_3, which captures the average treatment effect. As table 3 shows, being part of the cash-transfer program reduces recipients' labor income. That is, participants earn less income compared to nonparticipants in the whole sample after controlling for all the compensation differentials. The negative effect ranges from USD 36 to USD 11. However, the results are not statistically significant. All the sociodemographic controls are statistically significant, except *Other Subsidies* for all specifications.

Table 3. Difference-in-differences results: net income

	Dependent Variable: Net Income									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
T	3.048	0.621	1.520	-1.767	-1.917	-1.273	-1.255	-3.124	-3.166	0.594
	(11.589)	(11.586)	(11.571)	(11.477)	(11.473)	(11.450)	(11.450)	(11.362)	(11.360)	(15.857)
Treated	-298.099***	-302.045***	-288.361***	-173.830*	-155.485*	-116.628	-116.614	-55.283	-55.309	-18.246
	(94.110)	(93.993)	(93.883)	(93.267)	(93.310)	(93.192)	(93.195)	(92.519)	(92.504)	(113.184)
ATE	-36.162	-34.415	-31.216	-28.458	-28.469	-29.080	-29.199	-17.828	-16.779	-11.238
	(133.091)	(132.922)	(132.748)	(131.661)	(131.609)	(131.342)	(131.346)	(130.328)	(130.308)	(159.318)
Age		25.676***	20.365***	20.986***	22.551***	20.925***	20.914***	23.679***	23.462***	16.943***
		(3.418)	(3.469)	(3.441)	(3.455)	(3.451)	(3.451)	(3.427)	(3.427)	(4.704)
Age^2		-0.282***	-0.233***	-0.211***	-0.228***	-0.214***	-0.214***	-0.221***	-0.218***	-0.149***
		(0.041)	(0.042)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.056)
Married			106.536***	100.864***	95.129***	98.806***	99.004***	105.816***	106.486***	67.029***
			(12.385)	(12.286)	(12.340)	(12.320)	(12.324)	(12.233)	(12.233)	(17.123)
High School				266.466***	274.127***	226.571***	226.134***	202.578***	202.222***	117.859***
				(12.425)	(12.523)	(13.269)	(13.287)	(13.233)	(13.231)	(18.336)
Male					58.074***	68.935***	69.399***	59.719***	57.721***	97.353***
					(12.184)	(12.202)	(12.223)	(12.137)	(12.152)	(17.454)
Urban						137.821***	137.574***	127.413***	126.130***	85.473***
						(12.920)	(12.926)	(12.835)	(12.839)	(17.996)
Other Subsidies							0.040	0.118*	0.123*	0.100
							(0.064)	(0.063)	(0.063)	(0.084)
Selfemployed								-256.462***	-253.696***	-139.696***
								(12.290)	(12.320)	(17.330)
Unemployed									-121.941***	-119.823**
									(38.864)	(50.502)
Informal										-191.429***
										(17.939)
Constant	473.727***	-65.522	19.933	-218.961***	-293.109***	-321.407***	-321.457***	-306.575***	-298.767***	-77.318
	(8.197)	(67.443)	(68.083)	(68.438)	(70.158)	(70.066)	(70.068)	(69.528)	(69.561)	(97.374)
Adjusted R2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
Observations	27,696	27,696	27,696	27,696	27,696	27,696	27,695	27,695	27,695	19,051

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

I also analyze the total hours worked as a dependent variable. In contrast to the results for labor income, transfer recipients work less hours with a statistical significance of 10 percent, as table 4 demonstrates when I only control for sociodemographic variables and *Other Subsidies*. Thus, the average recipient works approximately three less hours per week compared to the rest of the sample. However, this effect goes away once I control for unemployment and the informal economy.

Table 4. Difference-in-differences results: hours worked

	Dependent Variable: Hours Worked									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
T	0.104	0.094	0.112	0.092	0.081	0.088	0.088	0.074	0.071	0.394**
	(.153)	(.153)	(.152)	(.152)	(.150)	(.150)	(.150)	(.149)	(.149)	(.191)
Treated	-7.012***	-7.037***	-6.769***	-6.066***	-4.718***	-4.285***	-4.285***	-3.851***	-3.853***	-2.559*
	(1.244)	(1.239)	(1.235)	(1.235)	(1.220)	(1.220)	(1.219)	(1.217)	(1.210)	(1.366)
ATE	-3.094*	-3.037*	-2.974*	-2.957*	-2.958*	-2.965*	-2.952*	-2.871*	-2.798	-1.735
	(1.759)	(1.752)	(1.746)	(1.743)	(1.721)	(1.719)	(1.718)	(1.714)	(1.705)	(1.922)
Age		0.698***	0.594***	0.598***	0.713***	0.695***	0.696***	0.716***	0.701***	0.653***
		(.045)	(.046)	(.046)	(.045)	(.045)	(.045)	(.045)	(.045)	(.057)
Age^2		-0.008***	-0.007***	-0.007***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
		(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Married			2.090***	2.055***	1.633***	1.674***	1.650***	1.698***	1.745***	1.748***
			(0.163)	(.163)	(.161)	(.161)	(.161)	(.161)	(.160)	(.207)
High School				1.634***	2.197***	1.668***	1.724***	1.557***	1.532***	0.337
				(0.165)	(.164)	(.174)	(.174)	(.174)	(.173)	(.221)
Male					4.270***	4.391***	4.334***	4.265***	4.125***	5.100***
					(0.159)	(.160)	(.160)	(.160)	(.159)	(.211)
Urban						1.533***	1.564***	1.492***	1.402***	0.471**
						(0.169)	(.169)	(.169)	(.168)	(.217)
Other Subsidies							-0.005***	-0.005***	-0.004***	-0.006***
							(0.001)	(.001)	(.001)	(.001)
Selfemployed								-1.813***	-1.619***	0.568***
								(.162)	(.161)	(.209)
Unemployed									-8.555***	-9.316***
									(.509)	(.609)
Informal										-5.878***
										(.216)
Constant	40.488***	26.985***	28.661***	27.196***	21.745***	21.430***	21.433***	21.538***	22.086***	25.223***
	(.108)	(.889)	(.896)	(.906)	(.918)	(.917)	(.916)	(.914)	(.910)	(1.175)
Adjusted R2	0.00	0.01	0.02	0.02	0.05	0.05	0.05	0.05	0.06	0.10
Observations	27,696	27,696	27,696	27,696	27,696	27,696	27,695	27,695	27,695	19,051

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

To test the savings-poverty-trap hypothesis, I use the outcome variable *Decapitalization*. As table 5 shows, transfer recipients take on average almost USD 9 more from their microenterprise for present consumption compared to nonrecipients. In other words, recipients are more willing to decapitalize their self-employment activity when they join BDH. This result goes against the savings-poverty-trap hypothesis but does not have statistical significance.

Table 5. Difference-in-differences results: decapitalization

	Dependent Variable: Decapitalization									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
T	0.994	1.042	0.916	0.980	0.991	1.106	1.092	1.438	1.475	0.827
	(2.850)	(2.853)	(2.851)	(2.844)	(2.845)	(2.844)	(2.844)	(2.830)	(2.830)	(2.891)
Treated	21.558	20.775	20.035	16.385	16.273	15.362	15.502	14.106	14.150	8.821
	(13.422)	(13.415)	(13.405)	(13.392)	(13.417)	(13.415)	(13.416)	(13.350)	(13.350)	(13.549)
ATE	-7.132	-7.006	-6.520	-7.376	-7.406	-8.118	-8.036	-8.038	-8.109	-8.856
	(19.905)	(19.891)	(19.873)	(19.824)	(19.828)	(19.819)	(19.820)	(19.720)	(19.721)	(20.286)
Age		-3.206***	-2.910***	-3.185***	-3.194***	-3.165***	-3.139***	-2.887***	-2.873***	-2.547**
		(1.090)	(1.093)	(1.092)	(1.094)	(1.093)	(1.094)	(1.089)	(1.089)	(1.125)
Age^2		0.034***	0.031***	0.033***	0.033***	0.033***	0.032***	0.030**	0.030**	0.026**
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Married			-8.926***	-9.556***	-9.505***	-9.717***	-9.688***	-9.707***	-9.834***	-7.620***
			(2.851)	(2.847)	(2.870)	(2.869)	(2.870)	(2.855)	(2.860)	(2.928)
High School				-14.372***	-14.414***	-12.144***	-12.404***	-10.515***	-10.513***	-6.475**
				(2.914)	(2.929)	(3.072)	(3.085)	(3.081)	(3.082)	(3.185)
Male					-0.408	-1.682	-1.472	0.265	0.496	-1.843
					(2.892)	(2.937)	(2.946)	(2.941)	(2.955)	(3.025)
Urban						-7.447**	-7.468**	-5.635*	-5.497*	2.351
						(3.052)	(3.053)	(3.048)	(3.053)	(3.236)
Other Subsidies							0.013	0.014	0.013	0.010
							(0.014)	(0.014)	(0.014)	(0.015)
Selfemployed								37.682***	37.529***	27.534***
								(5.405)	(5.408)	(5.593)
Unemployed									5.361	3.186
									(6.657)	(6.844)
Informal										31.629***
										(3.524)
Constant	-64.124***	7.956	4.648	21.045	21.462	23.636	22.946	-20.776	-21.315	-46.467*
	(2.028)	(23.865)	(23.866)	(24.038)	(24.221)	(24.225)	(24.237)	(24.917)	(24.927)	(25.928)
Adjusted R2	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.02	0.04
Observations	4,691	4,691	4,691	4,691	4,691	4,691	4,691	4,691	4,691	4,541

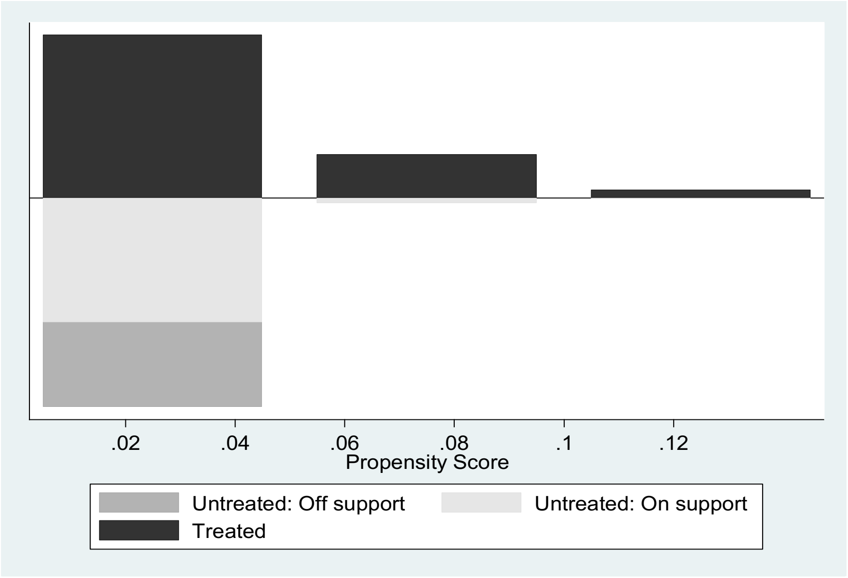
*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

To construct better counterfactuals, I proceed to apply propensity score matching as a prefilter for the difference-in-differences analysis. I use the first nearest neighbor to create a control group with replacement with the same covariates as before except the informal-economy dummy, given that there was no transition in the treated group between 2018 and 2019. Table 6 shows the covariate balance. All covariates are well balanced between the treated and control groups. Similarly, figure 2 indicates the distribution of the propensity scores. All treated units share a common support.

Table 6. Propensity-score covariate balance

Variable	Treated	Control	%Bias	t	p>t	V(T)/ V(C)
Age	42.00	42.18	-1.6	-0.1	0.91	0.92
Age^2	1,894.70	1,921.00	-2.7	-0.2	0.85	0.91
Married	0.28	0.30	-4.1	-0.3	0.76	.
High School	0.22	0.21	2.2	0.17	0.87	.
Male	0.38	0.35	6	0.43	0.67	.
Urban	0.26	0.28	-4.2	-0.3	0.76	.
Other Subsidies	19.96	15.91	5.6	0.57	0.57	0.87
Self Employed	0.66	0.64	4	0.29	0.77	.
Unemployed	0.04	0.05	-5.6	-0.3	0.74	.

Figure 2. Distribution of the propensity score



I next run a difference-in-differences regression but only consider units that match the treated units as a control group. Table 7 presents the new results for net income using propensity score matching as a filter. In this case, the average treatment effect for labor income is negative and statistically significant for almost all of my specifications. The results indicate that labor income is reduced by approximately USD 68 for the average recipient when I control for sociodemographic variables and *Other Subsidies*. Importantly, this amount is close to the minimum BDH cash transfer (USD 50). When I add self-employment status and unemployment as control variables, the 10 percent statistical significance disappears but the effect is still negative. Table 8 shows the results for hours worked in a week as an outcome variable. I find that hours worked fall by approximately five hours for the average beneficiary. The statistical significance goes away when I control for unemployment. For decapitalization, negative but nonsignificant effects persist after applying the propensity-score-matching filter as shown in table 9. The average recipient takes roughly USD 4 extra from their self-employment activity.

Table 7. Propensity score and difference-in-differences results: net income

	Dependent Variable: Net Income (PS Filter)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T	39.918	41.801	42.636	38.738	37.966	38.477	39.254	33.089	31.975
	(27.459)	(27.264)	(27.111)	(27.074)	(26.663)	(26.508)	(26.547)	(25.762)	(25.569)
Treated	-64.189**	-66.184**	-67.129**	-67.174**	-69.424***	-67.895***	-67.483***	-64.317**	-65.955***
	(26.993)	(26.801)	(26.651)	(26.547)	(26.151)	(26.006)	(26.029)	(25.239)	(25.054)
ATE	-70.177*	-69.492*	-72.012*	-68.028*	-66.782*	-67.262*	-67.790*	-56.776	-54.850
	(38.174)	(37.890)	(37.688)	(37.593)	(37.024)	(36.807)	(36.838)	(35.775)	(35.509)
Age		9.563*	10.520*	12.486**	16.308***	15.276***	15.236***	16.265***	16.338***
		(5.753)	(5.734)	(5.794)	(5.802)	(5.784)	(5.788)	(5.614)	(5.572)
Age^2		-0.133**	-0.141**	-0.158**	-0.204***	-0.192***	-0.192***	-0.197***	-0.198***
		(0.067)	(0.067)	(0.067)	(0.068)	(0.067)	(0.067)	(0.065)	(0.065)
Married			-49.740**	-45.807**	-44.925**	-39.184*	-40.373*	-22.753	-19.961
			(21.075)	(21.082)	(20.763)	(20.783)	(20.863)	(20.516)	(20.387)
High School				47.753**	61.302***	52.144**	50.358**	55.680**	56.397**
				(23.590)	(23.528)	(23.706)	(23.853)	(23.146)	(22.971)
Male					72.008***	81.264***	79.490***	49.031**	48.917**
					(19.782)	(20.048)	(20.215)	(20.483)	(20.327)
Urban						51.564**	52.616**	74.122***	71.249***
						(21.698)	(21.762)	(21.512)	(21.375)
Other Subsidies							-0.120	-0.024	-0.012
							(0.169)	(0.165)	(0.164)
Selfemployed								-107.544***	-101.094***
								(21.055)	(21.035)
Unemployed									-114.626***
									(43.256)
Constant	237.804***	89.464	79.854	18.587	-82.577	-80.064	-76.193	-43.222	-44.065
	(19.416)	(117.728)	(117.125)	(120.530)	(121.909)	(121.199)	(121.398)	(117.858)	(116.959)
Adjusted R2	0.06	0.08	0.09	0.10	0.12	0.13	0.13	0.18	0.20
Observations	402	402	402	402	402	402	402	402	402

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

Table 8. Propensity score and difference-in-differences results: hours worked

	Dependent Variable: Hours Worked (PS Filter)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T	1.784	1.764	1.757	1.633	1.585	1.575	1.610	1.591	1.439
	(1.954)	(1.956)	(1.958)	(1.964)	(1.942)	(1.944)	(1.948)	(1.952)	(1.898)
Treated	-4.071**	-4.092**	-4.085**	-4.086**	-4.227**	-4.256**	-4.237**	-4.228**	-4.450**
	(1.921)	(1.922)	(1.925)	(1.925)	(1.905)	(1.907)	(1.910)	(1.912)	(1.860)
ATE	-4.822*	-4.826*	-4.807*	-4.680*	-4.602*	-4.593*	-4.617*	-4.583*	-4.321
	(2.716)	(2.718)	(2.722)	(2.726)	(2.697)	(2.699)	(2.703)	(2.711)	(2.636)
Age		0.452	0.445	0.508	0.746*	0.765*	0.764*	0.767*	0.777*
		(.413)	(.414)	(.420)	(.423)	(.424)	(.425)	(.425)	(.414)
Age^2		-0.005	-0.005	-0.005	-0.008*	-0.008*	-0.008*	-0.008*	-0.009*
		(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Married			0.382	0.508	0.563	0.453	0.400	0.455	0.834
			(1.522)	(1.529)	(1.513)	(1.524)	(1.531)	(1.555)	(1.514)
High School				1.524	2.368	2.542	2.462	2.479	2.576
				(1.711)	(1.714)	(1.738)	(1.750)	(1.754)	(1.706)
Male					4.485***	4.309***	4.230***	4.136***	4.121***
					(1.441)	(1.470)	(1.483)	(1.552)	(1.509)
Urban						-0.981	-0.935	-0.868	-1.258
						(1.591)	(1.597)	(1.630)	(1.587)
Other Subsidies							-0.005	-0.005	-0.003
							(0.012)	(.012)	(.012)
Selfemployed								-0.331	0.544
								(1.595)	(1.562)
Unemployed									-15.557***
									(3.212)
Constant	37.485***	27.702***	27.776***	25.821***	19.520**	19.472**	19.644**	19.746**	19.631**
	(1.381)	(8.444)	(8.459)	(8.742)	(8.881)	(8.888)	(8.906)	(8.930)	(8.684)
Adjusted R2	0.05	0.05	0.05	0.05	0.07	0.07	0.07	0.07	0.12
Observations	402	402	402	402	402	402	402	402	402

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

Table 9. Propensity score and difference-in-differences results: decapitalization

	Dependent Variable: Decapitalization (PS Filter)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T	-2.827	-3.470	-4.393	-3.627	-3.653	-3.199	-2.788	-2.784	-2.803
	(12.333)	(12.376)	(12.311)	(12.226)	(12.212)	(12.247)	(12.269)	(12.307)	(12.356)
Treated	15.997	16.490	16.214	17.713	17.000	17.402	18.076	18.034	18.016
	(11.387)	(11.413)	(11.344)	(11.287)	(11.291)	(11.322)	(11.363)	(11.452)	(11.499)
ATE	-3.574	-3.889	-2.445	-4.688	-3.915	-3.888	-3.785	-3.780	-3.756
	(16.928)	(16.951)	(16.868)	(16.783)	(16.777)	(16.802)	(16.819)	(16.870)	(16.934)
Age		-3.696	-4.080	-5.017	-4.849	-4.847	-4.805	-4.800	-4.801
		(3.203)	(3.191)	(3.205)	(3.205)	(3.209)	(3.213)	(3.226)	(3.235)
Age^2		0.043	0.049	0.058	0.054	0.055	0.054	0.054	0.054
		(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Married			-15.303*	-18.485**	-18.988**	-18.143**	-17.400*	-17.425*	-17.397*
			(8.659)	(8.756)	(8.757)	(8.850)	(8.906)	(8.957)	(9.022)
High School				-21.625*	-22.046*	-23.377**	-23.326**	-23.295**	-23.285**
				(11.392)	(11.385)	(11.554)	(11.566)	(11.630)	(11.669)
Male					11.485	11.959	12.846	12.919	12.900
					(9.768)	(9.805)	(9.875)	(10.095)	(10.140)
Urban						6.992	6.959	6.973	6.933
						(9.845)	(9.855)	(9.891)	(9.986)
Other Subsidies							0.071	0.071	0.071
							(0.087)	(0.087)	(0.088)
Selfemployed								1.538	1.549
								(41.092)	(41.217)
Unemployed									-0.590
									(17.001)
Constant	-58.804***	14.889	27.007	54.320	50.966	47.804	44.995	43.375	43.450
	(8.295)	(69.335)	(69.253)	(70.225)	(70.205)	(70.448)	(70.602)	(82.986)	(83.264)
Adjusted R2	0.00	0.00	0.01	0.03	0.03	0.03	0.02	0.02	0.01
Observations	179	179	179	179	179	179	179	179	179

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

Table 10 demonstrates the dynamic behavior of BDH recipients. We can see that income and hours worked decreased from 2018 to 2019. Similarly, we can observe that self-employment and unemployment increased in the same period. We might be facing a confounding-variable problem. To mitigate this, I run the analysis with an exact matching in all labor market covariates: self-employment, unemployment, and informal economy. In this subsample, there are no jumps or transitions between the categories of the labor market characteristics. This means that all the treated and donor-pool units stayed self-employed, unemployed, and in the informal economy from 2018 to 2019, which was the most repeated combination in the treated group, as shown in table 10. Doing exact matching eliminates the possibility of confounding variables in the analysis period. However, I had to sacrifice units from the treated group, which experienced some transition or stayed in a combination in which only a few units were available. As a result, the treated sample drops below fifty-two units for some outcome variables.

Table 10. Treated-group dynamics

Variable	2018	2019
Net Income	175.63	142.51
Hours Worked	33.48	30.49
Decapitalization	(42.57)	(48.70)
BDH Amount		52.40
Age	42.21	43.35
Married	0.29	0.26
High school	0.22	0.21
Male	0.38	0.38
Urban	0.26	0.26
Other Subsidies	19.77	23.13
Self Employed	0.67	0.71
Unemployed	0.04	0.05
Informal	0.94	0.94

Table 11 shows the covariate balance for the propensity-score-matching analysis. Similarly, figure 3 indicates the distribution of the propensity score for exact matching. Table 12 presents the results for labor income. I find negative but not statistically significant effects. This time the effects are smaller, ranging from USD 22 to USD 35.

This means recipients decreased their income by at least 50 percent of the minimum cash transfer of USD 50. The same can be said regarding hours worked. Table 13 indicates a reduction of one to two hours of work a week for people who received BDH transfers. Last, table 14 shows how decapitalization is exacerbated when an individual participates in BDH. An additional USD 32 is taken every month by recipients when compared to their counterfactuals.

Figure 3. Distribution of the propensity score for exact matching

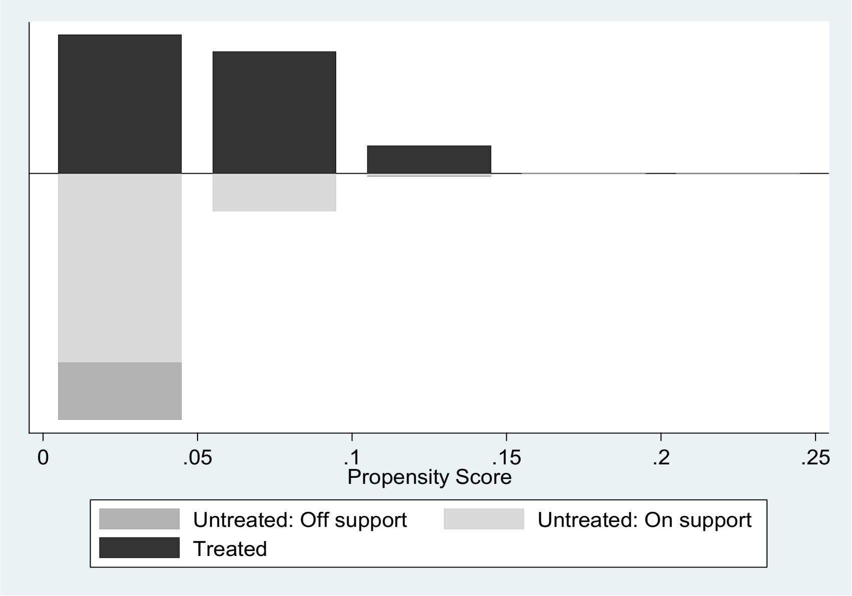


Table 11. Propensity-score exact-matching covariate balance

Variable	Treated	Control	%Bias	t	p>t	V(T)/ V(C)
Age	42.83	41.58	11.40	0.58	0.56	1.12
Age^2	1959.30	1840.50	12.40	0.64	0.53	1.16
Married	0.33	0.31	4.00	0.21	0.84	-
High School	0.23	0.25	-4.10	-0.23	0.82	-
Male	0.25	0.21	8.40	0.46	0.65	-
Urban	0.38	0.48	-19.40	-0.98	0.33	-
Other Subsidies	27.81	45.39	-22.50	-0.96	0.34	0.28*

Table 12. Difference-in-differences, propensity-score, and exact-matching results: net income

	Dependent Variable: Net Income (PS Filter + Exact Matching)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T	43.275	41.855	41.087	41.242	38.513	39.511	34.196
	(42.118)	(42.026)	(41.899)	(42.241)	(40.970)	(40.883)	(40.955)
Treated	-73.018*	-70.597*	-70.141*	-70.159*	-72.635*	-69.742*	-73.562*
	(41.915)	(41.834)	(41.705)	(41.813)	(40.554)	(40.516)	(40.505)
ATE	-35.371	-30.746	-31.150	-31.303	-27.370	-28.747	-21.952
	(59.277)	(59.152)	(58.969)	(59.283)	(57.499)	(57.377)	(57.436)
Age		18.311*	16.530	16.382	20.871*	18.815	19.739*
		(10.948)	(10.979)	(11.814)	(11.521)	(11.591)	(11.581)
Age^2		-0.217*	-0.196	-0.195	-0.253*	-0.229*	-0.238*
		(0.125)	(0.125)	(0.133)	(0.130)	(0.131)	(0.130)
Married			-48.026	-48.305	-62.988*	-61.862*	-67.892**
			(32.030)	(33.108)	(32.353)	(32.290)	(32.492)
High School				-1.322	24.115	15.544	12.034
				(38.249)	(37.730)	(38.155)	(38.141)
Male					131.483***	135.375***	132.242***
					(35.721)	(35.751)	(35.731)
Urban						41.381	49.612
						(30.042)	(30.530)
Other Subsidies							-0.247
							(0.175)
Constant	194.922***	-166.608	-115.500	-111.692	-220.882	-199.344	-209.567
	(29.782)	(230.959)	(232.751)	(258.027)	(251.972)	(251.886)	(251.359)
Adjusted R2	0.04	0.04	0.05	0.04	0.10	0.10	0.11
Observations	206	206	206	206	206	206	206

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

Table 13. Difference-in-differences, propensity-score, and exact-matching results: hours worked

	Dependent Variable: Hours Worked (PS Filter)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T	1.157	0.932	1.031	1.133	0.930	0.865	-0.031
	(2.935)	(2.927)	(2.878)	(2.901)	(2.797)	(2.792)	(2.724)
Treated	-2.390	-2.511	-2.570	-2.582	-2.766	-2.955	-3.599
	(2.921)	(2.914)	(2.865)	(2.872)	(2.769)	(2.767)	(2.694)
ATE	-2.368	-2.251	-2.199	-2.300	-2.008	-1.918	-0.772
	(4.131)	(4.120)	(4.051)	(4.072)	(3.926)	(3.919)	(3.820)
Age		0.918	1.147	1.049	1.383*	1.518*	1.673**
		(.763)	(.754)	(.811)	(.787)	(.792)	(.770)
Age^2		-0.009	-0.012	-0.011	-0.015*	-0.016*	-0.018**
		(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
Married			6.178***	5.993***	4.902**	4.828**	3.811*
			(2.201)	(2.274)	(2.209)	(2.205)	(2.161)
High School				-0.874	1.018	1.579	0.988
				(2.627)	(2.576)	(2.606)	(2.537)
Male					9.777***	9.522***	8.994***
					(2.439)	(2.442)	(2.376)
Urban						-2.710	-1.323
						(2.052)	(2.030)
Other-Subsidies							0.042***
							(0.012)
Constant	36.275***	14.449	7.875	10.391	2.272	0.861	-0.862
	(2.075)	(16.088)	(15.990)	(17.722)	(17.203)	(17.204)	(16.717)
Adjusted R2	0.00	0.01	0.04	0.04	0.11	0.11	0.16
Observations	206	206	206	206	206	206	206

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

Table 14. Difference-in-differences, propensity-score, and exact-matching results: decapitalization

	Dependent Variable: Decapitalization (PS Filter + Exact Matching)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T	14.510	14.275	14.256	13.735	13.917	14.295	14.684
	(16.131)	(16.197)	(16.259)	(16.376)	(16.460)	(16.441)	(16.512)
Treated	25.642*	25.179	25.126	25.212	25.411	27.076*	27.448*
	(15.291)	(15.344)	(15.404)	(15.458)	(15.546)	(15.590)	(15.658)
ATE	-31.873	-33.516	-33.430	-32.717	-33.217	-32.500	-32.644
	(22.412)	(22.560)	(22.649)	(22.810)	(23.021)	(22.997)	(23.071)
Age		-0.734	-0.851	-0.260	-0.438	-0.605	-0.341
		(4.411)	(4.477)	(4.774)	(4.868)	(4.863)	(4.910)
Age^2		0.014	0.016	0.010	0.012	0.015	0.011
		(0.049)	(0.050)	(0.053)	(0.054)	(0.054)	(0.054)
Married			-2.040	-1.345	-1.111	-0.350	0.303
			(11.645)	(11.839)	(11.936)	(11.937)	(12.054)
High School				5.867	5.144	2.052	2.386
				(16.073)	(16.502)	(16.692)	(16.758)
Male					-2.802	-1.004	-0.486
					(13.446)	(13.516)	(13.603)
Urban						14.652	13.510
						(12.588)	(12.857)
Other Subsidies							0.040
							(0.086)
Constant	-62.667***	-59.389	-56.135	-71.096	-66.984	-72.203	-78.083
	(11.319)	(95.314)	(97.457)	(106.029)	(108.241)	(108.184)	(109.235)
Adjusted R2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	136	136	136	136	136	136	136

*Notes: *, **, and *** denote statistical significance at the 10,5 and 1 percent levels, respectively.*

Throughout the analysis, I have found negative effects on income and hours worked. The estimates for earnings range from −6 to −41 percent if we compare it to the labor-income base level in 2018 for BDH beneficiaries. The estimates range from −3 to −13 percent for hours worked and −6 to 79 percent for decapitalization. Despite their statistical significance, these results suggest that BDH beneficiaries are changing their behavior in the labor market. Recipients are substituting leisure for work hours and earning less income, which is consistent with the standard microeconomic theory. Additionally, instead of BDH boosting the savings rate and fostering capital accumulation as the savings-poverty-trap hypothesis predicts, I find evidence of the opposite. Once recipients receive the cash transfer, they take more money from their self-employment activity for present consumption. This result suggests that recipients start to rely more on government subsidies than on their own work once they enter BDH.

V. Discussion

I used Instituto Nacional de Estadisticas y Censo's panel data from 2018 to 2019 to investigate whether BDH recipients changed their labor market behavior measured using three outcome variables: net income, total hours worked, and decapitalization. I ran a difference-in-differences regression on the whole sample and found negative and statistically significant results for hours worked, after controlling for sociodemographic variables and *Other Subsidies*. Then, I constructed a control group using propensity score matching as a prefilter and only considered data from 2018. When running the difference-in-differences regression on the reduced sample, I found that net income and hours worked fall for the average recipient with a 10 percent significance level when I only controlled for sociodemographic variables and *Other Subsidies*. Finally, to avoid confounding variables from the labor market, I did an exact matching for self-employment, unemployment, and the informal economy. I still found negative effects on earnings, working hours, and decapitalization, but they are not statistically significant.

These results suggest that in the case of Ecuador, the conditional cash-transfer program affects recipients' attitude toward the labor market. The income effect is positive for leisure, implying that it is a normal good. As microeconomic theory predicts, recipients allocate less hours to work and more to leisure after receiving the transfer. In addition, I found the recipients take more money from their self-employment activity after entering BDH. That is, transfer recipients are more willing to decapitalize their own businesses than individuals who do not receive the cash transfer. This finding goes against the savings-poverty-trap hypothesis. Moreover, this result implies that BDH might cause more dependency on government subsidies.

From a policy perspective, the Ecuadorian government should explore other mechanisms that help the most vulnerable households but incentivize work, enabling higher income levels and capital accumulation. My results suggest that unemployment, self-employment, and being part of the informal sector are the largest contributors to low income. This finding is consistent with research on the informal sector in Ecuador (Bastidas and Acosta 2019; Matano, Obaco, and Royuela 2020). The government should push for a labor reform that reduces the cost of being part of the economy's formal sector, including by revising minimum wage laws and reducing hiring costs (Velín-Fárez 2021).

This research suffers from a data limitation. The analysis period is only two years. This means that if BDH affects the labor supply, my study cannot capture any long-run effects. Similarly, the study only considers 105 recipients, which accounts for roughly 0.05 percent of the total BDH population for the analysis period.

Future research on the size of BDH transfers can examine recipients' behavior in the labor market, as effects may vary depending on the amount received, which ranges from USD 50 to USD 100. Another area of interest is BDH's effect on labor allocation between the formal and informal economy. Finally, it is important to consider the general equilibrium effects of the cash-transfer program, given its potential long-run impact on human capital through education and health care.

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