Volume LXII No. 1
June 2025

p-ISSN 1655-1516
e-ISSN 2984-8156

The Philippine Review of Economics

ARTICLES IN THIS ISSUE

A joint publication of the
University of the Philippines
School of Economics
and the **Philippine Economic Society**

PRE

The Philippine Review of Economics

A joint publication of the UP School of Economics (UPSE)
and the Philippine Economic Society (PES)

Aims and Scope: *The Philippine Review of Economics* (PRE) invites theoretical and empirical articles on economics and economic development. Papers on the Philippines, Asian and other developing economies are especially welcome. Book reviews will also be considered.

The PRE is published jointly by the UP School of Economics and the Philippine Economic Society. Its contents are indexed in Scopus, the *Journal of Economic Literature*, EconLit, and RePec. PRE's readership includes economists and other social scientists in academe, business, government, and development research institutions.

Publication Information: The PRE (p-ISSN 1655-1516; e-ISSN 2984-8156) is a peer-reviewed journal published every June and December of each year. A searchable database of published articles and their abstracts is available at the PRE website (http://pre.econ.upd.edu.ph).

Subscription Information:
Subscription correspondence may be sent to the following addresses:

- css@pssc.org.ph and pes.eaea@gmail.com
- PSSC Central Subscription Service,
  PSSCenter, Commonwealth Avenue, 1101, Diliman,
  Quezon City, Philippines.
  2/F Philippine Social Science Center, Commonwealth
  Avenue, Diliman, Quezon City 1101
- PHONE: (02) 8929-2671, FAX: 8924-4178/8926-5179

Submissions: Authors may submit their manuscripts to the addresses below:

- pre.upd@up.edu.ph
- The Editor, The Philippine Review of Economics,
  School of Economics, University of the Philippines,
  Diliman, Quezon City, 1101.

Manuscripts must be written in English and in MS Word format. All graphs and tables must be in Excel format. Submission of a manuscript shall be understood by the PRE as indicating that the manuscript is not under consideration for publication in other journals. All submissions must include the title of the paper, author information, an abstract of no more than 150 words, and a list of three to four keywords. Complete guidelines can be viewed in the PRE's website.

Acknowledgments: The PRE gratefully acknowledges the financial support towards its publication provided by the Philippine Center for Economic Development (PCED). The *Review* nonetheless follows an independent editorial policy. The articles published reflect solely the editorial judgement of the editors and the views of their respective authors.

The Philippine Review of Economics

Vol. LXII No. 1
June 2025

p-ISSN 1655-1516
e-ISSN 2984-8156
DOI: 10.37907/ERP5202J

The Philippine Review of Economics
62(1):77-111. DOI:10.37907/4ERP5202J

Do cash transfers mitigate risks and crowd out informal insurance? Evidence from a randomized experiment in the Philippines

Angelica Maddawin*
National Graduate Institute for Policy Studies (GRIPS)
Asian Development Bank Institute

Kazushi Takahashi
National Graduate Institute for Policy Studies (GRIPS)

This study evaluates the impact of a Conditional Cash Transfer (CCT) program on risk mitigation and informal insurance systems among poor Filipino households during exposure to negative income shocks. CCTs can reduce dependence on informal arrangements by increasing beneficiaries' income, making them more resilient to shocks and less reliant on informal networks. Conversely, it can reinforce informal arrangements by enhancing the financial capacity of eligible households, enabling them to lend money to others during shocks. Theoretical outcomes can thus be ambiguous. Using a sample of 1,415 households from 130 village clusters randomly assigned to treatment and control groups, intention-to-treat (ITT) estimates suggest that CCT has unintended consequences on risk mitigation and positive spillover effects on the informal system. Beneficiaries' medical expenses and borrowings from the informal system increased during shocks. Additionally, increased lending support was observed among ineligible households in treatment areas, along with a decrease in their borrowings from the informal system.

JEL classification: O1, P36
Keywords: cash transfer, informal insurance, income shocks

1. Introduction

Poor households in both rural and urban areas of low-income countries face a myriad of challenges arising from various types of shocks, including aggregate events like natural disasters, pest and disease outbreaks, as well as idiosyncratic shocks such as death [Dercon et al. 2006], illness (Gertler and Gruber [2002]; Mehmood [2021]), and job loss (Skoufias and Parker [2006]; Morduch, [1999]).

* Address all correspondence to abmaddawin@gmail.com.

These adverse shocks can significantly diminish household incomes. In response, poor households employ a range of ex-ante and ex-post self-coping strategies, such as distress sales of assets, increased labor supply, migration for employment opportunities, reduced consumption by cutting back on non-essential expenses, and intertemporal resource allocation through borrowing and savings. However, these self-coping mechanisms often fall short in providing complete recovery from the impact of the shock.

Another common strategy adopted by households to cope with financial hardships is through informal arrangements within their social networks, commonly observed among extended families, ethnic groups, and neighbourhoods [Dercon 2002]. For instance, Fafchamps and Lund [2003] examined risk-sharing arrangements, such as gifts, loans, and asset sales, among rural Filipino households in four villages in the Cordillera Mountains of northern Philippines. Their research revealed that gifts and loans from friends and relatives served as effective risk-coping mechanisms during shocks, while informal insurance helped households manage the financial burden of funerals. However, these arrangements had limited impact on coping with shocks induced by crop failure, minor illnesses, or unemployment of household members other than the household head and spouse. Covariate shocks inherently challenge informal insurance mechanisms due to liquidity constraints and limits on aggregate resources. However, some evidence suggests that informal insurance could work under covariate shocks given certain conditions. Informal system is possible under covariate stress if accompanied by microinsurance and index insurance [Mobarak and Rosenzweig 2012]. While there may be temporary breakdowns after covariate shocks, informal networks can be restructured with new link formations, hence, may continue their existence [Ambrus et al. 2014].

CCT programs also function as a form of coping mechanism. Conceptually, CCTs entail government subsidies for education, health, and food, contingent upon compliance with certain conditions related to improvements in health and educational outcomes. These cash transfers have been shown to mitigate various shocks, such as school dropout rates [de Janvry et al. 2006] and teenage pregnancies [Baird et al. 2010]. However, the spending of these transfers is ultimately at the discretion of the household. Indeed, evidence indicates that cash transfers can serve as safety nets during adverse events, such as negative weather shocks affecting agricultural production, as seen in countries like Zambia (Lawlor et al. [2019]; Asfaw [2017]), Niger (Premand and Stoeffler [2020]), Kenya (Dietrich and Schmerzeck [2019]), and Indonesia [Christian et al., 2018].

While there is ample evidence supporting the positive effects of CCTs on risk mitigation, recent studies have raised concerns about potential unintended adverse consequences. For example, Filmer et al. [2021] identified a negative externality on the health outcomes of non-beneficiary children in the Philippines, attributed to an increase in the price of perishable foods in local markets.

Similarly, Olinto et al. [2006] observed that CCTs potentially crowded out private food transfers and money/food transfers from non-governmental organizations in Nicaragua, particularly in instances where CCTs were sufficiently large, thereby affecting private networks and informal insurance schemes. This crowding-out phenomenon arises from households withdrawing from existing risk-sharing arrangements, particularly when informal insurance mechanisms are weak [Morduch 1999]. Consequently, it is essential to examine the impact of cash transfer programs on the pre-existing informal support networks provided by family, friends, and community members.

In examining the case of the Philippines, our study seeks to determine whether CCTs can effectively mitigate the negative income shocks experienced by poor households. Additionally, we aim to investigate whether CCTs have the potential to alter existing informal risk-sharing arrangements between beneficiaries and non-beneficiaries of cash transfer programs in the presence or absence of negative income shocks. Specifically, while Filmer et al. [2021] attribute negative consequences for non-beneficiaries to higher food prices in treated areas, we explore another potential channel whereby negative outcomes for non-beneficiaries are exacerbated through the reduction of informal risk-sharing in treated areas.

Our approach is aligned with several studies that have investigated similar phenomena. For instance, Olinto et al. [2006] examine two scenarios of cash transfer programs—one where the CCT program is substantial enough to influence private transfers and another where the CCT program is too small to significantly impact private transfers. They identify two distinct effects on private transfers, including remittances and transfers from non-governmental organisations. In our analysis, we focus specifically on the crowding-out effects of CCTs, particularly considering the conditions under income shocks. Furthermore, we delve into the impact of informal arrangements within networks of friends and community members, as opposed to private transfers from non-government organizations (NGOs), as informal safety nets have been shown to effectively protect poor households from irreversible shocks as evidenced by studies in the Philippines [Fafchamps and Lund 2003], Ethiopia, and Tanzania [Dercon et al. 2006]. Alatas et al. [2012] find in their experimental study in Indonesia that treated households increased informal transfers to others through their informal network and that the spillover effects were measurable in nearby households. Moreover, Haushofer and Shapiro [2018] analysed the impact of unconditional cash transfers on both recipients and non-recipients within the same communities and found spillover effects to ineligible households in villages where others received cash transfers through informal sharing mechanisms.

The main findings of our study suggest that CCTs have the potential to strengthen the informal support system. We observe an increase in borrowings and lending among eligible households, indicating that CCTs have improved the creditworthiness and financial capacity of these households. Conversely, we find a decrease in borrowings and an increase in lending among ineligible households, suggesting that CCTs have diminished the confidence of ineligible households in borrowing money due to uncertainty regarding their economic conditions. Nevertheless, the trust in eligible households to repay debts remains high, leading to an increase in lending from ineligible households to eligibles within the informal system.

Our study contributes to several strands of literature. First, while existing studies have explored the impact of public transfers on informal transfers, the findings have been mixed. In contrast to some previous research, our study reveals that CCT recipients actually increased their borrowing. Theoretically, CCTs could enhance households' self-financing capacity, potentially reducing their reliance on informal arrangements. However, CCTs may also bolster households' financial standing, prompting them to support neighbors and friends, thereby reinforcing informal arrangements. This latter effect is particularly pronounced when norms of sharing are strong. Much of the evidence suggests that replacing informal risk protection mechanisms with government cash transfers in low- and middle-income countries could lead to social welfare losses [Nikolov and Bonci 2020]. However, in contexts such as rural Suriname and French Guiana, public transfers strengthened informal insurance systems when informal risk-sharing arrangements proved insufficient in addressing persistent adverse conditions like physical disabilities [Heemskerk et al. 2004]. Similarly, in Tanzania, a formal cash transfer program did not crowd out informal safety nets; instead, it encouraged beneficiary households to engage with them [Evans and Kosec 2020]. While acknowledging this evidence, our study adds to the literature by examining the impact of the Philippines CCT program to determine whether it leads to crowding-out effects or generates positive spillover effects in informal social safety nets.

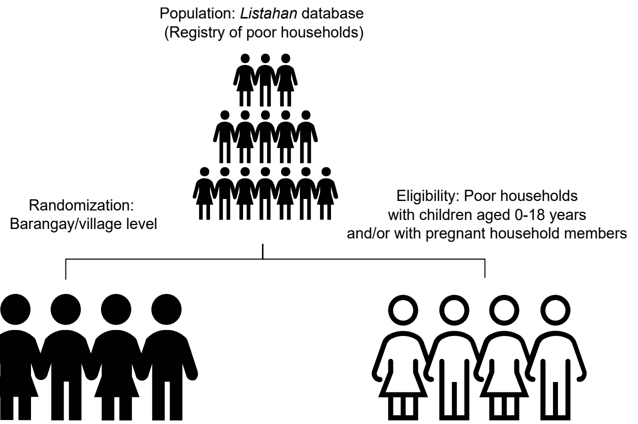
Second, the literature identifies the presence of unintended consequences of cash transfers, such as stunting among non-beneficiary children in the Philippines [Filmer et al. 2021], child labor in Mexico [de Janvry et al. 2006], and teenage pregnancies in Malawi [Baird et al. 2010]. Our study contributes to this growing literature by providing insights into the differential effects of cash transfer programs on beneficiaries and non-beneficiaries. While Albarran and Attanasio [2003] evaluated the impact of a cash transfer program in Mexico, they assumed that the crowding effect was consistent for both beneficiaries and non-beneficiaries. In contrast, our study analyzes the disparity in the average outcomes of the program for beneficiary and non-beneficiary groups.

Finally, we emphasize the effects of CCTs on risk events or shocks, particularly harvest failure. Our findings indicate that while negative income shocks impact consumption levels in poor households in the Philippines, CCTs have a risk-mitigating impact on recipient households. Additionally, we observe a positive spillover effect among ineligibles in treated areas when covariate shocks occur, as they increase lending support to informal insurance and decrease borrowings to avoid exhausting the resources of the informal risk-sharing network. The decrease in borrowings from the informal network among ineligibles suggests that during shocks, their confidence in their ability to repay loans may diminish due to uncertainty about their economic conditions, leading them to be reluctant to borrow from informal insurance systems. Therefore, ineligibles may perceive that excessive borrowing could deplete the network's resources, rendering it unsustainable and ineffective during shocks. Thus, our findings suggest that CCTs have the potential to strengthen the informal system, and these results remain robust across various specifications.

1.1. Background and RCT setting

As large-scale cash transfer programs gained traction in Latin America and Africa, similar initiatives emerged in Southeast Asia, including Indonesia and the Philippines. The Pantawid Pamilyang Pilipino Program (4Ps) was introduced by the Philippines government's Department of Social Welfare and Development (DSWD) in 2008 as a response to the food, fuel, and global financial crises. A randomized experiment was conducted to evaluate the program's impact on health and educational outcomes. The eligibility criteria for the program's treatment group included households with children aged 0 to 18 years and/or pregnant household members. Household poverty status was determined using scores from the Proxy Means Test (PMT), which predicts household income based on socioeconomic indicators such as household demographics, education, occupation, housing conditions, access to basic services, asset ownership, and location. Households with PMT scores below the poverty threshold were classified as poor and listed in *Listahanan*, a population database and official registry of poor households that is utilized in various government programs, including the PhilHealth Universal Health Care program.

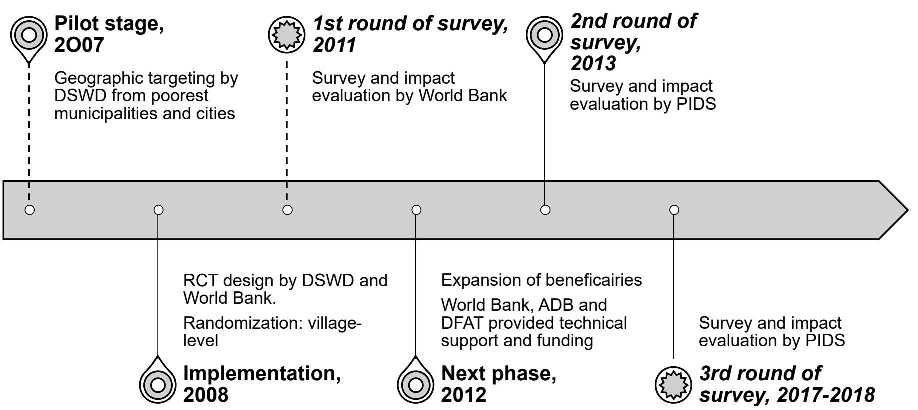
FIGURE 1. RCT design



Similar to CCT programs in other countries, eligible households under the 4Ps are required to meet specific conditions to receive cash grants. These conditions include ensuring immunization of children, monitoring their weight and deworming, receiving pre- and postnatal care, accessing delivery services from skilled health professionals for pregnant mothers, and ensuring 85 percent school attendance for children attending kindergarten, elementary, and high school. Parents are also required to attend monthly family development seminars aimed at promoting family and community development. Once these conditions are met, the eligible household receives various benefits, including a school fee allowance for up to three children, a budget for basic maternal and child health services, and a rice subsidy. Specifically, the household receives ₱300 per child attending kindergarten and elementary school, ₱500 for children attending high school, ₱500 for basic maternal and child health services, and ₱500 for rice subsidies on a monthly basis.

Initially, the program was piloted in selected areas before being gradually expanded nationwide through a phased implementation approach. Unlike CCT programs in other countries, the initial implementation of 4Ps did not involve the development of baseline data. Instead, three rounds of ex-post sample surveys were conducted with the head of households serving as the main respondent in 2011, 2013, 2017, and 2018 to assess the program's impact on various health, education, and behavioral outcomes.[1] While an initial randomized controlled trial (RCT) design was employed in 2011 with random assignment of the program at the village level, ethical concerns arising from the experiment led to a later implementation stage adopting a non-RCT-based framework.

FIGURE 2. Timeline of implementation



[1] However, implementing an RCT for this program necessitates technical support from academia, government, and international organisations to guide the program implementer in executing the experiment properly. Therefore, the absence of baseline data may not have been a significant issue.

1.2. Data and sample survey

For this study, we extensively utilize data collected in 2011 from a population of 376,000 households covered during the initial phase of the program's implementation in 2008. The sample encompasses households both below and above the PMT poverty threshold in treated and control villages, which were either assigned to participate in the program or not. The total sample consists of 1,415 households from 130 villages, spanning eight municipalities and four provinces across three major islands of the Philippines. Specifically, eligible households below the PMT poverty threshold represent 581 observations from randomly assigned program (treated) villages, and 608 observations from non-program (control) villages. In contrast, the sample size of ineligible households (those above the PMT poverty threshold) includes 120 observations from the treatment village and 106 observations from the control village. We exclusively utilize the 2011 data, as follow-up surveys employed a regression discontinuity design for impact evaluation, which is not suitable for examining the differential impacts of CCT on eligible and ineligible households.

Overall, the sample comprises 130 village clusters from eight municipalities across the three major islands of the Philippines. The dataset also provides information regarding the proportion of eligible households in the treatment village receiving benefits from the cash transfer, which closely aligns with the program assignment at 94 percent.

The survey employed separate instruments for household heads, mothers, female household members with partners, school-aged children, school principals, rural health officers, barangay officials, and local government mayors. Questionnaires collected data on various socioeconomic characteristics, reproductive history and contraception, school participation and child labor, health and nutrition, anthropometric measurements of children aged 0 to 5 years, cognitive assessment tests, barangay characteristics, and local government characteristics.

1.3. Estimation strategy

Our goal is to maintain homogeneity among groups, so we separately examine the impacts of the program for eligible and ineligible households, leveraging the advantages of an RCT design. We compared households with PMT scores below the poverty threshold in the treatment village to those with PMT scores below the poverty threshold in the control village, applying the same approach for ineligible households, considering the randomized treatment assignment at the village level.

First, we assessed if the program could mitigate negative income shocks. To estimate the program's risk-mitigation effects, we conducted an intention-to-treat (ITT) estimation which focuses on the random treatment assignment. ITT was used since it is policy-relevant estimation that examines the average impact of exposure to the treatment rather than the uptake. The rate of non-compliance is moderate at eight percent in the below PMT group and 13 percent in the above PMT group. Given the low non-compliance rate, the ITT can be close to the average treatment effect. The risk-mitigation effects are estimated using the following equation:

$$Cons_{ij} = \beta_0 + \beta_1 T_j + \beta_2 (T_j \times IS_{ij}) + \beta_3\, IS_{ij} + \boldsymbol{X}_{ij}\, \theta + \omega_j + \epsilon_{ij}\ , \qquad (1)$$

where $Cons_{ij}$ represents the outcome indicator of household i's consumption in village j, separately estimated for eligible (below PMT poverty threshold) and ineligible (above PMT poverty threshold) households. We assessed per capita consumption, decomposed into food products (e.g., dairy, meat, alcohol) and non-food products (e.g., education, medical expenditures). Dairy and meat consumption indicates a potential improvement in living standards (because these items are relatively expensive), while alcohol consumption reflects changes in temptation goods. Total consumption, education, and medical expenditure per capita were transformed using natural logarithmic functions to make the distribution normal, while dairy, meat, and alcohol consumption per capita were transformed using inverse hyperbolic sine functions to preserve the meaning of zero values. Inverse hyperbolic sine is used for these variables instead of *log* transformation plus a small constant because it accommodates zeros without needing arbitrary adjustments.

T_j denotes the random treatment assignment in the program, while IS_{ij} is an income shock variable proxied by harvest failure due to typhoons, floods, and other weather-related disasters, considered exogenous. We excluded idiosyncratic shocks (e.g., illness, death of family members) from our estimations due to their likely endogeneity. $\boldsymbol{X}_{ij}$ is a vector of controls including household head's demographic characteristics (e.g., age, gender), household characteristics (e.g., size, durable asset index) and barangay characteristics (e.g., natural disaster index, log of barangay population and number of households). ω_j is fixed effects at the municipal level.

β_2 is the main coefficient of interest, estimating the differential impact of aggregate shocks on consumption between the treatment and control groups. It quantifies the risk-mitigation effects of program assignment. β_3 provides the estimate of the average impact of shocks on the control group's consumption, while β_1 measures the impact of the program on the consumption of households in the treatment group when there is no shock. θ is the vector of coefficients associated with the control variables.

Second, to more directly examine evidence of spillover effects on informal arrangements, we estimated two models to compare the impact of receiving grants from the CCT program. The first model is given by Equation (2). This allowed us to examine the average effect on the informal system and to explore if CCT potentially improves informal risk-sharing through an increase in the overall available funds in a community.

$$Informal_{ij} = \delta_0 + \delta_1\ T_j + \boldsymbol{X}_{ij}\theta + \omega_j + \epsilon_{ij}\ , \tag{2}$$

The dependent variable $Informal_{ij}$ represents money borrowed and lent by households i in village j, excluding gifts received and given (e.g., church donations), migrant remittances, borrowing from moneylenders (e.g., Bombay 5-6)[2] or borrowing against land as collateral. This is measured by continuous variables, such as the amount of money borrowed from and lent to neighboring households or relatives. Borrowing and lending are estimated separately to better understand the inflow and outflow of transactions in the informal system. We focused on the impact of informal borrowing and lending because gifts are minimal and are not received regularly. $\boldsymbol{X}_{ij}$ is a vector of controls including the household head's characteristics (e.g., age, gender, marital status, nature of employment, having a bank account, and having a loan), household characteristics (e.g., size, durable asset index, social insurance index including life, health, housing, and other social insurance schemes), barangay characteristics such as health facility index (including barangay health station, rural health center, traditional birth attendant, private clinic, government hospital, private hospital, barangay pharmacy, and private pharmacy), barangay population, and fixed effects at the municipal level. These vectors of controls are included to adjust for imbalances from random differences.

δ_1 indicates whether the program crowds in or out informal arrangements. A positive δ_1 denotes that the program increases the household's total available funds (supply), and community demand provides positive spillover effects to households belonging to informal risk-sharing schemes, while a negative δ_1 suggests the opposite. Regarding borrowing outcomes, a negative coefficient implies that CCT is effective in reducing financial vulnerability by making eligible households less reliant on borrowing. Conversely, a positive coefficient may indicate that CCT has improved the creditworthiness of eligible households, encouraging ineligible households in the informal network to lend money to them, anticipating that the borrowings will be repaid in the future.

As it is not possible to identify if program-eligible households increase or decrease informal arrangements with ineligible households within a village, we again estimated Equation (2) separately for eligible households (i.e., those below the PMT threshold) and ineligible households (i.e., those above the PMT threshold). We expect that when we observe a positive δ_1 for outflows among eligible households, we will also see a positive δ_1 for inflows among ineligible households in the case of positive spillovers.

Out of the 1,189 observations that fall below the PMT, 636 observations (53 percent of poor households) reported positive borrowing from, and 46 observations (four percent of poor households) reported positive lending to

[2] The variable for borrowings from moneylenders is included to illustrate another typical coping mechanism among poor households in the Philippines.

informal systems, respectively, through friends and relatives. In contrast, among the sample size of 226 observations that fall above the PMT, 128 observations (only 57 percent of "near-poor" households) reported borrowings from, and 26 observations (seven percent of "near-poor" households) lent to informal systems, respectively, through friends and relatives.

As it is not possible to take the log for these observations due to the significant number of zeros, we used the inverse hyperbolic sine or arcsine transformation. For outcomes using the inverse hyperbolic sine transformation, we consistently employed Tobit regression to censor the outcome variables at lower limits. The estimates from this Tobit regression represents the effect of the independent variables on the latent variable y_i^* which has values censored at lower limits. They do not represent the effect of independent variables on the probability of being censored or the expected value of the observed outcome variables. Hence, the coefficients are not marginal effects.

We used the second model to examine if the program causes households in treated villages to leave, stay but reduce their engagement, or stay and engage with the informal insurance system when there is an income shock, represented by harvest failures. This helped us identify the mechanism by which the program reduces vulnerability to common shocks through engagement in risk-sharing activities. The estimation model is given by

$$Informal_{ij} = \alpha_0 + \alpha_1 T_j + \alpha_2 (T_j \times IS_{ij}) + \alpha_3 IS_{ij} + \boldsymbol{X}_{ij}\theta + \omega_j + \epsilon_{ij}, \qquad (3)$$

In this model, α_2 captures the ITT spillover effects of the program on informal arrangements. We expect CCT-eligible households to contribute to the informal system in which poor households are likely to adopt risk-coping mechanisms when covariate shocks occur. It is also likely that program eligibles will reduce their reliance on the informal insurance system, contingent on the strength or enforceability of the sharing norm. A positive coefficient, α_2, can be expected from an increase in lending from CCT eligibles, largely driven by cash flows received from the program. It can also be expected from an increase in borrowings after proving their credibility for debt repayment. Debt repayment credibility within a community positively influences an individual's ability to better access and manage credit. However, it is also possible that there will be no change in the lending or borrowing transactions if the cash received from the program is sufficient to mitigate the risk from covariate shocks.

The mechanisms that are directly examined through the empirical methodology are the changes in the informal risk-sharing network resulting from CCT, particularly the changes in the borrowings and lending of eligible and ineligibles. We specifically consider the following conceptual framework that describes possible reasons why borrowings and lending of eligibles and ineligibles increase or decrease, with a visual diagram provided in Figure 3.

a. Borrowing from informal insurance among eligible households increases if: (1) creditworthiness improves due to the regular cash transfers received from CCT. In such cases, ineligibles within the informal network are motivated to lend to eligibles, especially in times of need. (2) The anticipation and assurance that borrowings will be repaid by the eligibles in the future facilitate an increase in their borrowings. (3) Sharing norms is strong, there is an increase of support from ineligibles to the informal network.
b. Lending to informal insurance among eligible households increases if: (1) CCT increases the financial capacity of eligibles, allowing them to lend money to others in times of shock. (2) Eligibles aim to diversify risk during shocks, leading to increased lending to the collective fund in the informal insurance.
c. Borrowing from informal insurance among eligible households decreases if: (1) CCT eligibles experience improved economic conditions due to the benefits they receive from CCT, enabling them to reduce borrowing from informal insurance. Experiencing financial stability due to CCT benefits leads the eligibles to diminish the need for borrowing from informal insurance. (2) Improved creditworthiness among CCT eligibles, resulting from CCT benefits, may grant them access to formal financial resources such as bank loans, reducing their reliance on informal insurance. (3) CCT can inadvertently increase implicit interest rates in informal network (e.g., Torkelson [2000]; Bold et al. [2012]) causing borrowings of the eligible households in the informal network to decrease.
d. Lending to informal insurance among eligible households decreases if: (1) CCT eligibles invest more in opening small businesses since CCT program implementers assist them in creating their own businesses. Consequently, instead of putting their money into the informal network through lending, they may reduce lending and allocate funds to their businesses as investments. (2) During shocks, eligibles may experience a sudden loss of income, limiting their ability to contribute to informal insurance. In such instances, if there is an increased demand for immediate cash during shocks, eligibles might prioritize basic needs, medical costs, and other necessities over contributing to communal funds in the informal network.
e. Borrowings from informal insurance among ineligible households increase if: (1) CCT eligibles in the informal network lend support to ineligibles to help them manage risk when they face financial challenges or require immediate assistance from informal networks. (2) Other forms of coping mechanisms such as illegal money lending (e.g., loan sharks) or microfinance may not lend money to ineligibles,

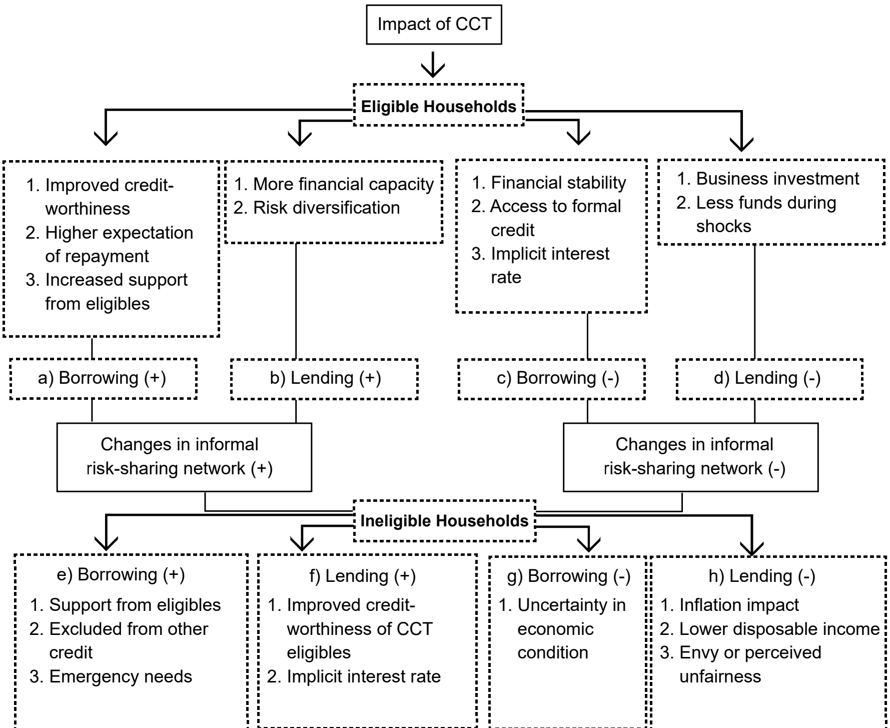
as these lending systems may prefer eligibles. In such cases, the only option for ineligibles may be informal insurance. (3) During shocks, ineligibles may require cash for house repairs, medical costs, and purchasing essential goods, especially when regular income is disrupted.

f. Lending to informal insurance among ineligible households increases if: (1) ineligibles trust CCT eligibles in the informal network because they receive benefits from CCT. Consequently, lending by ineligibles in the informal network increases. (2) CCT can inadvertently increase implicit interest rates in the informal network as eligible households will be viewed by ineligible households to be richer. This encourages ineligible households to increase their lending to the informal network.
g. Borrowings from informal insurance among ineligible households decrease if, during shocks, the ineligibles' confidence in their ability to repay loans is low due to uncertainty in their economic condition. In such cases, they may be reluctant to borrow from informal insurance systems.
h. Lending to informal insurance among ineligible households decreases if: (1) CCT results in upward pressure on prices of goods and services in the local market, negatively affecting ineligibles' income, leading to a decrease in lending to the informal network. (2) During shocks, ineligibles may face economic hardship, leading to a reduction in disposable income. Hence, their limited income may be redirected towards immediate personal needs rather than contributions to informal insurance systems. (3) perceptions of inequality or unfairness, such as envy towards eligible households (e.g., Fafchamps and Lund [2003]; Dercon, et al. [2006]) persist.

The validity of these different consequences can be assessed with the proposed model (equation 3) because (a) to (h) suggest scenarios for increase or decrease in borrowings and lending of eligibles and ineligibles of CCT who engage with the informal network when there is shock. We believe that these mechanisms are the underlying interactions among eligibles and ineligibles in the informal network since it is a system where individuals can support each other during times of crisis and borrowing and lending of money are the ways to support each other within the informal system.

Since the theoretical consequences are not unique, this is an empirical question. Again, we estimated Equation (3) separately for eligible (PMT below the threshold) and ineligible (PMT above the threshold) households.

FIGURE 3. Pathways linking CCT to informal insurance



1.3.1. Summary statistics

Table 1 presents the mean differences between treatment and control households, separately for samples below and above the PMT threshold in 2011. A detailed description of the variables used can be found in Appendix C. The null hypothesis of equal means was rejected for four of the 21 and five out of 21 pre-determined characteristics used in the estimation model for samples below and above the PMT threshold, respectively. These differences may be attributed to the small sample variation at the provincial level, as it covers only four provinces. However, these four provinces are representative of the three major islands in the Philippines: Luzon, Visayas, and Mindanao. Among the covariate shock variables, the household-level shock shows balance, but the village-level shocks such as flood and drought show imbalance between the treatment and control groups. The means of flooding and drought are higher in the treatment group, suggesting that treatment villages are more prone to flooding and drought than control villages for both the below and above PMT groups. To address this concern, a sub-group analysis will be presented after the main analysis. A love plot for standard mean difference (SMDs) is shown in Appendix D, indicating that SMDs are close to zero after matching.

TABLE 1. Balance on demographic characteristics, shocks, consumption outcome, and lending and borrowings outcomes

	Below PMT				
		(1) Treatment		(2) Control	(3) *t*-test Difference
Variable	**N**	**Mean [SE]**	**N**	**Mean [SE]**	**(1)-(2)**
Household head characteristics					
Age	581	43.114 [0.435]	608	43.400 [0.440]	-0.286
Gender (1=Female)	581	0.16 [0.02]	608	0.17 [0.02]	-0.01
Educational attainment (1=High school graduate)	555	5.90 [0.15]	585	5.87 [0.14]	0.03
Marital status (1=Married)	575	0.91 [0.021]	600	0.92 [0.01]	-0.01
Nature of employment (1=Permanent)	527	0.59 [0.02]	526	0.55 [0.02]	0.04
Household characteristics					
Household size	581	6.40 [0.09]	608	6.30 [0.09]	0.10
Durable asset index	581	1.30 [0.06]	608	1.41 [0.06]	-0.12
Has an outstanding loan (1=Yes)	581	0.52 [0.02]	608	0.55 [0.02]	-0.04
Has bank account (1=Yes)	573	0.07 [0.01]	595	0.08 [0.01]	-0.01
Insurance index (health, life, housing, and other social insurance)	581	0.95 [0.03]	608	0.77 [0.02]	0.18***
Barangay characteristics					
Health facility index (rural health center, clinic, hospital, pharmacy etc.)	581	1.85 [0.06]	608	1.84 [0.05]	0.02
Log of barangay population	558	7.27 [0.04]	566	7.33 [0.03]	-0.07
Log of number of households in barangay	558	5.66 [0.03]	562	5.76 [0.03]	-0.10**
Covariate shocks					
Harvest failure (household-level)	578	0.16 [0.02]	608	0.15 [0.02]	0.01
Flood (village-level)	581	0.587 [0.020]	608	0.510 [0.020]	0.077***
Earthquake (village-level)	581	0.621 [0.020]	608	0.635 [0.020]	-0.014
Drought (village-level)	581	0.484 [0.021]	608	0.411 [0.020]	0.072**
Natural disaster intensity (1=more than 2 disasters) (village-level)	581	0.549 [0.021]	608	0.536 [0.020]	0.013
Location characteristics					
Municipality (1=Basay)	581	0.076 [0.011]	608	0.082 [0.011]	-0.007
Province (1=Lanao Del Norte)	581	0.344 [0.020]	608	0.301 [0.019]	0.043

TABLE 1. Balance on demographic characteristics... (continued)

Variable	N	(1) Treatment Mean [SE]	N	(2) Control Mean [SE]	(3) *t*-test Difference (1)-(2)
Below PMT					
Outcome variables					
Household consumption					
Per capita consumption	581	14,284.845 [462.755]	608	14,097.627 [402.919]	187.218
Per capita education expenditure	579	379.363 [42.559]	607	382.947 [40.904]	-3.585
Per capita medical expenditure	578	281.613 [33.093]	608	245.736 [32.863]	35.878
Per capita of dairy consumption	579	496.929 [37.746]	608	428.041 [36.614]	68.888
Per capita of meat consumption	580	634.493 [40.224]	608	713.540 [43.449]	-79.047
Per capita of alcohol consumption	580	93.294 [11.258]	608	153.584 [19.034]	-60.289***
Total borrowings from and lending to friends and relatives	581	3,299.324 [478.562]	608	2,090.155 [517.152]	1209.169*
Borrowings from friends and relatives	581	4,017.757 [491.255]	608	3,923.434 [658.130]	94.323
Borrowings from moneylender	581	918.072 [209.745]	608	1900.220 [423.449]	-982.148**
Lending to friends and relatives	581	192.754 [108.288]	608	66.447 [17.584]	126.307
Borrowings from friends and relatives (1=Yes)	581	0.516 [0.021]	608	0.553 [0.020]	-0.036
Borrowings from moneylender (1=Yes)	581	0.102 [0.013]	608	0.138 [0.014]	-0.037*
Lending to friends and relatives (1=Yes)	581	0.041 [0.008]	608	0.036 [0.008]	0.005
Bank borrowings	581	1,206.540 [415.359]	608	1,473.487 [550.828]	-266.946
Above PMT					
Household head characteristic					
Age	119	46.345 [1.261]	106	44.670 [1.333]	1.675
Gender (1=Female)	120	0.275 [0.041]	106	0.151 [0.035]	0.124**
Educational attainment (1=High school graduate)	120	0.233 [0.039]	106	0.189 [0.038]	0.045
Marital status (1=Married)	120	0.758 [0.039]	105	0.848 [0.035]	-0.089*
Nature of employment (1=Permanent)	90	0.578 [0.052]	86	0.453 [0.054]	0.124

TABLE 1. Balance on demographic characteristics... (continued)

	Above PMT				
		(1) Treatment		(2) Control	(3) *t*-test Difference
Variable	**N**	**Mean [SE]**	**N**	**Mean [SE]**	**(1)-(2)**
Household characteristics					
Household size	120	4.600 [0.178]	106	4.462 [0.169]	0.138
Durable asset index	120	3.292 [0.205]	106	3.349 [0.247]	-0.057
Has an outstanding loan (1=Yes)	120	0.550 [0.046]	106	0.585 [0.048]	-0.035
Has bank account (1=Yes)	118	0.280 [0.041]	101	0.188 [0.039]	0.092
Insurance index (health, life, housing, and other social insurance)	120	1.200 [0.081]	106	0.868 [0.076]	0.332***
Barangay characteristics					
Health facility index (rural health center, clinic, hospital, pharmacy etc.)	120	2.158 [0.125]	106	2.274 [0.135]	-0.115
Log of barangay population	120	7.530 [0.093]	95	7.510 [0.079]	0.020
Log of number of households in barangay	120	5.813 [0.077]	97	5.821 [0.075]	-0.009
Covariate shocks					
Harvest failure (household-level)	120	0.150 [0.033]	106	0.085 [0.027]	0.065
Flood (village-level)	120	0.658 [0.043]	106	0.462 [0.049]	0.196***
Earthquake (village-level)	120	0.617 [0.045]	106	0.717 [0.044]	-0.100
Drought (village-level)	120	0.492 [0.046]	106	0.321 [0.046]	0.171***
Natural disaster intensity (1=more than 2 disasters) (village-level)	120	0.567 [0.045]	106	0.519 [0.049]	0.048
Location characteristics					
Municipality (1=Basay)	120	0.100 [0.028]	106	0.057 [0.023]	0.043
Province (1=Lanao Del Norte)	120	0.217 [0.038]	106	0.189 [0.038]	0.028
Outcome variables					
Household consumption					
Per capita consumption	120	28,762.549 [2763.593]	106	32,902.831 [3,978.807]	-4,140.282
Per capita education expenditure	120	1,382.998 [470.779]	106	992.498 [222.719]	390.500
Per capita medical expenditure	120	2,024.836 [1254.856]	106	899.277 [283.392]	1,125.559

TABLE 1. Balance on demographic characteristics... (continued)

Above PMT					
		(1) Treatment		(2) Control	(3) *t*-test Difference
Variable	**N**	**Mean [SE]**	**N**	**Mean [SE]**	**(1)-(2)**
Per capita of dairy consumption	120	896.433 [140.584]	106	991.619 [162.618]	-95.186
Per capita of meat consumption	120	1,679.531 [195.289]	106	1,729.406 [318.328]	-49.875
Per capita of alcohol consumption	120	138.886 [29.733]	106	505.766 [150.959]	-366.881**
Total borrowings from and lending to friends and relatives	120	2,116 [523.742]	106	3,790.566 [1029.648]	-1,674.566
Borrowings from friends and relatives	120	377.750 [177.413]	106	413.208 [298.123]	-35.458
Borrowings from moneylender	120	1,095.833 [391.448]	106	9,048.113 [5,749.650]	-7,952.280
Lending to friends and relatives	120	2,750.750 [601.821]	106	12,283.962 [5,793.592]	-9,533.212*
Borrowings from friends and relatives (1=Yes)	120	0.550 [0.046]	106	0.585 [0.048]	-0.035
Borrowings from moneylender (1=Yes)	120	0.300 [0.042]	106	0.415 [0.048]	-0.115*
Lending to friends and relatives (1=Yes)	120	0.083 [0.025]	106	0.057 [0.023]	0.027
Bank borrowings	120	6,600 [2,185.527]	106	2,000 [1,021.688]	4,600*

Note: Insurance index, health facility index and natural disaster index are created by summing multiple variables for each observation. Insurance index covers health, life, housing, and other social insurance (index ranged from zero to four). Health facility index covers the presence of barangay health station, rural health unit, traditional birth attendant, private clinic, government hospital and pharmacy in the barangay or village (index ranged from zero to six). Natural disaster intensity is equal to one if village suffered from more than two disasters, which covers either flood, earthquake, or drought).
The values displayed in the last column are *p*-values for *t*-tests for the equality of means across the groups. ***, **, and * indicate significance at the one percent, five percent, and ten percent levels, respectively. Standard errors in brackets.

4. Empirical results

4.1. Estimates of risk-mitigating effects

Table 2 presents the estimates of the program effect, covariate shocks, and risk-mitigating effects of the program on the natural logarithmic forms of total consumption per capita, education cost per capita, medical cost per capita, and the inverse hyperbolic transformations of dairy, meat, and alcohol consumption per capita. Panels A and B provide the results for eligible and ineligible households, respectively.

In Panel A, the results show that the program significantly increased the log of total consumption per capita and education expenditure per capita for eligible households. The consumption of dairy and meat products separately indicated an increase in food consumption, with high protein serving as a proxy for better living standards among the poor. Rice is the dominant staple in the Filipino diet, particularly in rural households. Protein-rich foods, such as dairy and meat, are relatively expensive for the poor; thus, improved income levels will likely increase the consumption of meat and dairy products (e.g., eggs, milk, butter, cheese). The program exhibits a positive consumption effect over virtuous or healthy products (e.g., dairy) and a negative effect on the consumption of sin or unhealthy products (e.g., alcohol in Panel A and Panel B).

These results are consistent with Hoddinott and Skoufias [2004], where they found that PROGRESA in rural Mexico enabled its beneficiaries to "eat better" by focusing on dietary quality rather than food quantity. The study further found a positive spillover to non-beneficiaries in the treatment localities due to the free flow of information within the community regarding good dietary practices.

The program reduces alcohol consumption because the eligible households focused on spending for education and health expenditures as conditionalities of the program. Moreover, continuous check-ups may have led to a lifestyle change. The Family Development Seminar (FDS) of the CCT program may train the eligibles to reduce spending on non-essential items and prioritize meeting basic needs such as food, health, and education as an incentive to sustain the benefits from the program. Similarly, Panel B also found a negative effect on the consumption of alcohol among the treatment group, suggesting the flow of information from eligibles to ineligibles regarding reduced spending on non-essential items, consistent with Hoddinott and Skoufias's [2004] findings.

TABLE 2. Risk-mitigating effects

	Log transformation of per capita			Arcsine transformation of per capita consumptions in		
	Total Consumption	Education cost	Medical cost	Dairy	Meat	Alcohol
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Eligible (below PMT)						
Program assignment (w/out covariate shock)	0.07* (0.04)	0.42* (0.22)	0.24 (0.26)	0.50*** (0.17)	0.05 (0.22)	-0.54*** (0.20)
Covariate shock (proxied by harvest failure)	-0.02 (0.08)	-0.20 (0.40)	-0.37 (0.46)	-0.63* (0.33)	-0.88** (0.38)	-0.92*** (0.29)
Program assignment X Covariate shock	-0.11 (0.10)	0.05 (0.51)	1.32** (0.60)	0.18 (0.43)	0.65 (0.50)	0.62 (0.46)

TABLE 2. Risk-mitigating effects (continued)

	Log transformation of per capita			Arcsine transformation of per capita consumptions in		
	Total Consumption	Education cost	Medical cost	Dairy	Meat	Alcohol
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	9.35*** (0.24)	3.80*** (1.38)	-0.59 (1.64)	5.91*** (1.01)	6.33*** (1.32)	1.97** (0.97)
Observations	1,102	1,100	1,099	1,100	1,101	1,101
Pseudo R^2	0.150	0.0256	0.0198	0.0363	0.0239	0.0215
Panel B: Ineligible (above PMT)						
Program assignment (w/out covariate shock)	-0.13 (0.08)	0.52 (0.67)	0.06 (0.51)	0.20 (0.34)	-0.18 (0.39)	-1.18*** (0.40)
Covariate shock (proxied by harvest failure)	-0.15 (0.20)	-1.13 (2.74)	-0.94 (1.39)	0.22 (1.09)	0.09 (0.50)	-1.02 (1.20)
Program assignment X Covariate shock	0.41 (0.26)	0.56 (3.05)	1.95 (1.78)	0.27 (1.25)	-0.19 (0.74)	1.49 (1.37)
Constant	10.14*** (0.39)	0.45 (4.00)	2.36 (2.73)	7.86*** (1.71)	8.81*** (2.03)	4.40* (2.63)
Observations	211	211	211	211	211	211
Pseudo R^2	0.221	0.0725	0.0368	0.0422	0.0483	0.0297

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations.
$*p<0.01$; $**p<0.05$; $***p<0.001$

The program's risk-mitigating effects, represented by the interaction term, are apparent in the cost of medical care such as drugs and medicines, hospital room charges, medical and dental charges, and other medical expenses of treated households when exposed to covariate shocks. Harvest failure substantially increased medical costs because it can lead to food shortages, causing malnutrition for residents in the village. A lack of essential nutrients makes individuals susceptible to disease or infection, thereby driving up medical costs for households. Given that health insurance coverage is limited in the Philippines, individuals often incur significant health costs, resulting in high out-of-pocket expenditures. The additional cash from the program may help alleviate the burden of medical expenses on poor Filipino households.

4.2. Estimates of informal transfers

Turning to the impacts on informal transfers, Table 3 presents the results of the spillover effects of CCT on the borrowing and lending behaviours of eligible and ineligible households. The model was also fitted for borrowing from formal sources to compare the spillover effects of CCT between informal and formal systems. Control variables, comprising household and barangay characteristics, and fixed effects at the municipal level were included in the model.

The inclusion of these control variables resulted in the omission of a few observations, further decreasing the number of observations to 966 below the poverty threshold and 161 above the poverty threshold. Approximately 19 percent of the observations were lost due to missing values on some covariates. To address this attrition problem, we examined if the omitted observations were random and found systematic differences in the average characteristics between the remaining and omitted observations. Thus, we estimated the non-attrition probit and used the inverse of the predicted value of non-attrition as weights (inverse probability weighting: IPW) to address the potential estimation bias (see Appendix A for the non-attrition probit estimation result).

The results suggest that CCT increased the engagement of its eligibles in informal borrowing and lending systems, as evidenced by the significant increase in total lending and borrowing in the informal system among eligible households. Eligibles of CCT also significantly increased their borrowings from formal banks (column 5), indicating that CCT may have improved their capability and credibility to borrow money from financial institutions. These results are consistent with the enhanced financial capacity of CCT eligibles due to the transfers.

On the other hand, CCT seems to have adversely affected the informal sharing schemes of ineligible households, as shown by the significant decrease in borrowing from friends. This result is also true with borrowings from moneylenders, commonly known in the Philippines as "loan sharks" or "5-6," which are informal in nature. Hence, while ineligibles decrease their borrowings in the informal insurance system, they simultaneously reduce vulnerability to predatory lending practices, as lenders often take advantage of borrowers through excessive interest rates. This result can be explained by the fact that ineligibles also face uncertainty in economic conditions, lowering their confidence to repay borrowings.

The inverse probability weighting (IPW) estimates show consistent results in Panels A and B. In Panel A, the IPW estimate for total borrowings and lending in the informal insurance and formal borrowing are positive and significant, which are consistent with the unweighted Tobit estimate. Likewise in Panel B, the IPW estimate for borrowings from friends is negative, which is consistent with the unweighted Tobit estimate.

TABLE 3. Spillover effects of CCT on informal systems and other coping mechanisms

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	Borrowings from bank
VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel A: Eligible (below PMT)					
Program assignment (w/out covariate shock)	1.48** (0.65)	2.73 (2.27)	-0.05 (0.48)	-3.05** (1.49)	3.34* (1.82)
Constant	-21.93*** (3.01)	-102.05*** (22.00)	-38.96*** (2.52)	-80.77*** (6.01)	-119.03*** (10.48)
Observations	966	966	966	966	966
Pseudo R^2	0.161	0.0756	0.264	0.142	0.186
IPW estimates					
Program assignment (w/out covariate shock)	1.43** (0.68)	2.97 (2.26)	-0.14 (0.50)	-4.45** (1.74)	3.79** (1.75)
Constant	-23.61*** (3.35)	-107.96*** (26.78)	-35.88*** (2.68)	-27.27*** (7.45)	-119.76*** (11.16)
Panel B: Ineligible (above PMT)					
Program assignment (w/out covariate shock)	-0.60 (2.16)	3.63 (4.39)	-2.97* (1.67)	-5.04* (3.00)	3.06 (3.98)
Constant	-17.70** (7.40)	-3.65 (15.29)	-48.67*** (7.04)	-76.73*** (14.27)	-110.36*** (15.71)
Observations	161	161	161	161	161
Pseudo R^2	0.0891	0.164	0.248	0.180	0.282
IPW estimates					
Program assignment (w/out covariate shock	-2.41 (2.07)	2.28 (4.66)	-3.47** (1.50)	-6.68* (3.81)	3.63 (3.94)
Constant	-15.92** (7.45)	1.64 (15.84)	-178.34*** (54.05)	-5.45 (11.24)	-103.46*** (15.74)

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations. *$p<0.01$; **$p<0.05$; ***$p<0.001$

Table 4 presents the results for Equation (3). The inclusion of the shock variable and controls from Equation (2) in Equation (3) has resulted in the omission of a few more observations, reducing the sample size to 963 for households below the poverty threshold and maintaining the same sample size of 161 for households above the poverty threshold. This result is consistent with the findings from Table 3, indicating that CCT has a positive and significant impact on total lending and borrowing in informal and formal systems among eligible households.

TABLE 4. Spillover effects of CCT on informal systems and other coping mechanisms in the presence of shocks

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	Borrowings from bank
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Eligible (below PMT)					
Program assignment (w/out covariate shock)	1.13* (0.67)	2.01 (2.45)	-0.39 (0.47)	-3.96** (1.56)	4.46** (1.93)
Covariate shock (proxied by harvest failure)	-2.09 (1.50)	-4.61 (5.03)	-2.13** (0.98)	-2.41 (2.59)	1.13 (3.82)
Program assignment X Covariate shock	2.7 (2.29)	6.32 (6.62)	2.63* (1.49)	6.99* (3.63)	-10.92* (5.75)
Constant	-21.23*** (3.06)	-100.72 (0.00)	-38.08*** (2.56)	-79.74*** (6.28)	-113.87*** (9.79)
Observations	963	963	963	963	963
Pseudo R^2	0.162	0.0771	0.265	0.144	0.192
IPW estimates					
Program assignment (w/out covariate shock)	1.53 (1.08)	1.93 (3.63)	-0.28 (0.45)	-4.45** (1.74)	5.55** (2.53)
Covariate shock (proxied by harvest failure)	-4.81* (2.78)	-8.17 (8.31)	-1.68* (0.91)	-1.66 (2.90)	3.84 (4.57)
Program assignment X Covariate shock	9.29** (3.98)	17.75** (7.52)	2.43* (1.44)	6.41 (4.18)	-19.96*** (6.41)
Constant	-29.70*** (5.01)	-33.13*** (10.95)	1.06 (2.15)	-27.27*** (7.45)	-43.26*** (9.00)

TABLE 4. Spillover effects of CCT on informal systems and other coping mechanisms in the presence of shocks (continued)

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	Borrowings from bank
VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel B: Ineligible (above PMT)					
Program assignment (w/out covariate shock)	-1.38 (2.16)	-0.05 (4.51)	-2.33 (1.73)	-4.84 (3.23)	2.48 (4.01)
Covariate shock (proxied by harvest failure)	-2.95 (5.25)	3.45 (9.32)	5.32** (2.58)	-3.06 (9.64)	-40.60*** (7.83)
Program assignment X Covariate shock	8.12 (5.76)	18.29 (11.45)	-9.31** (4.68)	-0.33 (11.81)	41.98*** (9.08)
Constant	-18.81** (7.71)	4.01 (14.92)	-47.42*** (7.05)	-74.85*** (15.54)	-104.17*** (15.05)
Observations	161	161	161	161	161
Pseudo R^2	0.0922	0.197	0.252	0.181	0.287
IPW estimates					
Program assignment (w/out covariate shock	-2.90 (2.03)	-1.26 (4.59)	-2.88* (1.51)	-5.30 (3.93)	3.00 (4.07)
Covariate shock (proxied by harvest failure)	-4.39 (4.99)	0.30 (9.92)	4.28* (2.25)	-1.55 (9.56)	-40.72*** (7.81)
Program assignment X Covariate shock	8.90 (5.71)	22.64* (12.40)	-7.78* (3.95)	-9.39 (12.32)	44.68*** (9.19)
Constant	-18.12** (7.38)	7.93 (15.40)	-42.08*** (6.15)	-2.96 (13.06)	-104.16*** (15.46)

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations.*p<0.01; **p<0.05; ***p<0.001

Panel A of Table 4 confirms the positive effect of CCT on the informal system among eligible households, wherein eligibles increase their borrowing during income shocks (column 3). The average daily income of individuals at the poverty threshold is ₱80.20 per day per person. Hence, a significant increase of 2.6 percent borrowings is economically significant. Since there was a significant number of zero borrowings (47 percent of the observations from above PMT observations and 43 percent from below the PMT), borrowings are highly skewed. However, arcsine transformation reduced the distortion of zero values and improved the model's fit.

Eligibility to receive money from the government may improve eligibles' borrowing credibility in informal risk-sharing because they are expected to consistently pay off their debt over time. CCT also seems to attract loan sharks during shocks as borrowing from moneylenders increased. The influx of cash into the community seems to attract the attention of loan sharks and gives them the opportunity to exploit the eligibles of CCT because of their access to more funds coming into the community through CCT. IPW estimates show a positive and significant increase in lending to friends and relatives, and total lending and borrowing show positive coefficients during shocks. This suggests that CCT increases the financial capacity of eligibles, allowing them to lend money to others when there is a shock. CCT eligibles may also diversify risk during shocks, leading to an increase in lending to collective funds in the informal insurance system. In contrast, program participation has a crowding-out effect on bank borrowing, as evidenced by the negative and significant decrease in bank borrowing in column 5 during the income shock. Therefore, during covariate shocks, the program eligibles engage with the informal system through positive borrowing and lending, thus keeping the informal system thriving. However, the CCT program, through eligibles, crowds out formal bank borrowing during shocks and attracts informal moneylenders, indicating that the eligibles prefer the informal insurance system and moneylenders over bank borrowing in times of emergencies brought about by natural disasters. This rests on the assumption that sharing norms are strong, resulting in an increase in support of ineligibles to the informal network.

Panel B of Table 4 shows the regression results for ineligible household samples. Performing the same Tobit regression and set of controls, the results show that ineligible households in the treated areas significantly decrease their borrowing from friends during shocks. This may be partly because the ineligibles' confidence about their ability to repay loans is low due to uncertainty in their economic condition during shocks. This low confidence leads them to reluctantly borrow more money from the informal insurance system. However, according to IPW estimates, among the above PMT group, the program significantly increases informal lending during covariate shocks. It appears that the program enhances informal transactions driven by lending from the "near-poor" households. This means that ineligibles trust CCT eligibles by lending money in the informal network because eligibles receive benefits from CCT. Since it is unlikely that eligibles, who are typically less wealthy, are lending money to relatively more wealthy ineligibles, the result suggests that eligibles increased borrowing from ineligibles.

4.3. Estimates on sub-groups analysis

This section analyzes the imbalance found in the village-level shock index of natural disasters in Table 1. To investigate whether pre-treatment imbalance affects our results, we examine the top three natural disasters reported by the barangay captain: flood, drought, and earthquake. Earthquake was reported as the highest among the natural disasters with more than 60 percent on average, followed by flood with almost 60 percent, and drought with more than 40 percent. Among the three natural disasters, flood and drought show significant mean differences between treatment and control groups, while earthquake remains balanced between the two groups. This may suggest that treatment villages are more prone to flooding and drought than control villages, although it was not explicitly mentioned in the implementation procedure. Given that possibility, we further examine if the villages that are more prone to natural disasters have stronger informal safety nets and social capital.

A natural disaster index was created covering the top three natural disasters mentioned above. The measurement represents an index assigned to each village ranging from zero to three, with zero being the lowest and three being the highest. Next, a natural disaster intensity is created based on the natural disaster index, which is equal to one if there are two or more natural disasters occurring in the village and zero otherwise. Separating the villages into two subgroups describing high and low intensities of climate risk is a more sensible approach and straightforward to interpret. Table 1 shows balance in means in treatment and control groups for the natural disaster intensity variable for the below and above PMT groups. This means that the two groups are now balanced and comparable, allowing us to test the hypothesis that CCT mitigates climatic risks and affects informal safety nets. It is expected that highly intensive natural disasters may damage infrastructure hugely and broadly affect a large number of residents in the village, making them incapable of helping their neighbours.

The result of the sub-group analysis of high and low natural disaster intensities in Table 5 suggests that CCT mitigates climatic risks and affects informal safety nets in villages with low intensities of climate risk. Under the assumption that CCT could mitigate climate risks and affect informal insurance in local communities where the financial system is operating and coordination and monitoring are possible, the results in Table 5 confirm it. The result from Panel A and C describing high-intensity natural disasters measured by two or more natural disasters suggests that CCT may not adequately mitigate climatic risk. This is especially true when the natural disaster is severe enough to devastate the local community by damaging infrastructure, making CCT challenging to implement in the locality. When there is no shock, CCT increases formal borrowing in intensively high natural disaster villages, as shown by positive and significant bank borrowing in Panel A. This suggests that the financial system may not operate well in intensively high climatic risk areas.

TABLE 5. Sub-group analysis: villages with high and low natural disaster intensity

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	**Lending to friends and relatives**	**Borrowings from friends and relatives**	**Borrowings from moneylender**	**Borrowings from bank**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Eligibles in high natural disaster intensity villages					
Program assignment (w/out covariate shock)	0.22 (0.28)	0.08 (0.14)	-0.19 (0.25)	-0.23 (0.27)	0.39* (0.22)
Covariate shock (proxied by harvest failure)	-0.94** (0.46)	-0.04 (0.14)	-0.66 (0.42)	0.30 (0.46)	0.64* (0.33)
Program assignment X Covariate shock	1.01 (0.82)	0.07 (0.35)	0.38 (0.80)	-0.60 (0.54)	-1.39** (0.56)
Constant	-0.64 (1.20)	0.12 (0.45)	-1.80* (0.99)	-1.19 (0.76)	-1.97** (0.93)
Observations	511	511	511	511	511
Pseudo R^2	0.0837	0.0129	0.156	0.0410	0.0597
Panel B: Eligibles in low natural disaster intensity villages					
Program assignment (w/out covariate shock)	0.94** (0.44)	-0.03 (0.09)	-0.11 (0.32)	-1.04*** (0.34)	0.34 (0.22)
Covariate shock (proxied by harvest failure)	-0.26 (0.70)	-0.51 (0.34)	-0.81 (0.81)	-0.89 (0.57)	-0.22 (0.60)
Program assignment X Covariate shock	0.43 (1.04)	0.48 (0.33)	1.75* (0.93)	2.05** (0.80)	-0.70 (0.56)
Constant	-4.20*** (1.17)	0.35 (0.69)	-4.07*** (1.28)	-0.10 (1.07)	-1.70** (0.78)
Observations	452	452	452	452	452
Pseudo R^2	0.0836	0.0310	0.150	0.0378	0.0317
Panel C: Ineligibles in high natural disaster intensity villages					
Program assignment (w/out covariate shock)	-1.57* (0.86)	-0.55 (0.60)	-2.03** (0.82)	-1.80** (0.77)	1.34 (0.84)
Covariate shock (proxied by harvest failure)	-0.76 (1.41)	0.78 (1.58)	0.29 (1.71)	-0.48 (2.39)	-0.57 (1.07)
Program assignment X Covariate shock	1.35 (1.74)	0.08 (1.60)	-2.25 (2.07)	-1.15 (2.57)	1.78 (1.39)

TABLE 5. Sub-group analysis (continued)

	Informal borrowings and lending			Other coping mechanisms	
	Total lending and borrowings	Lending to friends and relatives	Borrowings from friends and relatives	Borrowings from moneylender	from bank
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Constant	1.52 (2.90)	2.30* (1.33)	0.05 (1.84)	0.74 (2.25)	-1.36 (1.87)
Observations	89	89	89	89	89
Pseudo R^2	0.0598	0.0525	0.157	0.0717	0.149
Panel D: Ineligibles in low natural disaster intensity villages					
Program assignment (w/out covariate shock	1.46 (1.02)	0.69 (0.58)	-0.33 (0.97)	-0.66 (0.74)	1.03 (0.92)
Covariate shock (proxied by harvest failure)	-3.36 (2.01)	0.27 (0.98)	-3.71* (2.05)	-3.81* (1.93)	0.07 (2.52)
Program assignment X Covariate shock	4.24** (1.64)	2.56*** (0.95)	4.10** (1.79)	4.46*** (1.58)	-1.45 (2.29)
Constant	6.38 (3.87)	3.48 (2.27)	1.09 (2.33)	-0.00 (1.60)	-3.11 (2.61)
Observations	71	71	71	71	71
Pseudo R^2	0.0934	0.110	0.123	0.0597	0.0984

Standard errors in parentheses are clustered by village. All regressions include controls for household head's characteristics—age, gender, and educational attainment; household characteristics—size and durable asset index; barangay characteristics—natural disaster index, log of barangay population and log of number of households; and fixed effect at municipality-level. Dependent variables per capita total consumption, education cost, and medical cost took the natural logarithmic transformations $ln(x)=log(x)$ to approximate normal distribution. Dependent variables per capita consumptions on dairy, meat and alcohol took the inverse hyperbolic sine transformation expressed as $\text{arcsinh}(x)=ln(x+\sqrt{(x^2+1)})$ to retain the zero-valued observations. $p<0.01$; $^{**}p<0.05$; $^{***}p<0.001$

5. Conclusion

This study employed a randomized experimental design to assess the impact of the CCT program, focusing on its risk-mitigating and spillover effects on informal insurance systems in the Philippines, where poor households frequently contend with income shocks from natural disasters. An ITT analysis was utilized to estimate the model with the program assignment.

The findings reveal the risk-mitigating effects of CCT on eligible households' medical expenses during covariate shocks such as harvest failure. The CCT program led to eligibles significantly increasing their borrowing in the informal risk-sharing system during shocks, opting for informal support over formal banking or microfinance options.

Furthermore, CCT potentially strengthened the informal insurance system, as ineligibles in the treatment areas increased their lending support in response to shocks. This can be attributed to CCT improving the creditworthiness of eligibles who receive regular cash transfers, thus fostering positive reputations within the informal network. The decrease in ineligibles' borrowings from the informal network may also suggest a positive spillover effect of CCT to informal insurance, as CCT's eligible households share the values of saving and mutual support with ineligibles, thereby avoiding overexploitation of resources within the informal insurance system. This is because the CCT program, through the monetary and other benefits, alters the behaviour of eligibles, creating a broad impact on the entire informal network, which in turn affects the ineligibles, given the high social capital within informal networks where members share common goals and values. Overall, this study sheds light on the unintended consequences of CCT programs in the Philippines and contributes to related studies on CCTs in Africa and Latin America.

However, the study has limitations. It only analysed the risk-mitigating effects of CCT for covariate shocks proxied by harvest failure, while informal risk-sharing arrangements often prove more effective during idiosyncratic shocks such as illnesses, death, and unemployment. Unfortunately, examining the impact of idiosyncratic shocks in the study model raises endogeneity issues. The bias is introduced by other factors that influence the individual's decision to participate in informal risk-sharing arrangements. For example, individuals with poor health or those who face high mortality risk are more likely to participate in informal risk-sharing arrangements, but healthy individuals are less likely to do so. Therefore, the decision to join or leave a risk-sharing network is not an arbitrary or chance event but is based on one's health status. The same is true for unemployment, where the decision to participate in informal insurance may be influenced by employment conditions, such as job loss, rather than a random choice. Therefore, instrumental variables are required to control for endogeneity; however, they are presently unavailable. Future studies should aim to address these limitations by identifying detailed channels through which public transfers affect existing informal arrangements, using instrumental variables to control for endogeneity.

While our analysis focuses on covariate shocks to shed light on the limitations of informal insurance mechanisms under widespread risk, we recognize that most households in reality are simultaneously exposed to both idiosyncratic and covariate shocks. Moreover, the structure and strength of informal insurance networks—as well as households' exposure to risk—vary considerably across geographic contexts, which may limit the generalizability of our findings. These differences underscore the importance of future research that explores how informal networks operate under more complex and heterogeneous shock environments. Our findings, which highlight the inherent constraints of informal risk-sharing in the face of covariate shocks, provide a conservative benchmark for evaluating the potential complementarity between informal arrangements and formal policy interventions.

References

Alatas, V., A. Banerjee, R. Hanna, B.A. Olken, and J. Tobias [2012] "Targeting the poor: evidence from a field experiment in Indonesia", *American Economic Review* 102(4):1206–1240.

Albarran, P. and O. Attanasio [2003] "Limited commitment and crowding out of private transfers: Evidence from randomized experiment", *The Economic Journal* 113(486). doi:10.1111/1468-0297.00112.

Ambrus, A., M. Mobius, and A. Szeidl [2014] "Consumption risk-sharing in social networks", *American Economic Review* 104(1):149–182. doi.org/10.1257/aer.104.1.149.

Asfaw, S., A. Carraro, B. Davis, S. Handa, and D. Seidenfeld [2017] "Cash transfer programmes, weather shocks and household welfare: evidence from randomized experiment in Zambia", *Journal of Development Effectiveness* 9(4):419–442. doi: 10.1080/19439342.2017.1377751.

Baird, S., E. Chirwa, C. McIntosh, and B. Özler [2010] "The short-term impacts of a schooling conditional cash transfer program on the sexual behavior of young women", *Health Economics* 19(S1):55–68. doi:10.1002/hec.1569.

Christian, C., L. Hensel, and C. Roth [2019] "Income shocks and suicides: causal evidence from Indonesia", *The Review of Economics and Statistics* 101(5):905–920. doi:10.1162/rest_a_00777.

de Janvry, A., F. Finan, E. Sadoulet, and R. Vakis [2006] "Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks?", *Journal of Development Economics* 79(2):349–373. doi:10.1016/j.jdeveco.2006.01.013.

Department of Social Welfare and Development [2021] "4PS law, Pantawid Pamilya", Available at https://pantawid.dswd.gov.ph/4pslaw. Accessed 23 May 2023.

Dercon, S. [2002] "Income risk, coping strategies, and safety nets", *The World Bank Research Observer* 17(2):141–166. doi:10.1093/wbro/17.2.141.

Dercon, S., J. de Weerdt, T. Bold, and A. Pankhurst [2006] "Group-based funeral insurance in Ethiopia and Tanzania", *World Development* 34(4):685–703. doi:10.1016/j.worlddev.2005.09.009.

Dietrich, S. and G. Schmerzeck [2019] "Cash transfers and nutrition: the role of market isolation after weather shocks", *Food Policy* 87:101739. doi:10.1016/j.foodpol.2019.101739.

Evans, D. and K. Kosec [2020] "Do cash transfers reduce trust and informal transfers within communities?" [Preprint]. doi:10.2499/p15738coll2.134236.

Fafchamps, M. and S. Lund [2003] "Risk-sharing networks in rural Philippines", *Journal of Development Economics* 71(2):261–287. doi:10.1016/s0304-3878(03)00029-4.

Filmer, D. et al. [2023] "Cash transfers, food prices, and nutrition impacts on ineligible children", *The Review of Economics and Statistics* 105(2):27–343. doi:10.1162/rest_a_01061.

Gertler, P. and J. Gruber [2002] "Insuring consumption against illness", *American Economic Review* 92(1):51–70. doi:10.1257/000282802760015603.

Gulesci, S. [2020]. "Poverty alleviation and interhousehold transfers: evidence from BRAC's graduation program in Bangladesh", *The World Bank Economic Review* 35(4):921-949.

Haushofer, J. and J. Shapiro [2016] "The short-term impact of unconditional cash transfers to the poor: experimental evidence from Kenya", *The Quarterly Journal of Economics* 131(4):1973–2042. doi:10.1093/qje/qjw025

Heemskerk, M., A. Norton, and L. de Dehn [2004] "Does public welfare crowd out informal safety nets? Ethnographic evidence from rural Latin America", *World Development* 32(6):941–955. doi:10.1016/j.worlddev.2003.11.009.

Hoddinott, J. and E. Skoufias [2004] "The impact of PROGRESA on food consumption", *Economic Development and Cultural Change* 53(1):37-61.

Lawlor, K., S. Handa, and D. Seidenfeld [2017] "Cash transfers enable households to cope with agricultural production and price shocks: evidence from Zambia", *The Journal of Development Studies* 55(2):209–226. doi:10.1080/00220388.2017.1393519.

Mehmood, Y., M. Arshad, N. Mahmood, H. Kächele, and R. Kong [2021] "Occupational hazards, health costs, and pesticide handling practices among vegetable growers in Pakistan", *Environmental Research* 200:111340. doi:10.1016/j.envres.2021.111340.

Mobarak, A. M. and M. R. Rosenzweig, [2012] "Selling formal insurance to the informally insured", Working Paper, Yale University and Yale Economic Growth Center.

Morduch, J. [1999] "Between the state and the market: Can informal insurance patch the safety net?", *The World Bank Research Observer* 14(2):187–207. doi:10.1093/wbro/14.2.187.

Nikolov, P. and M. Bonci [2020] "Do public program benefits crowd out private transfers in developing countries? A critical review of recent evidence", *World Development* 134:104967. doi:10.1016/j.worlddev.2020.104967.

Olinto, P. and M.E. Nielsen [2006] "Do conditional cash transfer programs crowd out private transfers?", *Remittances and Development* 253–298. doi:10.1596/978-0-8213-6870-1_ch08.

Premand, P. and Q. Stoeffler [2020] "Do cash transfers foster resilience? evidence from rural Niger", *Policy Research Working Papers* [Preprint]. doi:10.1596/1813-9450-9473.

Ruiz-Conde, E., F. Mas-Ruiz, and J. Parreño-Selva [2021] "Consumption threshold at which virtue products become vice products: The case of beer", *Foods* 10(8):1688. doi:10.3390/foods10081688.

Skoufias, E. and S.W. Parker [2005] "Job loss and family adjustments in work and schooling during the Mexican peso crisis", *Journal of Population Economics* 19(1):163–181. doi:10.1007/s00148-005-0005-3.

Appendix A. Inverse Probability Weighting (IPW) estimation and the non-attrition probit model

This section explains the procedure for estimating Equations 2 and 3 using IPW to address the loss of observations caused by missing data in the covariates $\boldsymbol{X}_{ij}$. First, we used the probit model for Equations 1 and 2 to predict the outcomes using samples without missing data. We then generated the inverse of the probability weights for each individual. The probability of non-attrition is given by:

$$P(T = 1 | \boldsymbol{X}_{ij})$$

Next, we re-estimated the models using the generated inverse probability weights. Table A1 shows the estimates for the non-attrition probit model, covering the samples from the covariates in Models 2 and 3 with non-missing values.

TABLE A.1. Estimation results for the non-attrition probit model

Variables	Non-attrition = 1
Age	-0.01* (0.01)
Gender (1=Female)	-1.12*** (0.14)
Married (1=Yes)	0.20 (0.19)
Nature of employment (1=Permanent)	1.64*** (0.17)
Household size	0.02 (0.03)
Durable Asset Index	-0.02 (0.04)
Has a loan (1=Yes)	0.23* (0.13)
Has a bank account (1=Yes)	0.09 (0.26)
Barangay population	0.00 (0.00)
Insurance index (health, life, housing, and other social insurance)	0.17 (0.10)
Health facility index (rural health center, clinic, hospital, pharmacy etc.)	-0.03 (0.05)
Municipality 2	0.02 (0.30)
Municipality 3	0.44 (0.29)
Municipality 4	0.27 (0.29)

TABLE A.1. Estimation results for the non-attrition probit model (continued)

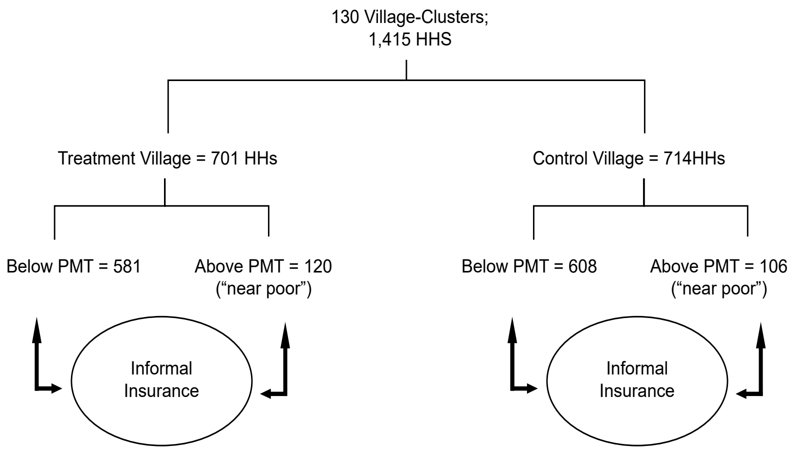
Variables	Non-attrition = 1
Municipality 5	0.47 (0.44)
Municipality 6	0.31 (0.40)
Municipality 7	0.06 (0.32)
Municipality 8	-0.18 (0.32)
Constant	0.65 (0.50)
Observations	1,124

Reference dummy for Municipality is Municipality 1. **p*<.01; ***p*<.05; ****p*<.001

Appendix B. Study design

Figure A.1 illustrates the study design, highlighting the randomization of treatment and control groups from the village clusters across the country. The study includes 1,415 households from 130 village clusters, with 701 households in treatment villages and 714 households in control villages. In the treatment villages, 581 households have PMT scores below the poverty threshold, and 120 households have PMT scores above the poverty threshold. In the control villages, 608 households have PMT scores below the poverty threshold, and 106 households have PMT scores above the poverty threshold. Households with PMT scores above the threshold are considered "near poor" because their scores are just above the poverty threshold.

FIGURE A.1. Study design

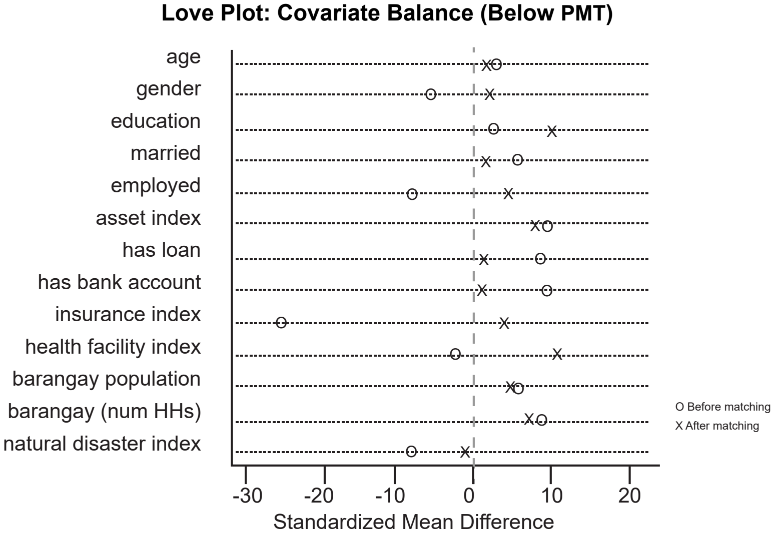


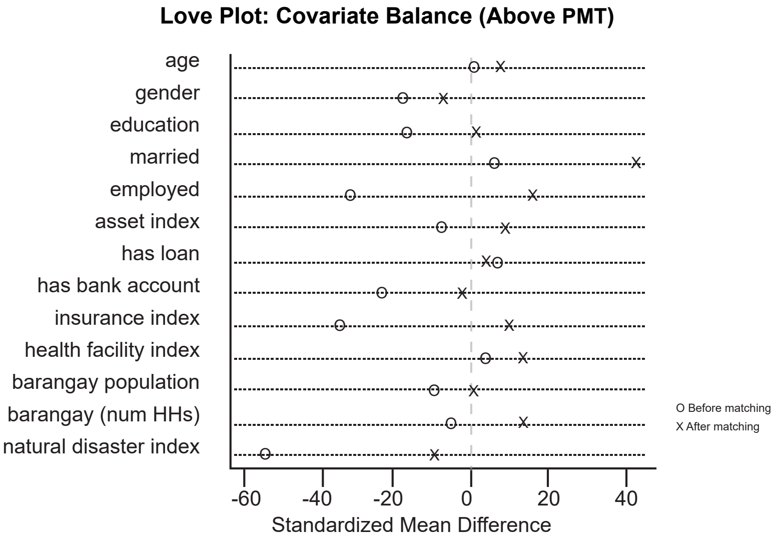
Appendix C. List of variables and their definitions

Variables	Definition
Age	Age of the household head
Gender	Gender of the household head
Educational attainment	Educational attainment of the household head
Marital status	Household head that is married
Nature of employment	Household head that is permanently employed
Household size	The number of family members in a household
Durable asset index	Assets owned by the household which covers the following: 1) Television set 2) VTR/VHS/VCD/DVD 3) Stereo / CD player 4) Refrigerator / freezer 5) Washing machine 6) Air conditioning 7) Living room or sala set 8) Dining set 9) Car or jeepney 10) Telephone or mobile phone 11) Personal computer 12) Microwave oven 13) Motorcycle
Has an outstanding loan	Currently has an outstanding loan
Has bank account	At least one of the household members has opened a bank account and it is active or usable.
Insurance index	At least one of the household members has any of the following social insurance programs: 1) Government Service Insurance System (GSIS) 2) Social Security System 3) Philippine Health Insurance Corporation (PhilHealth) 4) Health insurance from private company 5) Life insurance
Harvest failure	The household experienced harvest failure and financial instability in the past 12 months.
Per capita consumption	Household's annual per capita consumption of all food and non-food items consumed, including purchases made in cash or on credit, gifts received, or items own-produced, over the past six months.
Per capita education expenditure	Household's annual education expenditure per child, covering tuition fees, graduation fees, allowances, books, school supplies, etc. These expenditures represent actual disbursements made, whether paid in cash or on credit, or received as gifts, over the past six months.
Per capita medical expenditure	Household's annual actual expenditures on medical care, including drugs & medicines, hospital room charges, medical and dental charges, other medical goods & supplies, herbal medicines, etc. These expenditures encompass payments made whether in cash or on credit, or received as gifts, over the past six months.

Per capita of dairy consumption	Household's annual per capita consumption of dairy products, including eggs, milk, ice cream, butter, cheese, fresh eggs, salted eggs, and duck eggs, consumed from purchases made whether in cash or on credit, or received as gifts, or self-produced during the past six months.
Per capita of meat consumption	Household's annual per capita consumption of meat and meat preparations, such as fresh chicken, fresh beef, fresh pork, corned beef, goat's meat, luncheon meat, meat loaf, vienna sausage, longanisa, chorizo, hotdog, tocino, tapa, etc., consumed from purchases made whether in cash or on credit, or received as gifts, or self-produced during the past six months.
Per capita of alcohol consumption	Household’s annual per capita consumption of alcoholic beverages, such as beer, tuba, basi, lambanog, brandy, whisky, rum, etc., consumed from purchases made whether in cash or on credit, or received as gifts, or self-produced during the past six months.
Total borrowings and lending to friends and relatives	The total amount of money currently borrowed and lent from friends and relatives
Borrowings to friends and relatives	The amount of money currently borrowed from friends and relatives
Borrowings to moneylender	The amount of money currently borrowed from moneylenders
Lending to friends and relatives	The amount of money lent to friends and relatives
Bank borrowings	The amount of money borrowed from banks.
Barangay population	The population of the barangay or village, as reported by the barangay or village captain.
Households in barangay	The number of households in the barangay or village, as reported by the barangay or village captain.
Health facility index	Whether flooding occurred in the barangay or village (which includes barangay health station, rural health unit / center, traditional birth attendant or “hilot,” private clinic, government hospital, private hospital, barangay pharmacy, private pharmacy). This information is provided by the barangay or village captain.
Flood	Whether flooding occurred in the barangay or village in the last five years that caused widespread disaster to most residents. This information is provided by the barangay or village captain.
Earthquake	Whether an earthquake occurred in the barangay or village in the last five years that caused widespread disaster to most residents. This information is provided by the barangay or village captain.
Drought	Whether a drought occurred in the barangay or village in the last five years that caused widespread disaster to most residents. This information is provided by the barangay or village captain.
Natural disaster intensity	Classified into two categories: high and low intensities. High intensity means that the barangay or village experiences two or more natural disasters, including floods, droughts, or earthquakes. Low intensity means that the barangay or village experiences not more than one natural disaster, whether floods, droughts, or earthquakes.

Appendix D.


Love Plot: Covariate Balance (Below PMT)
age
gender
education
married
employed
asset index
has loan
has bank account
insurance index
health facility index
barangay population
barangay (num HHs)
natural disaster index
O Before matching
X After matching
-30
-20
-10
0
10
20
Standardized Mean Difference


Love Plot: Covariate Balance (Above PMT)
age
gender
education
married
employed
asset index
has loan
has bank account
insurance index
health facility index
barangay population
barangay (num HHs)
natural disaster index
O Before matching
X After matching
-60
-40
-20
0
20
40
Standardized Mean Difference

The Philippine Economic Society

Founded 1961

The Philippine Economic Society (PES) was established in August 1962 as a nonstock, nonprofit professional organization of economists.

Over the years, the PES has served as one of the strongest networks of economists in the academe, government, and business sector.

Recognized in the international community of professional economic associations and a founding member of the Federation of ASEAN Economic Associations (FAEA), the PES continuously provides a venue for open and free discussions of a wide range of policy issues through its conference and symposia.

Through its journal, the *Philippine Review of Economics* (PRE), which is jointly published with the UP School of Economics, the Society performs a major role in improving the standard of economic research in the country and in disseminating new research findings.

At present, the Society enjoys the membership of some 500 economists and professionals from the academe, government, and private sector.

- Lifetime Membership – Any regular member who pays the lifetime membership dues shall be granted lifetime membership and shall have the rights, privileges, and responsibilities of a regular member, except for the payment of the annual dues.
- Regular Membership – Limited to individuals 21 years of age or older who have obtained at least a bachelor's degree in economics, or who, in the opinion of the Board of Directors, have shown sufficient familiarity and understanding of the science of economics to warrant admission to the Society. Candidates who have been accepted shall become members of the Society only upon payment of the annual dues for the current year.
- Student Membership – This is reserved for graduate students majoring in economics.

For more information, visit: economicsph.org.