The Behavioral Effects of Unconditional Cash Transfers: Evidence from Indonesia



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The Behavioral Effects of Unconditional Cash Transfers: Evidence from Indonesia

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> > Editor

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ABSTRACT

The Behavioral Effects of Unconditional Cash Transfers: Evidence from Indonesia

Ridho Al Izzati, Daniel Suryadarma, and Asep Suryahadi

Dependence on cash transfer programs, either universal basic income, targeted conditional, or unconditional programs, could produce an undesirable behavioral response among the beneficiaries. Potential adverse outcomes include reduced labor market participation, reduced economic activity, lack of insurance or savings, or increased risky health behavior, such as smoking. We estimate the effects of receiving unconditional cash transfers on individual behavior. The unconditional cash transfer program targeting poor households in Indonesia began in 2005. With 15.5 million beneficiary households, the program remains one of the largest cash transfer programs in the world. We utilize three waves of the Indonesian Family Life Survey (IFLS), a household-level longitudinal dataset. To identify causal relationship, we implement coarsened exact matching to achieve balance in the characteristics of beneficiaries and nonbeneficiaries in the baseline year before the cash transfer program was implemented. We then estimate a difference-in-differences specification to remove time-invariant unobserved heterogeneity. We find no evidence that receiving the unconditional cash transfer program altered employment status or working hours. We also find no significant effects on risky behavior, such as smoking behavior, insurance purchasing, risk or time preferences, or health-related behaviors. Overall, we do not find any evidence that the cash transfer program produced undesirable or risky behaviors.

Keywords: cash transfer, behavioral effects, labor market outcomes, poverty, Indonesia JEL Codes: D10, I12, I31, I38

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LIST OF ABBREVIATIONS

Abbroviations	Indonasian	English
Abbreviations	Indonesian	English
ARA		absolute risk aversion
BDT	Basis Data Terpadu	Unified Database
BKKBN	Badan Kependudukan dan Keluarga Berencana Nasional	National Population and Family Planning Agency
BLSM	Bantuan Langsung Sementara Masyarakat	Temporary Direct Cash Transfer
BLT	Bantuan Langsung Tunai	Direct Cash Transfer
BPS	Badan Pusat Statistik	Indonesia Statistics
CEM		Coarsened Exact Matching
CGE		Computable General Equilibrium
DID		difference-in-differences
IFLS	Survei Aspek Kehidupan Rumah Tangga Indonesia (Sakerti)	Indonesian Family Life Survey
JKN	Jaminan Kesehatan Nasional	Indonesian National Health Insurance
PDM-DKE	Pemberdayaan Daerah dalam Mengatasi Dampak Krisis Ekonomi	Regional Empowerment to Overcome the Impact of the Economic Crisis
PIP	Program Indonesia Pintar	Scholarship for Students from Poor Households
РКН	Program Keluarga Harapan	Household Conditional Cash Transfer
PMT		proxy means test
PPLS	Pendataan Program Perlindungan Sosial	Data Collection for Social Protection Programs
PSE	Pendataan Sosial-Ekonomi	Socioeconomic Data Collection
PSM		Propensity Score Matching
Rastra	Beras Sejahtera	Rice for the Poor
RCT		randomized controlled trial
SKTM	surat keterangan tidak mampu	financial eligibility statement
Susenas	Survei Sosial-Ekonomi Nasional	National Socioeconomic Survey
ТNР2К	Tim Nasional Percepatan Penanggulangan Kemiskinan	National Team for the Acceleration of Poverty Reduction
UCT		unconditional cash transfer

I. INTRODUCTION

Governments provide social protection to mitigate adverse impacts of shocks, especially to those who are at risk or have fallen into poverty. Social protection programs are designed such that once a shock is over and the beneficiaries recover, the assistance would cease. An exception to this is the permanent assistance provided to chronically poor individuals, for example, the disabled or elderly.

However, receiving government cash transfers could alter the behavior of beneficiaries. Specifically, they could expose themselves to unnecessary risks and do not sufficiently insure themselves. Furthermore, they may participate less in the labor market because they assume that the government would provide cash transfers indefinitely. Evidence from the United States shows that farmers reduce insurance purchases as expectations of government disaster payments increase (Deryugina and Kirwan, 2016). Ashenfelter and Plant (1990) found that households reduce labor supply as subsidies get higher. Kousky, Kerjan, and Raschky (2014) used a panel dataset from Florida and showed that increases in federal post-disaster assistance grants significantly decrease individual insurance coverage.

Raschky and Schwindt (2009) estimated the impact of foreign aid on the beneficiary country's preparedness against natural disasters and found that increases in the level of past foreign aid imply higher death tolls resulting from natural disasters. This result implies that foreign aid in previous periods provided perverse incentives in terms of a country's effort to provide protective actions for their citizens.

In contrast to these findings, Banerjee et al. (2017) found no statistically significant effects of receiving cash transfers on employment. They summarized RCT studies conducted in six countries, including those on Indonesia's conditional cash transfer program, and used working status and working hours as outcome variables. Also related to labor market outcome, Bosch and Schady (2019) used regression discontinuity design and found that Ecuador welfare payments did not reduce labor supply over a five-year period.

Marinescu (2018) also found no statistically significant effects of receiving cash transfers on employment. Furthermore, this study finds positive effects of cash transfers on health and education outcomes, while decreasing criminality as well as drug and alcohol use. Looking specifically at Native American children, Akee et al. (2018) found positive effects of unconditional cash transfers on behavioral and personality traits.

Meanwhile, Handa et al. (2018) evaluated a large-scale government unconditional cash transfer in Sub-Saharan Africa. Findings from their investigation reject the perception regarding negative effects of the cash transfer that (i) it induces higher spending on alcohol or tobacco; (ii) it is fully consumed rather than invested; (iii) it creates dependency, for example, by reducing participation in productive work; (iv) it increases fertility; (v) it leads to negative community-level economic impacts (including price distortion and inflation); and (vi) it is fiscally unsustainable. Similarly, Evans and Popova (2017) reviewed 19 studies on the effects of cash transfers on expenditure on temptation goods. Overall, they found a negative and significant effect. In summary, the literature provides mixed results on the behavioral effects of government cash transfer programs.

In Indonesia, after a shock due to fuel subsidy reduction in late 2005, the government implemented a large unconditional cash transfer (UCT) program called BLT (Bantuan Langsung Tunai, or Direct Cash Transfer) to mitigate the impacts. Yusuf and Resosudarmo (2008) used Computable General Equilibrium (CGE) modelling and found all households to be affected by the fuel subsidy reform,

although the richer households are more impacted. They found that BLT could compensate the poor from higher prices induced by the fuel subsidy reduction, especially in rural areas. While some of the poorest urban poor gain positive (nominal) income because of the transfer, the net real expenditure effect is still negative. On the other hand, a study by Bazzi, Sumarto, and Suryahadi (2015) evaluates the implementation of BLT and shows that a timely receipt of a cash transfer is important for consumption smoothing. They found that there is no difference on per-capita expenditure growth between beneficiaries and nonbeneficiaries if a cash transfer is received timely. However, a delayed receipt reduces expenditures of beneficiaries by 7.5 percentage points.

In this paper, we estimate the behavioral effects of BLT and its successor, BLSM (Bantuan Langsung Sementara Masyarakat, or Temporary Direct Cash Transfer), which was implemented in 2013. BLT and BLSM had about 15.5 million beneficiary households each. The program¹ remains one of the largest cash transfer programs in the world. We use a wide range of outcomes, from smoking to insurance purchase and labor market participation. We also test the effects of the cash transfers to risk aversion and time preferences. We find no evidence that receiving the unconditional cash transfer program changes the behavior of the beneficiaries. We also find no evidence of effect heterogeneity by sex, education level, and level of welfare. Therefore, our results add to the literature that finds no evidence of unintended behavioral effects of cash transfers.

We organize the rest of the paper as follows. The next section provides further information on the unconditional cash transfers in Indonesia. Section 3 presents the estimation strategy. Section 4 discusses the findings. Section 5 concludes.

II. INDONESIA'S UNCONDITIONAL CASH TRANSFERS

Introduced in the last quarter of 2005, Indonesia's first unconditional cash transfer was intended to reduce the impact of a fuel subsidy reduction—hence an increase in domestic fuel prices—by reallocating the budgetary savings as direct benefit given to poor and vulnerable households which were most at risk from induced general price increases (World Bank, 2017). The fuel subsidy reduction was necessitated by a steep increase in international oil prices that, given the fixed domestic fuel prices, caused ballooning fuel subsidy in the government budget. At the beginning, the program, which was called BLT, was targeted at the poorest 30% of households. The initial program ran for one year, until September 2006. It was later re-implemented several times intermittently whenever the government reduced fuel subsidies and consequently increased domestic fuel prices.

Figure 1 shows the years the unconditional cash transfers were implemented as well as the number of beneficiaries and the amount of budget allocated for each year. In 2005/2006 (BLT I), there were initially 15.4 million beneficiary households before an increase to 18 million households. They received a transfer of Rp1.2 million for one year, provided on a quarterly basis (Rp300,000 per three month). That benefit is around 15% of the quarterly expenditures for the average beneficiary (Bazzi, Sumarto, and Suryahadi, 2015). In 2008/2009 (BLT II), another cash transfer was made by the government to respond to the global financial crisis. This time, the cash transfer targeted 19 million

¹The program refers to both BLT and BLSM, two similar unconditional cash transfers that were implemented in different years and with different targeting schemes (see Section II).

households. The amount of benefit was the same at Rp100,000 per month, but only provided to cover nine months (Rp900,000 in total per household). The cash transfer was again made in 2013 under a different name (BLSM) for a few months. In 2014/2015, the government eliminated the fuel subsidy to relieve the national budget and as the consequence, another transfer of Rp150,000 per month was made to 15.5 million people for several months. However, the BLSM in 2014/2015 had a lower total benefit compared to BLT in 2005/2006.

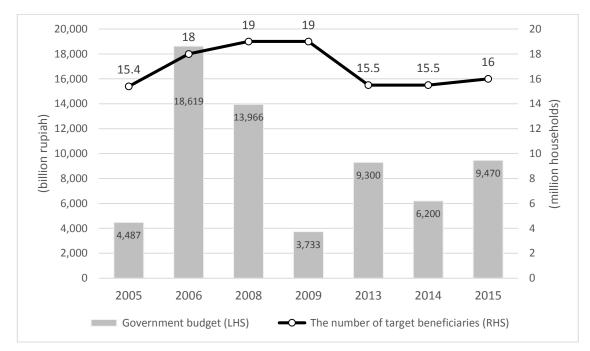


Figure 1. The numbers of target beneficiaries and budget allocations for Indonesia's unconditional cash transfers over the years

Source: World Bank, 2017.

III. EMPIRICAL ESTIMATION STRATEGY

3.1 Data

We use four rounds of the Indonesian Family Life Survey (IFLS)²: 1997, 2000, 2007, and 2014. IFLS is a large ongoing longitudinal household survey in Indonesia, representative of 83% of the Indonesian population (Strauss, Witoelar, and Sikoki, 2016). The first wave, conducted in 1993, consisted of over 30,000 individuals in about 7,000 households in 13 of 27 provinces. The second and third waves were conducted in 1997 and 2000, respectively. The same household respondents were re-interviewed in late 2007 as part of IFLS wave 4 and in late 2014 as IFLS wave 5. The IFLS has a low attrition rate. Strauss, Witoelar, and Sikoki (2016) claimed that 92% of households that were interviewed in 1993 were successfully re-interviewed in all subsequent rounds.

The IFLS has a specific module related to social assistance programs in Indonesia (KSR Section of Book 1). The module has similar questions in the last three rounds that we analyze. We use the

²IFLS is publicly available at https://www.rand.org/labor/FLS/IFLS.html.

questions on the unconditional cash transfers from the government. Figure 2 shows the time horizon of IFLS data and cash transfers in Indonesia. IFLS wave 3 was conducted in late 2000. From the dataset, only about 27 households (or 0.3% out of the total households) indicated that they have ever received an unconditional cash transfer.³ Coincidentally, the last two survey rounds (2007 and 2014) coincided with the years the largest unconditional cash transfer program was being implemented. The IFLS wave 4, conducted between late 2007 and early 2008, recorded the beneficiaries of BLT. There were 2,771 households (or 22% out of the total households) that received BLT I in IFLS wave 4 and only 2% of those households that received BLT 2008 (BLT II) because IFLS wave 4 was being enumerated until mid-2008. Meanwhile, IFLS wave 5, conducted between late 2014 and early 2015, recorded the beneficiaries of BLSM. There were 1,800 households (12% out of the total households) that received BLSM in IFLS wave 5. There were 60% of households that received BLSM and ever received BLT II in 2008.

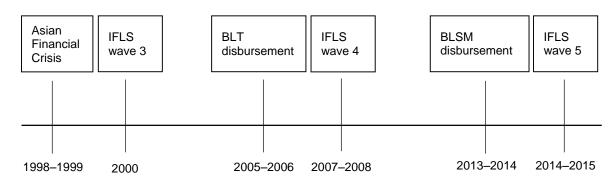


Figure 2. Time horizon of IFLS data and cash transfer disbursements

Regarding the targeting of the unconditional cash transfer program, BLT 2005 used PSE (Pendataan Sosial-Ekonomi, or Socioeconomic Data Collection) 2005 database as the targeting tool. PSE 2005 is a survey that was conducted by Statistics Indonesia (Badan Pusat Statistik or BPS). BPS collected data on the socioeconomic characteristics of poor households listed through interviews with village heads and community leaders. The household list was crosschecked with other poverty information sources, such as BKKBN⁴ data and poverty surveys conducted by the provinces. The PSE 2005 survey collected 14 nonmonetary variables to use in measuring the welfare of the households. BPS then used a proxy means test (PMT) to determine the eligibility of beneficiaries. Based on the PMT result, 19.1 million households were recorded in the PSE 2005 as extreme poor, poor, or near poor.

A similar survey was also conducted in 2008 for targeting households for the disbursement of BLT 2008 program (BLT II). The survey was called PPLS (Pendataan Program Perlindungan Sosial, or Data Collection for Social Protection Programs) 2008. The survey's process and method were similar to those of PSE 2005. The PPLS then expanded to PPLS 2011 or BDT (Basis Data Terpadu, or Unified Database) 2011, but with some improvements in its method and sampling frame (TNP2K, 2015). BDT 2011 was also conducted by BPS. BDT 2011 used Population Census 2010 as the baseline data. BDT 2011 collected more variables than PSE 2005. In total, BDT 2011 surveyed 45% of households in Indonesia compared to only 29% in PSE 2005. It means that BDT 2011 also covered nonpoor but

³This is likely from PDM-DKE (Pemberdayaan Daerah dalam Mengatasi Dampak Krisis Ekonomi, or Regional Empowerment to Overcome the Impact of the Economic Crisis), a social safety net program during the Asian Financial Crisis which provided block grants to communities. Some communities had used the grants to provide cash transfers to poor households.

⁴BKKBN or Badan Kependudukan dan Keluarga Berencana Nasional is the National Population and Family Planning Agency.

considered vulnerable households. The BDT database is the embryo of the unified database used by many social protection programs in Indonesia in the last decade.

3.2 Matching Process

We aim to estimate the effect of receiving BLT and BLSM on individual attitude and behavior. The identification challenge pertains to the fact that BLT and BLSM were not randomly assigned. It targeted the poorest households. Hence, we need to circumvent the selection bias. To identify the effects of BLT, we use the nonbeneficiary households that have observably similar preprogram characteristics as a control group. Practically, these households were the ones that suffer from undercoverage; they should have received the program but for some reason did not.

Like many targeted social assistance programs in other countries, the unconditional cash transfer program in Indonesia also contains targeting error⁵, which includes undercoverage (or exclusion error) and leakage (or inclusion error). Using Susenas (Survei Sosial-Ekonomi Nasional, or National Socioeconomic Survey; the official annual household socioeconomic survey) data, we calculate the exclusion and inclusion errors for BLT I, BLT II, and BLSM. The exclusion errors for BLT I, BLT II, and BLSM are 47%, 54%, 66%, respectively. Meanwhile, their inclusion errors are 21%, 18%, and 12%, respectively. The exclusion and inclusion errors for BLT and BLSM are relatively comparable with similar programs in other developing countries (Sumarto and Bazzi, 2011).

To estimate the effects of the unconditional cash transfers on behavior, we prepare our data in the following manner. The first dataset is an individual-level longitudinal dataset from IFLS 2000 and 2007. The former covers pre-BLT I, while the latter post-BLT I. The second dataset is also an individual-level longitudinal dataset, created from IFLS 2007 and 2014. It covers the pre- and post-BLT II and BLSM.

We show the comparative statistics on a set of household and individual characteristics between cash transfer beneficiaries (treatment group) and nonbeneficiaries (control group) for these two datasets separately in Table 1. The comparison shows that the beneficiaries have lower education, are poorer, reside mainly in rural areas, and have lower access to safe drinking water and proper sanitation compared to nonbeneficiaries in the initial year. In addition, they have a higher proportion of both receiving a cash transfer and having a *surat miskin*⁶ in the initial year. Almost all covariates that we test are significantly different. Note that the nonbeneficiaries in this table covers both the poor who were supposed to receive the program but did not, and the nonpoor who were not supposed to receive the program and the nonpoor who were not supposed to receive the program and the nonpoor who were not supposed to receive the program and the nonpoor who were not supposed to receive the program and the nonpoor who were not supposed to receive the program and the nonpoor who were not supposed to receive the program and the nonpoor who were not supposed to receive the program and the nonpoor who were not supposed to receive the program but did.

In order to balance the characteristics of the treatment and control groups, we then match the pre-BLT characteristics between the beneficiaries and nonbeneficiaries based on the BLT beneficiary status in 2007 using Coarsened Exact Matching (CEM). We prefer to use CEM because the method requires fewer assumptions, is more easily automated, and possesses more attractive statistical properties for many applications than Propensity Score Matching (PSM) or any other matching

⁵Undercoverage or exclusion error in this paper is defined as the proportion of households that were eligible but did not receive the program. Meanwhile, leakage or inclusion error is defined as the proportion of households that were not eligible but received the program. The targeting figure we get for BLT and BLSM has a similar pattern with other programs, such as Rastra (Rice for the Poor), PKH (Household Conditional Cash Transfer), and PIP (Scholarship for Students from Poor Households). See Rahayu et al. (2018) for further review.

⁶Surat miskin or surat keterangan tidak mampu (SKTM) is a financial eligibility statement issued by the village office.

method (Blackwell et al., 2009). The matching aims to improve the estimation of causal effects by removing the imbalance in pretreatment covariates between the treatment and control groups (lacus, King, and Porro, 2012). Finally, CEM calculates sample weights, which we use in the regressions.

Variables -		cteristics in 2000 for Characteristics in 20 reatment in 2007 Treatment in 20 (Dataset 1) (Dataset 2)					
Valiables -	Mean of Control Group	Difference to Treatment Group	p-value	Mean of Control Group	Difference to Treatment Group	p-value	
Poor status (yes=1)	0.11	0.16	0.00	0.04	0.08	0.00	
Ever received cash transfer (yes=1)	0.01	0.01	0.00	0.19	0.29	0.00	
Having card for the poor (yes=1)	0.05	0.04	0.00	0.10	0.10	0.00	
Female (yes=1)	0.53	0.02	0.00	0.53	0.01	0.18	
No schooling (yes=1)	0.08	0.12	0.00	0.07	0.03	0.00	
Primary schools (yes=1)	0.37	0.18	0.00	0.34	0.20	0.00	
Junior secondary schools (yes=1)	0.17	-0.02	0.00	0.18	0.03	0.00	
Senior secondary schools (yes=1)	0.28	-0.18	0.00	0.30	-0.15	0.00	
University (yes=1)	0.09	-0.09	0.00	0.11	-0.10	0.00	
Other schools (yes=1)	0.01	0.00	0.12	0.01	0.00	0.96	
House ownership (yes=1)	0.80	0.04	0.00	0.77	0.02	0.00	
Safe drinking water (yes=1)	0.88	-0.05	0.00	0.76	0.03	0.00	
Own toilet with septic tank (yes=1)	0.56	-0.30	0.00	0.68	-0.22	0.00	
Having land for farming (yes=1)	0.37	0.00	0.93	0.33	-0.06	0.00	
Urban residence (yes=1)	0.52	-0.18	0.00	0.52	-0.07	0.00	

Table 1. Prematching Characteristics in the Initial Year Based on UCTs Beneficiary Status

Note: The number of observations in 2000 is 16,587 for the control group and 5,117 for the treatment group. Meanwhile, the number of observations in 2007 is 22,076 for the control group and 3,443 for the treatment group. The mean difference estimation is conducted by using simple regression that estimates the characteristics in the initial year as listed above to the unconditional cash transfer status in the treatment year.

We match between cash transfer beneficiary households and nonbeneficiary households with similar characteristics. As a rich dataset, IFLS allows us to control for a set of socio-demographic characteristics in the baseline. Specifically, for Dataset 1, we match individual characteristics in 2000 using the unconditional cash transfer status in 2007. Similarly, for Dataset 2, we match individual characteristics in 2007 using the unconditional cash transfer status in 2014. We use the variables from Bazzi, Sumarto, and Suryahadi (2015) for the matching. These variables significantly affect the likelihood of households to receive the unconditional cash transfers.

The main characteristics that we match are the poverty status, ever received social assistance in cash, and having *surat miskin* in the baseline year. We also match on more individual and household characteristics: sex, education level, housing status, drinking water sources, sanitation, land ownership, and urban status in the baseline year. Those variables capture the aspects of poverty. More deprived individuals in all those aspects have a higher probability to receive the cash transfers

in the treatment years. We also control for regional heterogeneity by including province fixed effects in the matching equation. Note that since behavioral variables are measured at the individual level, while cash transfer receipt is measured at the household level, we include all adults in the households. As such, we assume that all household members benefit from the unconditional cash transfers.

Table 2 shows the CEM summary. Our matched dataset contains 13,155 nonbeneficiary individuals and 4,631 beneficiary individuals for Dataset 1, a total of 17,786 individuals out of the initial total sample of 21,704 individuals. Meanwhile, for Dataset 2, we match 13,985 nonbeneficiary individuals and 2,920 beneficiary individuals with a total of 16,905 individuals. We use these observations in our estimations. From the final sample, as many as 26% and 17% of individuals were exposed to the unconditional cash transfers in both datasets, respectively.

	Dataset	Dataset 2 (2007–2014)				
	Nonbeneficiaries	Beneficiaries	- Total	Nonbeneficiaries	Beneficiaries	Total
	(UCT=0)	(UCT=1)	- Total	(UCT=0)	(UCT=1)	Total
All	16,587	5,117	21,704	22,076	3,443	25,519
Matched	13,155	4,631	17,786	13,985	2,920	16,905
Unmatched	3,432	486	3,918	8,091	523	8,614

Table 2. Coarsened Exact Matching Summary

In Table 1, before matching, the multivariate imbalance $(L1)^7$ is 0.56. After matching, the multivariate imbalance decreases considerably to 0.15 for both datasets. Similarly, the imbalance of each covariate also decreases significantly. Since CEM ensures baseline balance between the treatment and control groups, we do not show the postmatching balance.

3.3 Difference-in-Differences (DiD) Estimation

After matching, we estimate a difference-in-differences model as follows:

$$behavior_{it} = \alpha + \beta UCT_{it} \times t_{it} + \theta t_{it} + \delta_i + \varepsilon_{it}$$
(1)

where $behavior_{it}$ is the behavior of individual *i* in year *t*; UCT_{it} is the unconditional transfer beneficiary status of the household; t_{it} is the year dummy (treatment year = 1); θ is the time effect that captures the outcome differences across time; δ_i is the individual fixed effect to control timeinvariant unobserved heterogeneity of individuals; and ε_{it} is the error term. The interaction variable $UCT_{it} \times t_{it}$ is the variable of interest which captures the effect of the program, while β is the magnitude of the effect. Meanwhile, α is the constant term which shows the mean of the outcome of the control group in the initial period.

By combining matching and difference-in-differences using fixed-effect estimation, our identifying assumption is that once observable differences and time-invariant unobserved heterogeneity are considered, no more sources of bias are present.

⁷L1 is an indicator in CEM that shows the multivariate imbalance test result with a value ranging from 0 (balance) to 1 (imbalance).

We estimate Datasets 1 and 2 together as a combined dataset. To control the outcome difference across datasets, we add a dummy which indicates the dataset.⁸ We also estimate model (1) separately for Datasets 1 and 2.

To further test the common trends assumption, we conduct placebo estimations. We estimate model (1) using the previous period. For Dataset 1, we use IFLS 1997 and 2000. For Dataset 2, we use 2000 and 2007 data.

3.4 Behavioral Indicators

The outcome variables come from the individual-related questionnaires contained in Books 3A and 3B of IFLS. Those modules were answered by household members who were 15 years old and older. Table 3 shows the behavioral indicators that we include as outcome variables. The more risky behavior is indicated by the negative direction of the indicators. Risk aversion is indicated in the opposite direction.

We include *arisan* membership as a behavioral indicator. *Arisan* is a rotating savings group (also known as RoSCA), an informal community gathering that involves a money saving activity across members. Value of 1 means that the individual has joined an *arisan* in the past year and 0 means otherwise. Following Brunette et al. (2013), we use this variable to examine whether receiving a government cash transfer reduces membership in informal insurance.

We define smoking behavior as an individual who (i) is currently not smoking or has totally stopped chewing tobacco, (ii) is not smoking a pipe or self-rolled cigarettes, or (iii) is not smoking cigarettes/cigars (1=yes, 0=otherwise). We construct the variable this way to ensure that in all our dependent variables, a positive answer is a good outcome.

The medical checkup variable means that an individual has ever checked his/her health at a medical facility in the last five years. Ownership of a private insurance is defined as an individual who holds a private insurance or savings-related insurance. We exclude the ownership of social insurance, such as the Indonesian National Health Insurance (Jaminan Kesehatan Nasional or JKN), which is fully subsidized by the government.

Working status is positive for individuals who worked at least one hour in the previous week, or the individual has a job but is temporarily not working in the past week. We define the working hour variable as the total number of hours worked in the last week. Since workers in Indonesia (especially the poor) mostly work in the agricultural or informal sector, and have a high likelihood of having multiple jobs, we sum all the working hours of the workers for both the main job and additional jobs.

Meanwhile, the variable working in a farm business is defined as a dummy variable taking the value of 1 if the individual is working in a farm business and 0 if otherwise. Similarly, the variable working in a nonfarm business is also a dummy variable that is equal to 1 for an individual who is working in a nonfarm business. We define the farm and nonfarm business activities when an individual is working in the agricultural and nonagricultural sectors, respectively, but with the type of job either self-employed, self-employed with unpaid family workers/temporary workers, or self-employed with permanent workers. For the indicators related to labor market (working hours, and farm and

⁸Technically, we modify model (1) and estimate: $behavior_{it} = \alpha + \beta UCT_{it} \times t_{it} + \theta t_{it} + \delta_i + \partial_d + \varepsilon_{it}$. Variable ∂_d is a dummy that has the value of 1 for Dataset 2 and 0 for Dataset 1.

nonfarm business activities), we estimate the effect exclusively for individuals who are currently working only during the survey round.

Variable	Description					
Main Outcome						
Participate in an <i>arisan</i> group (rotating savings group)	Have you participated in <i>arisan</i> in the last 12 months? (Yes=1, 0=otherwise)					
Currently not smoking (quit smoking or never smoke)	Are you currently not smoking or have you totally quit smoking? (Yes=1, 0=otherwise)					
Having medical check	Have you had a general checkup performed in the last 5 years? (Yes=1, 0=otherwise)					
Having private insurance	Private insurance or benefits ownership (Yes=1, 0=otherwise)					
Currently working	During the past week, did you work to get paid? (Yes=1, 0=otherwise)					
Working hours in the past week	What was the total number of hours you worked during the past week (on your job)? (in hours)					
Working in farm business	Working in farm business (Yes=1, 0=otherwise)					
Working in nonfarm business	Working in nonfarm business (Yes=1, 0=otherwise)					
Outcomes Only Available in IFLS 2007 and 2014						
Hypothetical risk aversion	Absolute risk aversion (ARA) index, higher index means more risk averse (value 0.005 to 0.250)					
Hypothetical time preference	Time preference index, higher index means more patience (value 1 to 5)					

Table 3. Behavioral Indicators

Additionally, we also use risk and time preferences as outcome variables. We use the preferable index of measuring hypothetical risk question, which is the Arrow-Pratt index, as a measure of absolute risk aversion (ARA) (Sanjaya, 2013). A higher ARA index means higher risk aversion. Meanwhile, the time preference variable is constructed with values ranging from 1 to 5. A larger value of time preference means that an individual is more patient.

In total, we have eight different main outcome variables divided into two groups. The first group contains variables that apply to all individuals. The second group contains variables that apply only to working individuals. To avoid overemphasizing and cherry-picking the result, we follow Kling, Liebman, and Katz (2007) to estimate the average effect of treatment to outcomes. For this purpose, we create an index of risk behavior called summary index that averages together the five measures of risky behavior for all sample and three measures for working individuals.

The summary index is defined such that more beneficial outcomes have higher scores. It is defined as z-scores that are calculated by subtracting each outcome with control group mean and then dividing the result with the control group standard deviation. After that, we average all the normalized z-scores of the variables and then standardize the average relative to the control group. Therefore, the value of index has an average of 0 with a standard deviation of 1 for the control group. We present findings from this summary index which aggregate information over all treatment effects to draw a general conclusion. Because it is in z-score, the summary index is known as standardized average effect.

IV. ESTIMATION RESULTS

4.1 Behavioral Effects of Receiving the Unconditional Cash Transfers

Table 4 and Table 5 show the main results⁹ on the effects of receiving the unconditional cash transfers on individual behavior. We find no evidence that an unconditional cash transfer receipt affects behavior. We can also rule out large effects. The coefficients of participation in *arisan*, smoking behavior, medical checkup, ownership of a private insurance, and working status are all statistically insignificant and almost zero. Similarly, among those who are working, receiving the unconditional cash transfers has no statistically significant effects on working hours in the past week and activities in a farm or nonfarm business. The last columns of Table 4 and Table 5 show the standardized average effects of receiving the unconditional cash transfers that confirm our findings, both of which are not statistically significant.

	Participate in <i>Arisan</i>	Quit Smoking /Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Standardized Average Effect
UCT x year	-0.006	-0.001	-0.003	-0.002	0.007	-0.008
	(0.008)	(0.005)	(0.006)	(0.001)	(0.009)	(0.018)
Mean of dependent variable	0.260	0.661	0.092	0.004	0.744	0.000
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Dataset fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	61,540	61,588	59,500	69,382	61,714	59,494
Number of individuals	30,770	30,794	29,750	34,691	30,857	29,747
R ²	0.645	0.889	0.501	0.463	0.627	0.620

Table 4. Estimation Results of the Effects of the UCTs on Behavior

Notes: Estimation results from this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

*** p<0.01

APPENDIX 1 and APPENDIX 2 show the main estimation results separated for Datasets 1 and 2. The results are similar. APPENDIX 3 shows the additional estimation results for Dataset 2 that estimate the effects of the unconditional cash transfer on risk aversion index and time preference index. The results are also similar with our main findings. The coefficient is almost zero and insignificant for the three indicators.

⁹The estimation results that are shown in the tables are estimated from model (1). For convenience, we only show coefficient β from the interaction of the unconditional cash transfer status and year dummy in the first row. Meanwhile, the mean of dependent variable is calculated using the mean of the outcome of the control group (see APPENDIX 16).

One possible reason for these findings is that the amount of the cash transfers received by the households is too small, around 15% of the total expenditure (Bazzi, Sumarto, and Suryahadi, 2015). To test this possibility, instead of using the beneficiary status dummy of the cash transfer, we estimate model (1) using the cash transfers received as a proportion of the annual household expenditure. The IFLS questionnaire also includes the amount of benefit received by the beneficiary households. The results are shown in APPENDIX 4. We find similarly statistically insignificant estimates, except for two outcomes: participation in *arisan* and ownership of a private insurance. However, the average effects of the treatment in the last column still show insignificant results.

	Working Hours	Working in Farm Business	Working in Non- farm Business	Standardized Average Effect
UCT x year	-0.260	-0.006	-0.006	-0.033
	(0.513)	(0.007)	(0.011)	(0.027)
Mean of dependent variable	42.081	0.211	0.250	0.000
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Dataset fixed effect	Yes	Yes	Yes	Yes
Number of observations	37,144	37,266	37,266	37,142
Number of individuals	18,572	18,633	18,633	18,571
R ²	0.555	0.735	0.705	0.652

Table 5. Estimation Results of the Effects of the UCTs on Behavior Conditional for Individuals Who Are Currently Working

Notes: Estimation results from this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

*** p<0.01

Our main findings are in line with the findings of Banerjee et al. (2017) in six developing countries, including Indonesia, in that unconditional cash transfers have a limited effect on behavior. It is also similar to the findings of Marinescu (2018) in the context of a developed country.

4.2 Heterogeneity Analysis

Table 6 and Table 7 show the results of effect heterogeneity analyses based on sex, education level, and median consumption expenditure. Table 6 shows that among females and males, the unconditional cash transfers have no significant effects on risky behavior. To avoid endogeneity concerns, we use the initial year level of per-capita household expenditure to separate individuals into below and above the median. Among individuals living in households with per-capita expenditures below the median, we find no effect of the cash transfers on behavior. This is also the case among individuals living in households above the median except for participating in *arisan*. Individuals who are exposed to the unconditional cash transfers and living in households above the median are 3.3 percentage points less likely to participate in *arisan* compared to nonbeneficiary individuals. However, the average effect is not significant.

Examining the effect heterogeneity based on education level, we find that the cash transfers decrease probability to not smoke by 1.7 percentage points for individuals with a high education level. However, this is a small effect compared to the mean being that 65% of the individuals from this group are currently not smoking. Despite that, the average effects of the treatment for the high-education group are not significant. Similar to the overall findings, the effects of the unconditional cash transfers on behavior for the group with low levels of education are almost zero and not statistically significant.

	Participate in <i>Arisan</i>	Quit Smoking/ Never Smoke	Having Medical Check	Having Private Insurance	Currently Working	Standardized Average Effect
			Fe	male		
UCT x year	-0.015	0.005	-0.003	-0.001	0.016	0.003
	(0.012)	(0.005)	(0.007)	(0.001)	(0.012)	(0.021)
Mean of dependent variable	0.346	0.959	0.088	0.003	0.622	0.229
Number of observations	33,869	33,897	32,925	37,534	33,973	32,923
Number of individuals	16,935	16,949	16,463	18,767	16,987	16,462
R ²	0.634	0.749	0.493	0.459	0.596	0.588
	<u> </u>		N	lale		
UCT x Year	0.007	-0.009	-0.004	-0.003	-0.004	-0.023
	(0.007)	(0.008)	(0.008)	(0.002)	(0.012)	(0.022)
Mean of dependent variable	0.150	0.280	0.097	0.005	0.900	-0.295
Number of observations	27,671	27,691	26,575	31,848	27,741	26,571
Number of individuals	13,836	13,846	13,288	15,924	13,871	13,286
R ²	0.611	0.776	0.511	0.466	0.554	0.591
	<u> </u>	Less or	Equal than \$	Six Years of S	chooling	
UCT x year	-0.006	0.003	-0.002	-0.000	0.006	0.001
	(0.009)	(0.007)	(0.005)	(0.000)	(0.012)	(0.021)
Mean of dependent variable	0.240	0.666	0.082	0.001	0.758	-0.035
Number of observations	32,491	32,515	31,180	36,829	32,577	31,178
Number of individuals	16,246	16,258	15,590	18,415	16,289	15,589
R ²	0.670	0.899	0.514	0.462	0.644	0.656
		Mor	e than Six Y	ears of Scho	oling	
UCT x year	-0.010	-0.017***	-0.004	-0.005	0.009	-0.036
	(0.015)	(0.005)	(0.012)	(0.003)	(0.017)	(0.045)
Mean of dependent variable	0.304	0.651	0.114	0.011	0.713	0.078
Number of observations	28,541	28,565	27,896	31,806	28,628	27,892
Number of individuals	14,271	14,283	13,948	15,903	14,314	13,946
R ²	0.648	0.889	0.550	0.492	0.663	0.628

Table 6. Estimation Results for Heterogeneity of the Effects of the UCTs onBehavior

	Participate in <i>Arisan</i>	Quit Smoking/ Never Smoke	Having Medical Check	Having Private Insurance	Currently Working	Standardized Average Effect
			Below Me	dian of PCE		
UCT x year	0.002	0.001	-0.007	-0.001	0.009	-0.005
	(0.009)	(0.006)	(0.008)	(0.001)	(0.011)	(0.023)
Mean of dependent variable	0.228	0.663	0.079	0.001	0.736	-0.064
Number of observations	30,572	30,586	29,526	34,332	30,646	29,526
Number of individuals	15,286	15,293	14,763	17,166	15,323	14,763
R ²	0.656	0.893	0.501	0.527	0.631	0.639
			Above Me	dian of PCE		
UCT x year	-0.033**	-0.002	0.004	-0.003	-0.011	-0.037
	(0.015)	(0.007)	(0.013)	(0.002)	(0.014)	(0.021)
Mean of dependent variable	0.298	0.659	0.108	0.008	0.753	0.076
Number of observations	30,968	31,002	29,974	35,050	31,068	29,968
Number of individuals	15,484	15,501	14,987	17,525	15,534	14,984
R ²	0.663	0.896	0.526	0.462	0.659	0.618
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Dataset fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation results from this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parentheses and are clustered at the provincial level. ** p<0.05

*** p<0.01

Meanwhile, Table 7 shows the estimation results conditional for only individuals who are currently working. We find no significant effects of the unconditional cash transfers on behavior almost for all subsample categories. There is a statistically significant effect for the variable 'standardized average effects' for individuals with more than six years of schooling related to working behavior. This effect is contributed by the negative effect for the variable 'working status in nonfarm business'; however, it is only weakly significant. Meanwhile, the other two variables in the same row are not statistically significant.

	Working Hours	Working in Farm Business	Working in Non- farm Business	Standardized Average Effect
		F	emale	
UCT x year	-0.172	0.003	-0.014	-0.028
	(0.704)	(0.014)	(0.014)	(0.025)
Mean of dependent variable	38.319	0.108	0.315	-0.159
Number of observations	14,812	14,824	14,824	14,810
Number of individuals	7,406	7,412	7,412	7,405
R ²	0.593	0.656	0.732	0.659
			Male	
UCT x year	-0.315	-0.012	-0.001	-0.037
	(0.710)	(0.007)	(0.013)	(0.036)
Mean of dependent variable	44.720	0.283	0.205	0.112
Number of observations	22,332	22,442	22,442	22,332
Number of individuals	11,166	11,221	11,221	11,166
R ²	0.513	0.744	0.672	0.633
		Less or Equal than	Six Years of Schoo	ling
UCT x year	0.262	-0.005	-0.007	-0.020
	(0.673)	(0.010)	(0.014)	(0.034)
Mean of dependent variable	41.267	0.248	0.250	0.036
Number of observations	20,869	20,911	20,911	20,867
Number of individuals	10,435	10,456	10,456	10,434
R ²	0.578	0.739	0.724	0.667
		More than Six	Years of Schooling	
UCT x year	-1.880	-0.015	-0.013	-0.089**
	(0.964)	(0.014)	(0.013)	(0.041)
Mean of dependent variable	44.029	0.117	0.252	-0.093
Number of observations	15,936	16,014	16,014	15,936
Number of individuals	7,968	8,007	8,007	7,968
R ²	0.596	0.767	0.726	0.681
		Below N	ledian of PCE	
UCT x year	1.258	0.001	-0.006	0.004
	(1.409)	(0.021)	(0.011)	(0.058)
Mean of dependent variable	40.524	0.226	0.211	-0.051
Number of observations	18,362	18,425	18,425	18,362
Number of individuals	9,181	9,213	9,213	9,181
R ²	0.708	0.806	0.809	0.770

Table 7. Estimation Results for Heterogeneity of the Effects of the UCTs onBehavior Conditional for Individuals Who Are Currently Working

	Working Hours	Working in Farm Business	Working in Non- farm Business	Standardized Average Effect
		Above M	ledian of PCE	
UCT x year	-1.003	-0.016	-0.020	-0.083
	(1.532)	(0.019)	(0.028)	(0.059)
Mean of dependent variable	43.973	0.193	0.298	0.063
Number of observations	18,782	18,841	18,841	18,780
Number of individuals	9,391	9,421	9,421	9,390
R ²	0.784	0.878	0.846	0.827
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Dataset fixed effect	Yes	Yes	Yes	Yes

Notes: Estimation results from this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

*** p<0.01

APPENDIX 5 shows the estimation results for the placebo test. All the coefficients are almost zero and not significant, which indicates that there is no significant difference of the outcome before the treatment period.

V. ROBUSTNESS CHECK

Some studies show that cash transfers have a spillover on the behavior of nonbeneficiaries. Angelucci and De Giorgi (2009) found a positive spillover. Not only that, a Mexican welfare program, Progresa, has a positive impact on consumption of the beneficiaries, but also a positive impact on the consumption of the ineligible households in the same treated villages. They showed that a cash injection into a group of households affects all families living in the same village. The mechanism behind the indirect effects of Progresa is that the ineligible households living in the treated villages receive more informal loans, receive more transfers from family and friends, and reduce their livestock and grains.

Meanwhile, Baird, de Hoop, and Özler (2013) found a negative spillover of cash transfers. They found that while cash transfers strongly reduced psychological distress among schoolgirls, there was also strong evidence of increased psychological distress among untreated schoolgirls in the treatment areas. The effects dissipated soon after the program ended.

Considering this, we need to examine whether our findings emerge due to a spillover. Consider a person who is supposed to receive BLT/BLSM but did not. The person then sees that her/his neighbor receives it. That event could change his/her behavior, for example, by stopping working due to disappointment, or taking up more smoking.

Since the treatment effects are all zero, the only way a spillover could cause this is when the risky behavior of the control group changes in the same direction as that of the treatment group. We check whether this is the case. APPENDIX 6 and APPENDIX 7 show the changes in our main

outcomes and confirm that there is no significant change between baseline and endline in the control group.

Second, spillovers are more likely to happen between neighbors, whereas our matching takes place at the provincial level. However, we check whether our results are different when we match treatment and control groups in a smaller area (such as the district or subdistrict level). The estimation results are shown in APPENDIX 8 to APPENDIX 11. Except the variable 'having private insurance' in the subdistrict-level matching, all the effects for the other variables are not statistically significant. The standardized average effects confirm our estimation that the effects are practically close to zero.

Third, the spillover could be a function of baseline expenditure levels. When richer people see that their equally rich neighbors get BLT/BLSM, the spillover would likely be smaller compared to when poor people see that their equally poor neighbors get BLT. So, the next robustness check is that we test the impact heterogeneity for the bottom 40% and top 40% of expenditures at baseline. The estimation results are shown in APPENDIX 12 to APPENDIX 15. We find no effect of the unconditional cash transfer on almost all outcomes for both expenditure groups. There is one significant result, that is, the effect for the variable 'standardized average effects' for the sample in top 40% related to working behavior, similar to the estimation result for individuals with more than six years of schooling. This effect is also contributed by the negative effect for the variable 'working status in nonfarm business'; however, it is only weakly significant. In conclusion, our estimates are unlikely to contain spillover bias.

VI. CONCLUSION

Cash transfers are currently a widely used tool in the portfolio of social protection programs in many developing countries. This was spurred by evidence which shows that cash transfers are effective in reducing poverty, increasing educational attainment, and improving health status of the poor. However, due to behavioral effects among the beneficiaries, cash transfers can have potential adverse outcomes, such as reduced labor market participation, reduced economic activity, lack of insurance or savings, or increased risky health behaviors, such as smoking. In this paper, we empirically examine the behavioral effects of a large-scale unconditional cash transfer program in Indonesia.

The unconditional cash transfer program targeting poor households in Indonesia began in 2005 to mitigate the impact of increasing fuel prices. Over the course of a decade, the program had been implemented intermittently whenever the government raised fuel prices. Covering between 15 up to 19 million households, Indonesia's unconditional cash transfer program is one of the largest of such programs in the world.

To examine the behavioral effects of this program, we use a wide range of outcomes of risk indicators, from smoking habit to insurance purchase and labor market participation. Our estimation results show no evidence that receiving the unconditional cash transfer program changes the behavior of the beneficiaries. We also find no effect heterogeneity either by sex, education level, and initial household welfare. Therefore, the experience in Indonesia shows that unconditional cash transfers have brought about positive effects with no evidence of negative unintended consequences on the behavior of their beneficiaries.

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APPENDICES

Table A1. Estimation Results of the Effects of the UCTs on Behavior Separated forDatasets 1 and 2

	Participate in <i>Arisan</i>	Quit Smoking/ Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Standardized Average Effect
			Dataset 1	(2000–2007)		
UCT x year	0.011	0.003	-0.010	-0.002**	0.012	0.002
	(0.015)	(0.010)	(0.010)	(0.001)	(0.012)	(0.026)
Mean of dependent variable	0.263	0.669	0.099	0.002	0.746	0.000
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	31,288	31,298	31,284	35,572	31,308	31,284
Number of individuals	15,644	15,649	15,642	17,786	15,654	15,642
R ²	0.692	0.895	0.542	0.522	0.665	0.657
			Dataset 2	(2007–2014)		
UCT x year	-0.001	-0.003	-0.021	-0.003	0.001	-0.056
	(0.020)	(0.007)	(0.017)	(0.001)	(0.016)	(0.038)
Mean of dependent variable	0.257	0.654	0.085	0.006	0.742	0.000
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	30,252	30,290	28,216	33,810	30,406	28,210
Number of individuals	15,126	15,145	14,108	16,905	15,203	14,105
R ²	0.698	0.911	0.545	0.525	0.680	0.661

Notes: The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

	Working Hours	Working in Farm Business	Working in Non-farm	Standardized Average Effect
	<u>.</u>	Dataset 1 (2)	Business	
UCT x year	-1.032	0.003	-0.001	-0.026
	(1.349)	(0.014)	(0.014)	(0.046)
Mean of dependent variable	42.910	0.231	0.256	0.000
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Number of observations	18,778	18,812	18,812	18,778
Number of individuals	9,389	9,406	9,406	9,389
R ²	0.607	0.760	0.739	0.697
		Dataset 2 (2	007–2014)	
UCT x year	-0.426	-0.033	-0.003	-0.068
	(0.878)	(0.016)	(0.027)	(0.057)
Mean of dependent variable	41.319	0.193	0.245	0.000
Year fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes
Number of observations	18,366	18,454	18,454	18,364
Number of individuals	9,183	9,227	9,227	9,182
R ²	0.603	0.770	0.737	0.682

Table A2. Estimation Results of the Effects of the UCTs on Behavior Separated forDatasets 1 and 2 Conditional on Individuals Who Are Currently Working

Notes: The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

Table A3. Additional Results of the Effects of the UCT on Behavior for Dataset 2

	More Risk Averse	More Patient
UCT x year	-0.003	0.052
	(0.004)	(0.053)
Mean of dependent variable	0.150	1.610
Year fixed effect	Yes	Yes
Individual fixed effect	Yes	Yes
Number of observations	27,842	27,842
Number of individuals	13,921	13,921
R ²	0.531	0.542

Notes: The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

Table A4. Estimation Results of the Effects of the UCTs on Behavior Using Share ofTransfer as Explanatory Variable

	Participate in Arisan	Quit Smoking/ Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Standardized Average Effect
Share of UCT benefit x year	-0.276***	0.089	0.089	-0.014***	-0.111	-0.104
	(0.033)	(0.067)	(0.067)	(0.004)	(0.114)	(0.208)
Mean of dependent variable	0.260	0.661	0.092	0.004	0.744	0.000
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Dataset fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	61,540	61,588	59,500	69,382	61,714	59,494
Number of individuals	30,770	30,794	29,750	34,691	30,857	29,747
R ²	0.645	0.889	0.501	0.463	0.627	0.620

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The variable shares of the unconditional cash transfers are calculated by dividing the benefit received by the households with the total household expenditure. The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

Table A5. Parallel Assumption Test

	Participate in <i>Arisan</i>	Quit Smoking /Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Working Hours	Working in Farm Business	Working in Non- farm Business
UCT x year	0.013	-0.003	0.001	-0.001	0.006	0.203	0.021	-0.014
	(0.009)	(0.004)	(0.021)	(0.001)	(0.012)	(0.869)	(0.016)	(0.029)
Mean of dependent variable	0.351	0.685	0.107	0.005	0.713	42.770	0.191	0.262
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dataset fixed effect	Yes	Yes	No	Yes	Yes	Yes	No	No
Number of observations	45,722	45,726	21,848	48,188	45,746	27,070	13,594	13,594
Number of individuals	22,861	22,863	10,924	24,094	22,873	13,535	6,797	6,797
R ²	0.681	0.896	0.542	0.445	0.658	0.582	0.753	0.740

Notes: Estimation results in this table include two datasets that combined dataset 1997–2000 for Dataset 1 (matching 2000–2006) and dataset 2000–2007 for Dataset 2 (matching 2007–2014). Meanwhile, the variables having medical checkup, working in farm business, and working in nonfarm business are only estimated using dataset 2000–2007 for Dataset 2. The robust standard errors are in parentheses and are clustered at the provincial level.

** p<0.05

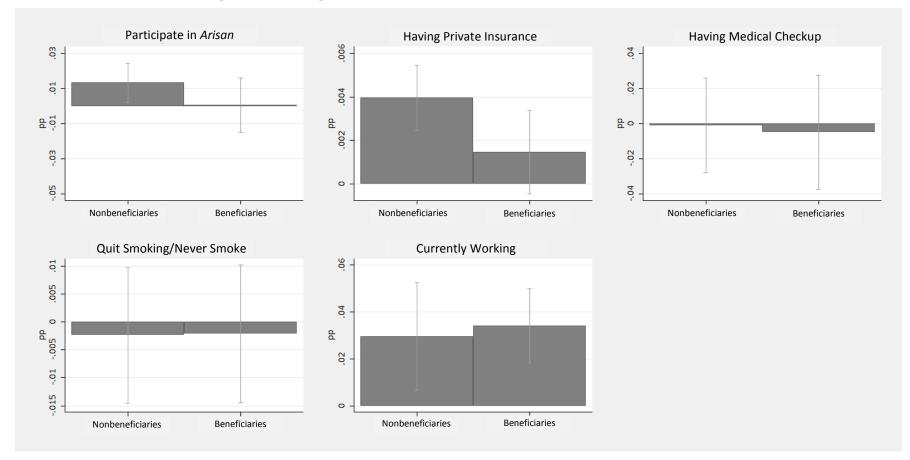


Figure A1. Changes in the Main Outcomes between Baseline and Endline

Note: The figures above show the β coefficient from the simplest fixed-effect model: **behavior**_{it} = $\alpha + \beta Endline_{it} + \delta_{t} + \partial_{d} + \varepsilon_{it}$, where $Endline_{it}$ is the dummy variable with value 1 indicating endline or treatment year and value 0 indicating baseline, while δ_{i} is the individual fixed-effect, ∂_{d} is the dummy indicating the dataset, and ε_{it} is the error term. The vertical axis label "pp" indicates the percentage point.

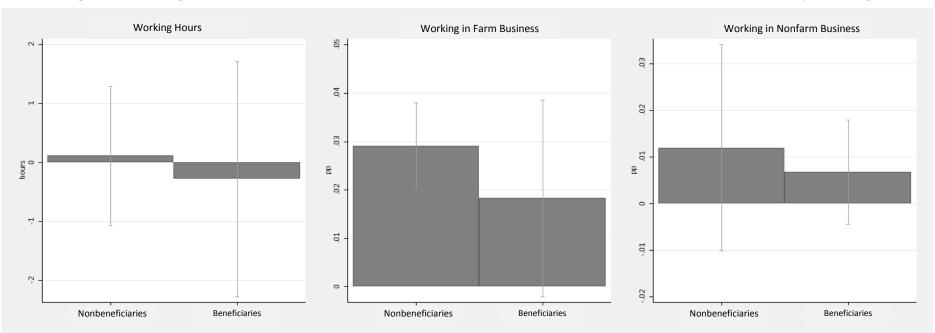


Figure A2. Changes in the Main Outcomes between Baseline and Endline for Individuals Who Are Currently Working

Note: The figures above show the β coefficient from the simplest fixed-effect model: **behavior**_{it} = $\alpha + \beta Endline_{it} + \delta_i + \partial_d + \varepsilon_{it}$, where **Endline**_{it} is the dummy variable with value 1 indicating endline or treatment year and value 0 indicating baseline, while δ_i is the individual fixed-effect, ∂_d is the dummy indicating the dataset, and ε_{it} is the error term. The vertical axis label "pp" indicates the percentage point.

Table A6. The Estimation Results of the Effects of the UCTs on Behavior Using District-Level Matching

	Participate in <i>Arisan</i>	Quit Smoking/ Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Standardized Average Effect
UCT x Year	-0.006	-0.002	-0.004	-0.002	0.007	-0.010
	(0.009)	(0.005)	(0.008)	(0.001)	(0.008)	(0.022)
Mean of dependent variable	0.258	0.663	0.092	0.004	0.743	0.000
Number of observations	60,696	60,744	58,718	68,446	60,864	58,712
Number of individuals	30,348	30,372	29,359	34,223	30,432	29,356
R ²	0.646	0.888	0.501	0.464	0.627	0.620

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parentheses and are clustered at the district level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

*** p<0.01.

Table A7. The Estimation Results of the Effects of the UCTs on Behavior Using District-Level Matching Conditional for Individuals Who Are Currently Working

	Working Hours	Working in Farm Business	Working in Nonfarm Business	Standardized Average Effect
UCT x Year	-0.290	-0.005	-0.008	-0.035
	(0.700)	(0.008)	(0.009)	(0.026)
Mean of dependent variable	42.061	0.212	0.254	0.000
Number of observations	36,626	36,744	36,744	36,626
Number of individuals	18,313	18,372	18,372	18,313
R ²	0.559	0.736	0.708	0.653

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parenthesis and are clustered at the district level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

Table A8. The Estimation Results of the Effects of the UCTs on Behavior Using Subdistrict-Level Matching

	Participate in <i>Arisan</i>	Quit Smoking/ Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Standardized Average Effect
UCT x Year	-0.007	-0.001	-0.004	-0.002**	0.007	-0.011
	(0.009)	(0.005)	(0.007)	(0.001)	(0.008)	(0.019)
Mean of dependent variable	0.259	0.662	0.092	0.004	0.744	0.000
Number of observations	60,230	60,278	58,262	67,924	60,398	58,256
Number of individuals	30,115	30,139	29,131	33,962	30,199	29,128
R ²	0.647	0.889	0.501	0.465	0.628	0.620

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parenthesis and are clustered at the subdistrict level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

Table A9. The Estimation Results of the Effects of the UCTs on Behavior Using Subdistrict-Level Matching Conditional for Individuals Who Are Currently Working

	Working Hours	Working in Farm Business	Working in Nonfarm Business	Standardized Average Effect
UCT x Year	-0.323	-0.004	-0.007	-0.034
	(0.703)	(0.009)	(0.009)	(0.025)
Mean of dependent variable	42.057	0.211	0.254	0.000
Number of observations	36,416	36,534	36,534	36,416
Number of individuals	18,208	18,267	18,267	18,208
R ²	0.560	0.737	0.709	0.654

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parenthesis and are clustered at the subdistrict level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

Table A10. Estimation Results of the Effects of the UCTs on Behavior for Individuals in the Bottom 40% of Per Capita Expenditure

	Participate in <i>Arisan</i>	Quit Smoking/ Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Standardized Average Effect
UCT x Year	-0.002	0.002	-0.010	-0.001	0.007	-0.017
	(0.011)	(0.006)	(0.011)	(0.001)	(0.012)	(0.031)
Mean of dependent variable	0.217	0.653	0.081	0.001	0.754	-0.077
Number of observations	24,474	24,488	23,606	27,466	24,534	23,606
Number of individuals	12,237	12,244	11,803	13,733	12,267	11,803
R ²	0.660	0.895	0.506	0.557	0.630	0.648

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parenthesis and are clustered at the provincial level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

Table A11. Estimation Results of the Effects of the UCTs on Behavior forIndividuals in the Bottom 40% of Per Capita Expenditure(Conditional for Individuals Who Are Currently Working)

	Working Hours	Working in Farm Business	Working in Nonfarm Business	Standardized Average Effect
UCT x Year	0.781	-0.002	0.010	0.020
	(1.299)	(0.009)	(0.014)	(0.038)
Mean of dependent variable	40.140	0.241	0.190	-0.084
Number of observations	36,416	36,534	36,534	36,416
Number of individuals	15,108	15,166	15,166	15,108
R ²	0.551	0.739	0.688	0.655

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parenthesis and are clustered at the provincial level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

Table A12. Estimation Results of the Effects of the UCTs on Behavior for Individuals in the Top 40% of Per Capita Expenditure

	Participate in <i>Arisan</i>	Quit Smoking/ Never Smoke	Having Medical Checkup	Having Private Insurance	Currently Working	Standardized Average Effect
UCT x Year	-0.039	-0.002	0.011	-0.003	-0.004	-0.022
	(0.025)	(0.009)	(0.019)	(0.002)	(0.012)	(0.028)
Mean of dependent variable	0.316	0.668	0.115	0.008	0.731	0.115
Number of observations	24,328	24,356	23,584	27,462	24,402	23,578
Number of individuals	12,164	12,178	11,792	13,731	12,201	11,789
R ²	0.665	0.894	0.530	0.467	0.665	0.617

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parenthesis and are clustered at the provincial level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

Table A13. Estimation Results of the Effects of the UCTs on Behavior for Individuals in the Top 40% of Per Capita Expenditure (Conditional for Individuals Who Are Currently Working)

	Working Hours	Working in Farm Business	Working in Nonfarm Business	Standardized Average Effect
UCT x Year	-2.769	-0.008	-0.030	-0.126**
	(1.898)	(0.013)	(0.017)	(0.046)
Mean of dependent variable	44.626	0.166	0.334	0.109
Number of observations	14,332	14,382	14,382	14,330
Number of individuals	15,108	15,166	15,166	15,108
R ²	0.591	0.756	0.734	0.677

Notes: Estimation results in this table include two datasets that combined Dataset 1 (matching 2000–2007) and Dataset 2 (matching 2007–2014). The robust standard errors are in parenthesis and are clustered at provincial level. For convenience, the year, dataset, and individual fixed effects are not shown but included in the estimation.

** p<0.05

Veriekles	Nonbeneficiaries			Beneficiaries						
Variables	Obs.	Mean	Std.dev	Min	Max	Obs.	Mean	Std.dev	Min	Max
					All Sa	ample				
Participate in arisan	48,138	0.260	0.439	0	1	13,402	0.244	0.429	0	1
Quit smoking/ never smoke	48,176	0.661	0.473	0	1	13,412	0.633	0.482	0	1
Having medical checkup	46,454	0.092	0.289	0	1	13,046	0.079	0.269	0	1
Having private insurance	54,280	0.004	0.063	0	1	15,102	0.001	0.034	0	1
Currently working	48,284	0.744	0.437	0	1	13,430	0.749	0.434	0	1
Standardized average effect	46,448	0.000	1.000	-1.854	18.032	13,046	-0.084	0.889	-1.854	14.357
	Individuals Who Are Currently Working									
Working hours	28,846	42.081	26.033	0	168	8,298	40.258	24.740	0	168
Working in farm business	28,942	0.211	0.408	0	1	8,324	0.225	0.418	0	1
Working in nonfarm business	28,942	0.250	0.433	0	1	8,324	0.213	0.409	0	1
Standardized average effect	28,844	0.000	1.000	-1.795	4.145	8,298	-0.090	0.974	-1.795	3.726
	All Sample for Dataset 2 Only									
More risk averse	22,942	0.150	0.088	0.005	0.250	4,900	0.150	0.088	0.005	0.250
More patient	22,942	1.610	1.082	1	5	4,900	1.617	1.087	1	5

Table A14. Statistical Summary of the Combined Sample

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