The Importance of Existing Social Protection Programs for Mental Health in Pandemic Times*

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Abstract

When it comes to mental health, do social protection programs matter more in times of crisis? Using panel data from the Philippines around the onset of the COVID-19 pandemic, we compare depression rates among beneficiaries of an existing conditional cash transfer (CCT) program to non-beneficiaries of similar socioeconomic status. Depression rates were almost identical for the two groups in late 2019, but significantly lower for CCT beneficiaries by July 2020, after the initiation of strict quarantine measures and a large emergency cash transfer program. One interpretation of the increased importance of the CCT program during the pandemic is that CCTs have larger protective effects in times of vulnerability. Another possible reason is that the existing infrastructure of the CCT program, by allowing for more timely distribution of the emergency cash, enhanced the effectiveness of the government's pandemic response for CCT beneficiaries. We find evidence supporting both explanations.

JEL Codes: I38, I31, H12

Keywords: social protection, cash transfers, crisis, mental health

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1 Introduction

A large and growing literature documents that cash transfers can improve mental health. While much of the earlier evidence on this topic comes from researcher-driven cash transfer experiments (Baird et al., 2013; Haushofer and Shapiro, 2016), there is now substantial evidence stemming from evaluations of government-run social protection programs.[1] However, what we know about the mental health benefits of government social protection programs derives almost exclusively from evaluations conducted in "normal" times. Little is known about how these benefits may differ in times of crisis.

Understanding how the mental health benefits of social protection might change in crisis times is important because societies face a drastically different mental health and policy landscape during a crisis. For example, the COVID-19 pandemic, along with the accompanying economic turmoil and mobility restrictions, had large detrimental effects on mental health across the globe (Adams-Prassl et al., 2022; Altindag et al., 2022; Baranov et al., 2022; Bau et al., 2022; Brodeur et al., 2021; Brülhart et al., 2021; El-Zoghby et al., 2020). At the same time, most governments responded by adapting or introducing new social protection policies, with cash transfers emerging as the most popular approach (Gentilini et al., 2022).

Because of this – both the enormous shock to mental health and the drastic government response – it is not clear whether existing social protection programs become more or less important for mental health during a crisis. On the one hand, if the magnitude of the mental health shock is simply too large, or if the new government policies end up taking precedence due to their scale, existing social protection programs might become less important during a crisis. On the other hand, if the benefits of social protection increase with levels of economic and social turmoil, or if existing programs enhance the effectiveness of new emergency programs, we might expect to see larger protective effects from existing social protection programs during a time of crisis.

A handful of studies have examined the mental health effects of existing social protection programs during the COVID-19 pandemic and have found positive effects.[2] Pension programs in Bolivia and South Africa significantly improved mental well-being (Alloush et al., 2022; Bottan et al., 2021). An ongoing universal basic income RCT in Kenya (which started two years before the pandemic) documented improvements in depression due to the transfers (Banerjee et al., 2020). All three studies find larger effects on hunger in pandemic compared to non-pandemic times, and given the well-documented link between food insecurity and mental health (Alloush and Bloem, 2022; Cole and Tembo, 2011; Fang et al., 2021; Jones, 2017; Pourmotabbed et al., 2020; Rahman et al., 2021), there is reason to predict that the mental health benefits of government social

[1] See, for example, the studies reviewed in several meta-analyses (McGuire et al., 2022; Wollburg et al., 2023; Zimmerman et al., 2021).

[2] Evidence from *emergency* cash transfer programs, designed specifically to respond to the COVID-19 pandemic, is more mixed (Cañedo et al., 2023; Jacob et al., 2022; Londoño-Vélez and Querubín, 2022; Pilkauskas et al., 2023).

protection programs might also be larger in pandemic times.[3] However, Banerjee et al. (2020) report finding similar estimates when they compare the effects of cash on mental health before the pandemic to effects during the pandemic. Alloush et al. (2022), which studies a nation-wide government program like we do (as opposed to a researcher-driven RCT as in Banerjee et al. (2020)), concludes that effects on psychological distress are at least as large, and possibly larger, in pandemic times.

In this paper, we ask whether social protection matters more for mental health during a pandemic – a question for which theoretical predictions are ambiguous and empirical evidence is scant. We use data from the Philippines, where the government imposed strict quarantine measures and rolled out a large emergency cash transfer program in response to the COVID-19 pandemic. We are interested in the importance of the pre-existing Pantawid Pamilyang Pilipino Program (commonly known as the "4Ps"), a national conditional cash transfer (CCT) program that distributes money to households who satisfy various education and health requirements.

Using a panel survey of low-income households who were just below and just above the poverty score cutoff used to determine 4Ps eligibility, we compare depression rates for 4Ps beneficiaries and for non-4Ps beneficiaries both before and during the pandemic. We find that rates of severe depression were similar for both groups prior to the pandemic (around 1%), but significantly lower for 4Ps beneficiaries as of July 2020. While depression increased for both groups, it increased substantially more for non-4Ps households (33 percentage points) than 4Ps households (23 percentage points). This is in spite of the more generous emergency cash transfers that were distributed to both groups.

That a large difference between beneficiaries and non-beneficiaries emerged only during the pandemic could be an indication that the the existing 4Ps program mattered more for mental health in crisis than non-crisis times. However, there could be other explanations for the larger increase in depression rates for non-4Ps compared to 4Ps households, which we explore and rule out. First, it is not the case that differences in baseline household characteristics between 4Ps and non-4Ps led to differential trends in depression rates over the study period. Second, the two groups seemed to have been affected similarly by the pandemic in terms of the economic outcomes we are able to measure – employment, income, and informal transfers. Moreover, the two groups were located in similar areas and therefore had similar exposure to province-specific quarantine measures. The incidence of illness was also similar across the two groups. Given this, we interpret our main finding – the emergence of a gap between 4Ps and non-4Ps households' depression rates during the pandemic – as evidence that the 4Ps program became more important for mental health during crisis.

One interpretation of these results is that the bimonthly CCTs distributed to the 4Ps beneficiaries (for

[3] A related paper, which only examines food security and not mental health, finds that Ethiopia's flagship food security program helped protect households from large increases in food security during the early months of the pandemic (Abay et al., 2023), which is consistent with social protection becoming more important for food security during crisis times.

which conditions were waived during the pandemic) have larger mental health benefits in times of vulnerability. Consistent with this, we find evidence that underscores the importance of the actual CCTs. Specifically, the gap in depression rates that emerged during the pandemic was driven primarily by lower depression rates among 4Ps beneficiaries who had received their CCT most recently.

Another important explanation for our results relates to the infrastructure of the 4Ps program as opposed to the CCTs themselves. In our context, the existence of the 4Ps program enhanced the effectiveness of the government's emergency response to the pandemic, by allowing for more timely distribution of the emergency COVID-19 cash to exisiting 4Ps beneficiaries. 4Ps households, most of whom were already receiving their CCTs electronically, received their emergency transfers much earlier than other recipients of the emergency cash, who had to visit their local government units (LGUs) in person to register and then to receive their funds. Heterogeneity analysis provides evidence that this contributed to the larger increases in depression rates for non-4Ps households. In particular, the non-4Ps who were the last to receive their transfers experienced the largest increases in depression. We also find higher levels of food insecurity among non-4Ps households during a period when they had not yet received their emergency transfers while the 4Ps already had. This suggests that timeliness could have been particularly important due to its effects on food insecurity.

The finding that cash transfer timing matters for mental health effects is important, especially given the substantial variation in the timeliness of COVID-19 transfers across countries (Beazley et al., 2021; Gentilini et al., 2022). More generally, issues of transfer timeliness have received little attention in the literature on cash transfers and mental health, though existing work documents that cash transfer timing has implications for consumption responses (Bazzi et al., 2015).

This paper contributes to our understanding of a critical issue in a world marked by natural disasters, epidemics, and economic instability: the effectiveness of social protection programs in mitigating covariate (as opposed to individual) shocks. A number of studies examine new programs or expansions of programs motivated by specific crises (Cañedo et al., 2023; Galasso and Ravallion, 2004; Ivaschenko et al., 2020; Londoño-Vélez and Querubín, 2022), though our paper is more closely related to studies examining the role of existing social protection programs. Much of this work has focused on whether these programs help mitigate the negative effects of weather shocks on economic outcomes (Asfaw et al., 2017; Pfutze, 2023), as well as child health and education outcomes (Adhvaryu et al., 2018; Aguilar and Vicarelli, 2022; De Janvry et al., 2006; Duque et al., 2018). In this paper, we examine a different and much larger shock (the COVID-19 pandemic) and focus on mental health, an outcome of particular importance in times of crisis.

There has been substantial discourse about the need for and the optimal design of shock-responsive social protection programs (Bowen et al., 2020; O'Brien et al., 2018a,b). Our results provide some lessons on the benefits of leveraging an existing program. The 4Ps beneficiaries were protected from the larger deterioration in mental health experienced by non-4Ps households, despite the fact that both groups eventually received the emergency transfers. This underscores the potential for a well-functioning social protection program to yield mental health benefits during crises, even when embedded within a broader emergency response effort.

2 Background

This section provides background information on the 4Ps and the Philippine government response to the COVID-19 pandemic. More details can be found in Cho et al. (2021a), Cho et al. (2021b), and Cho et al. (2020), upon which much of this discussion is based. Because the data used in this paper were collected from November 2019 to October 2020, we focus our discussion of the Philippines' pandemic response on events during this time period.

2.1 4Ps program

The 4Ps program was piloted in 2008 and has since become the flagship social protection program of the Philippines. Households are eligible for the 4Ps if they have at least one child (or a pregnant woman) and if their poverty score falls below a pre-determined cutoff. By the time of the COVID-19 pandemic, the most recent update to these poverty scores had taken place in 2010.

The 4Ps is a CCT program that provides cash to eligible households who meet a set of education and health requirements. During the 10-month school year, households receive PhP 300, 500, or 700 per month per child (depending on age) who is enrolled in and consistently attending school, for a maximum of three children. The year-round health component of the program involves PhP 750 monthly transfers for households who satisfy all health requirements, including vaccinating their children and participating in Family Development Sessions. The majority of households (95% in our sample) receive their transfers electronically through a Land Bank ATM card. Transfers are paid every two months.

4Ps households also benefit from other social programs. They are eligible for free national health insurance (PhilHealth), rice subsidies, and unconditional cash transfers (UCTs) under the Tax Reform for Acceleration and Inclusion (TRAIN) law. A household with three children (one child in each of the three different age categories) who complies with all conditions will receive PhP 2,250 per month through the 4Ps program (PhP 1,500 education payment and PhP 750 health payment) and an additional PhP 900 through the TRAIN UCT and rice subsidy programs.

2.2 COVID-19 Pandemic Response

Less than a week after the World Health Organization declared a global pandemic on March 11, 2020, President Duterte declared a State of Calamity in the Philippines. This involved the implementation of a set of severe mobility restrictions, labeled Enhanced Community Quarantine (ECQ). ECQ was first implemented in Metro Manila and eventually expanded to most provinces in the country. Under ECQ, all non-essential businesses were required to close and individuals were required to remain at home, except to acquire basic necessities and (for essential workers only) to go to work. By May 2020, the ECQ was replaced with a more lenient General Community Quarantine (GCQ) in most provinces, though restrictions continued to change – both tightening and loosening – for the next two years.

In order to support vulnerable households during a period of almost complete economic shutdown, the government rolled out a large-scale emergency social protection program, known as the Social Amelioration Program (SAP), announced at the end of March. The SAP aimed to provide unconditional cash transfers to 18 million households, or 70% of the population. It succeeded in reaching 68% of the population and was the sixth largest COVID-19 cash transfer program in the world in terms of total beneficiary counts (Gentilini et al., 2022).

SAP transfer amounts ranged from PhP 5,000 to PhP 8,000 (100 to 160 in 2020 USD), depending on the province, which roughly amounts to the monthly wage of a minimum wage worker. The majority of targeted beneficiaries received these transfers in April and May of 2020. There was a second SAP transfer targeted to a smaller subset of beneficiaries ("waitlisted" households unable to receive the first SAP payment and recipients of the first SAP transfer living in regions still under ECQ in May 2020), distributed throughout the months of June to November.

Of the 18 million households targeted for the first SAP transfer, 4 million were already part of the 4Ps program. Because the majority of these households already had an ATM card to receive their 4Ps funds, these households received a SAP payment top-up (the difference between the SAP total amount and their regular 4Ps payment) electronically around April 3-5, less than two weeks after the SAP had been announced. New beneficiaries, on the other hand, had to manually register for the program using paper application forms at their local government units (LGUs). Recipients also had to pick up their transfers in person. Because of this, transfer receipt was substantially delayed. According to administrative records, only one-fourth of the targeted new beneficiaries had received a SAP payment by April 25. The median SAP receipt date for new beneficiaries in our dataset was April 28.[4]

There were also differences in the timeliness of the second SAP payment. Most of the of 4Ps households

[4]We display the entire distribution of SAP receipt dates in Figure 4.

eligible for a second SAP payment (because they were living in areas under ECQ in May of 2020) received it by the end of June (DSWD, 2020), but almost none of the non-4Ps in our sample had received a second SAP payment by this time. By the end of July, about 22% of non-4P SAP recipients had received a second payment.[5]

The 4Ps households continued to receive 4Ps transfers every other month (in May, July, and September 2020 during our study period), in addition to the two SAP top-ups. The government waived the program requirements during our entire study period and paid households their full transfer amount each pay period. These bimonthly cash transfers were much smaller than the SAP transfer amount, especially during summer vacation (April-May), when households do not receive the education component of the 4Ps grant.

3 Data

We rely on a panel survey of low-income households across the Philippines. The baseline wave of this survey was conducted, in person, starting in November of 2019 for a separate project on cash transfers and domestic violence (Sahay et al., 2023). The sample consists of households with children and which, at the time of an impact evaluation of the program in 2014, had poverty scores just below and above the 4Ps eligibility cutoff. Cho et al. (2021a), which includes a more detailed description of the data, shows this sample is fairly representative of the poor and near-poor in the Philippines – specifically, the bottom 40% of the region-specific per capita income distribution.

The remaining survey waves were conducted during the pandemic and therefore over the phone. Wave 1 took place at the end of April, wave 2 at the end of June, wave 3 at the end of July, and wave 4 at the end of October. The timeline in Figure 1 depicts the events discussed in the previous section along with the timing of each survey wave. We also report the share of non-4Ps in our sample who had received a SAP payment by the end of wave 2 (70%) and wave 3 (73%). Of the non-4Ps who were going to receive a SAP payment, the majority had received it by the end of June.

The shaded areas in Appendix Figure A1 highlight the 26 provinces represented in our data. No single province or region dominates the sample. Importantly, as we show in Appendix Table A1, the geographic distribution of the 4Ps is very similar to that of the non-4Ps, which indicates that the groups were balanced in terms of the severity of the mobility restrictions they experienced, as these were largely determined at the province level.

We compare the baseline characteristics of 4Ps and non-4Ps households in Table 1. 4Ps households are significantly larger than non-4Ps households, but on many other important dimensions, the two groups are

[5]This is slightly smaller than but similar to the share of 4Ps beneficiaries who were eligible for a second SAP payment, according to DSWD (2020).

Figure 1: Timeline of Pandemic Events and Survey Waves

Nov. 2019	**Wave 0 (face-to-face)**.
Mar. 11, 2020	WHO declares pandemic.
Mar. 16, 2020	ECQ implemented in Luzon.
Mar. 24, 2020	SAP announced.
Apr. 3-5, 2020	First SAP top-up distributed to 4 million 4Ps beneficiaries with cash card.
Apr. 20-May 4, 2020	**Wave 1 (phone)**.
By Apr. 25, 2020	1/4 of non-4Ps recipients had received SAP transfer (according to administrative reports).
end of May 2020	4Ps beneficiaries scheduled to receive bimonthly payment.
end of Jun. 2020	**Wave 2 (phone)**.
	70% of non-4Ps in sample had received one SAP payment.
	1.3 million 4Ps beneficiaries with cash card and eligible for 2nd SAP received payment (according to administrative reports).
end of Jul. 2020	**Wave 3 (phone)**.
	73% of non-4Ps in sample had received at least one SAP payment, 22% of whom had received a second payment.
	4Ps beneficiaries scheduled to receive bimonthly payment.
end of Sep. 2020	4Ps beneficiaries scheduled to receive bimonthly payment.
end of Oct. 2020	**Wave 4 (phone)**.

very similar. There are no significant differences in terms of urban status, education levels, business or farm ownership, employment shares, weekly earnings, or mobile phone access. This is likely because the sample already restricts to low-income households with poverty scores just below and just above the 4Ps eligibility cutoff (in 2010). In addition, the lack of updates to the 4Ps beneficiary list means that changes in income over time could have led to a narrowing of the gap between the 4Ps and non-4Ps households in the sample. We also report statistics on job types: the share of households with at least one member working as private sector employee, government employee, freelance agricultural worker, freelance non-agricultural worker, and self-employed worker. These are also similar across the two groups.

We note, however, two important differences between 4Ps and non-4Ps households, which are a result of the 4Ps program itself. In wave 1 (this information was not collected at baseline), a much larger share of 4Ps households were part of the national health insurance program, PhilHealth (83% compared to 69% of non-4Ps). This is because 4Ps beneficiaries are eligible for free PhilHealth membership. It is also the case that 4Ps beneficiaries are significantly more likely to report having a bank account (a difference of 63 percentage points). This could be due to their use of the Land Bank ATM card and bank account to receive 4Ps payments (even though this is not a regular bank account that supports financial transactions).

Table 1: Baseline Household Characteristics by 4Ps status

	(1)	(2)	(3)
	Non-4Ps	4Ps	Difference
Urban	0.28	0.29	0.02
	(0.45)	(0.46)	(0.04)
Household Size	5.30	5.96	0.67***
	(1.61)	(1.85)	(0.17)
N. Children	2.71	3.10	0.39**
	(1.19)	(1.59)	(0.13)
N. Adults	2.66	2.95	0.28*
	(1.08)	(1.27)	(0.11)
N. Elderly	0.08	0.08	-0.00
	(0.28)	(0.27)	(0.03)
Highest Ed Level: None	0.01	0.01	-0.00
	(0.10)	(0.09)	(0.01)
Highest Ed Level: Primary	0.22	0.24	0.02
	(0.42)	(0.43)	(0.04)
Highest Ed Level: Secondary	0.59	0.59	-0.01
	(0.49)	(0.49)	(0.05)
Highest Ed Level: Tertiary	0.18	0.16	-0.01
	(0.38)	(0.37)	(0.04)
Owns Household Business	0.27	0.31	0.04
	(0.45)	(0.46)	(0.04)
Owns Farm	0.10	0.07	-0.03
	(0.30)	(0.26)	(0.03)
Observations	216	222	438

	(1)	(2)	(3)
	Non-4Ps	4Ps	Difference
Adult Employment Share	0.58	0.59	0.00
	(0.30)	(0.28)	(0.03)
Weekly Earnings (per capita)	450.48	495.22	44.74
	(404.82)	(490.19)	(42.95)
Private sector employee in HH	0.11	0.13	0.02
	(0.31)	(0.34)	(0.03)
Government employee in HH	0.02	0.01	-0.01
	(0.15)	(0.09)	(0.01)
Freelance ag worker in HH	0.02	0.03	0.01
	(0.14)	(0.16)	(0.01)
Freelance non-ag worker in HH	0.04	0.02	-0.02
	(0.20)	(0.15)	(0.02)
Self-employed worker in HH	0.08	0.10	0.02
	(0.27)	(0.29)	(0.03)
Number of Mobile Phones (Wave 1)	1.81	1.86	0.06
	(1.24)	(1.31)	(0.12)
Number of Smart Phones (Wave 1)	1.08	1.13	0.05
	(1.17)	(1.24)	(0.12)
PhilHealth Insurance (Wave 1)	0.69	0.83	0.14***
	(0.46)	(0.38)	(0.04)
Has Bank Account (Wave 1)	0.20	0.83	0.63***
	(0.40)	(0.38)	(0.04)
Observations	216	222	438

Notes: Standard deviations (in columns 1 and 2) and standard errors (in column 3) reported in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$.

Our main outcome of interest is mental health, which was measured in the baseline and third waves of the survey. All adult respondents responded to the PHQ-9 in the baseline, but only the main respondent answered the MHI-5 questions in wave 3. Another difference is that in the baseline wave, the Patient Health Questionnaire (PHQ-9) was used, but in wave 3, the Mental Health Inventory 5 (MHI-5) was used instead. As we describe in section A.1, although the instruments are different, both of these measures can be used to categorize a respondent as having severe depression, moderate depression, mild depression, or no/minimal depression. We therefore use indicators for different categories of depression as our outcome variables. This has the added advantage of avoiding the cardinal use of an ordinal variable, shown to be problematic by Bond and Lang (2019).

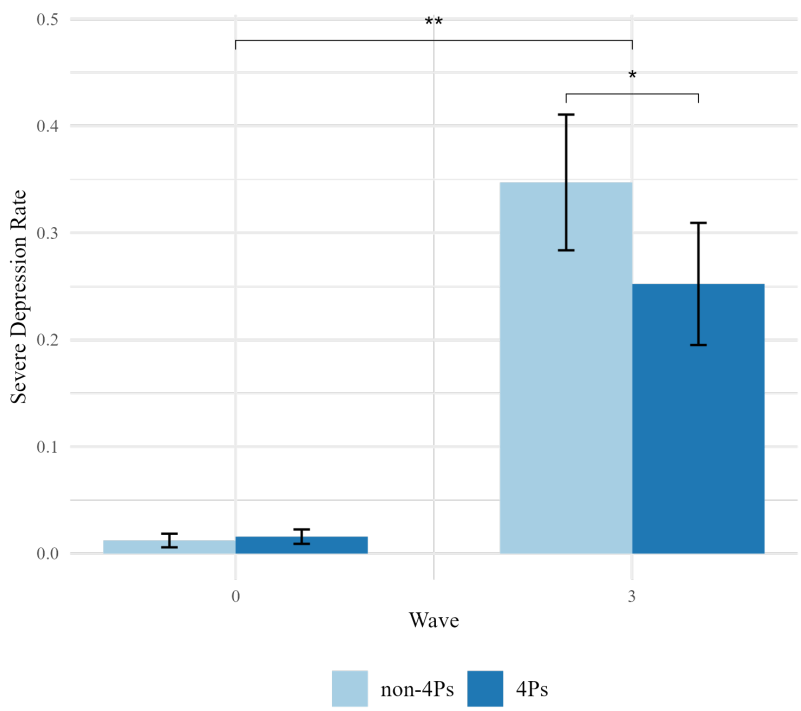
We use several other variables in our analysis. Food security questions were included in waves 1 to 4 of the survey. Because only one question was asked in wave 1 ("In the past 7 days, did you or any other family member eat fewer meals in a day because of lack of food?"), we restrict our attention to this question in all waves, even though waves 2 through 4 included a more detailed set of food security questions (described in section A.2). Income and employment (for which we report baseline levels in Table 1) were collected in all waves of the survey. We also examine an indicator for whether the household reported receiving remittances. This is obtained from the wave 3 survey, during which respondents are asked two separate questions: whether they were receiving remittances before the lockdown in March, and whether they had received any remittances since the lockdown in March. We assign the answer to the first question to the baseline wave and the answer to the second question to the third wave.

Because we will be examining changes in depression rates over time, we restrict our sample to households with mental health information in both the baseline and wave 3 surveys. This ensures that any change in average depression across waves is not driven by changes in the composition of the sample due to attrition. In Table A2, we show that attrition from the sample (which was 10%) was largely unrelated to household characteristics, which indicates that our restricted sample is fairly representative of the original sample. Specifically, when we relax our sample restriction to include all households with baseline mental health measures and regress a dummy for household attrition on baseline household characteristics, only one coefficient is statistically significant at the 10% level (primary education). With the exception of this variable and the severe depression variable (which measures the share of household respondents with severe depression at baseline), all other coefficients are small in magnitude. The large positive (but statistically insignificant) coefficient on severe depression suggests households with severely depressed individuals were more likely to attrit from the sample. However, because all of our analysis restricts to households found in both waves, as noted above, differential attrition by household characteristics does not affect the internal validity of the results described in the next section.

4 Results

4.1 Main Results

Figure 2: Severe Depression by 4Ps Status and Survey Wave



Notes: Figure generated from individual-level data. Error bars represent 95% confidence intervals. (* p< 0.1, ** p< 0.05, *** p< 0.01)

Figure 2 reports rates of severe depression by survey wave, separately for 4Ps and non-4Ps households. At baseline, depression rates were very low (less than 2%) and not significantly different across the two groups. By wave 3 (about four months into the pandemic), depression rates had increased dramatically for both groups, but the increase is notably larger for non-4Ps households than for 4Ps households.

Column 1 of Table 2 reports the results of the regression analog to Figure 2. For individual i living in household j in wave t, we estimate

$$\text{Depression}_{it} = \beta_1 4\text{P}_{j(i)} + \beta_2 \text{Wave3}_t + \beta_3 4P_{j(i)} \times \text{Wave3}_t + \epsilon_{it}. \quad (1)$$

Depression_{it} is an indicator for severe depression, $4\text{P}_{j(i)}$ is a dummy equal to 1 for 4Ps households, and Wave3_t is a dummy equal to 1 for wave 3 (and 0 for the baseline wave). The 4Ps coefficient, which represents the difference between 4Ps and non-4Ps in the baseline wave, is small in magnitude and statistically insignificant.

Table 2: Severe Depression by 4Ps Status and Survey Wave

	(1) Severe Depression	(2) Severe Depression	(3) Severe Depression	(4) Severe Depression
4Ps	0.0036			
	(0.010)			
Wave=3	0.33***	0.33***	0.33***	0.33***
	(0.037)	(0.037)	(0.038)	(0.037)
Wave=3 x 4Ps	-0.099**	-0.098**	-0.094**	-0.093**
	(0.044)	(0.044)	(0.045)	(0.044)
Observations	2906	2906	2906	858
Baseline Mean Outcome	0.01	0.01	0.01	0.02
Fixed Effects	None	Household	Household	Individual
Controls	None	None	Age/Gender	N/A
Sample	All	All	All	Panel indiv.

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01.

The coefficient on the wave 3 dummy is 0.33 ($p < 0.01$), indicating that non-4Ps households experienced a large increase in severe depression relative to the baseline mean of 0.01. The coefficient on the interaction term indicates this increase was 10 percentage points smaller ($p < 0.05$) for 4Ps beneficiaries. In other words, consistent with Figure 2, these regressions reveal that a gap in depression rates only emerges during the pandemic, with the non-4Ps suffering from higher rates of depression than the 4Ps.

Results remain similar when we add household fixed effects (column 2) and subsequently, age and gender fixed effects (column 3). In column 4, we include individual fixed effects, which means we restrict to panel respondents who responded to the depression question in both waves. Despite the much smaller sample and controls for time-invariant, individual-specific unobservables, our conclusions remain the same. In Appendix Table A3, we show similar patterns for moderate depression and any depression, but none of the interaction terms are statistically significant. In Appendix Table A4, we show that results are almost identical when we drop any non-4Ps households who did not receive the SAP payment (27% of the non-4Ps sample). This implies that the lower likelihood of SAP receipt by non-4Ps is not driving the results reported in Table 2.

4.2 Interpretation of Results

What do these findings tell us about our main research question (that is, whether the impact of 4Ps on mental health differs in normal and crisis times)? To provide a concrete interpretation of β_3 in the above regression, we model depression (Y) as a function of CCT program participation and a vector of observed and unobserved characteristics (X). Notably, the parameters of this function are different in normal and crisis times. Suppose Y in normal times is determined by the following expression

$$Y = \alpha_0 + \alpha_1 \text{CCT} + \alpha_2 X, \tag{2}$$

and Y in crisis times is determined by a different relationship:

$$Y = \tilde{\alpha}_0 + \tilde{\alpha}_1 \text{CCT} + \tilde{\alpha}_2 X. \tag{3}$$

Defining $\bar{Y}_{kt}$ as the sample average for the group with CCT=k in wave t, it can be shown that E(β_3) from equation (1) is equivalent to:

$$\begin{aligned}
&= E(\bar{Y}_{13} - \bar{Y}_{10} - (\bar{Y}_{03} - \bar{Y}_{00})) \\
&= \tilde{\alpha}_1 - \alpha_1 \\
&+ \tilde{\alpha}_2 \left[E(X|4Ps = 1, t = 3) - E(X|4Ps = 0, t = 3)\right] \\
&- \alpha_2 \left[E(X|4Ps = 1, t = 0) - E(X|4Ps = 0, t = 0)\right].
\end{aligned} \tag{4}$$

The first part of the last expression is our parameter of interest, $\tilde{\alpha}_1 - \alpha_1$, which represents the difference in the impact of a CCT program in crisis versus non-crisis times. However, β_3 also incorporates two other terms that involve differences in X across 4Ps and non-4Ps, both in wave 3 ($E(X|4Ps = 1, t = 3) - E(X|4Ps = 0, t = 3)$) and in wave 0 ($E(X|4Ps = 1, t = 0) - E(X|4Ps = 0, t = 0)$). Therefore, β_3 fails to capture our parameter of interest if either of the following two scenarios are true:

1. There are differences in X across 4Ps and non-4Ps, and the effect of these X on Y differs in normal and crisis times ($\tilde{\alpha}_2 \neq \alpha_2$).

2. The effect of X on Y is the same across settings ($\tilde{\alpha}_2 = \alpha_2$), but the X's themselves change over time in different ways for 4Ps and non-4Ps households, for reasons unrelated to the CCT program.

We have already established that, though fairly similar, 4Ps and non-4Ps households differed on a few important characteristics at baseline (see Table 1). In particular, 4Ps households are larger, more likely to be insured by PhilHealth, and more likely to have a bank account. Therefore, to address whether scenario 1 might be resulting in a biased estimate of $\tilde{\alpha}_1 - \alpha_1$, we test whether the relationship between each of these variables and depression differs in wave 0 and wave 3. To do this, we estimate our baseline specification with the addition of the following variables: household size, a PhilHealth indicator, and a bank account indicator, along with each of these variables each interacted with the wave 3 dummy. In Table A5, none of the additional interaction coefficients are significantly different from zero, which means we cannot reject that $\tilde{\alpha}_2 = \alpha_2$ for these characteristics. However, because the interaction coefficients on bank account ownership and PhilHealth insurance are large in magnitude, we conduct an additional test. We run separate regressions for each of the following sub-samples: households with PhilHealth, without PhilHealth, with a bank account, and without a bank account. In Appendix Table A6, we show that the pattern of results holds within each of the four groups (though the size of the interaction term is much smaller among households without a bank account). Taken together, the results in Tables A5 and A6 suggest that differences in household size, insurance, or bank access are not driving the differential trends in depression documented in Figure 2 and Table 2.

We next explore the plausibility of scenario 2 by examining trends in various economic variables separately for 4Ps and non-4Ps households. We examine adult employment shares, household earnings per capita, and remittance receipt, variables which should capture whether one group may have been hit harder by the pandemic. Figure 3 suggests the economic effects of the pandemic were similar for both groups. Employment and earnings trends exhibit similar patterns – a large drop in wave 1, followed by a slow recovery in the remaining waves. Remittance receipt, for which we only have an extensive margin indicator measured at 2 different periods, are similar across groups both before and during the pandemic.[6] Columns 1 through 6 of Table A8 confirm the absence of significantly different trends across groups. These findings are consistent with the fact that the 4Ps and non-4Ps were balanced in terms of their geographic location (which is the key driver of variation in the severity of mobility restrictions), and also in terms of their jobs at baseline, an important source of variation in vulnerability to the pandemic shock.

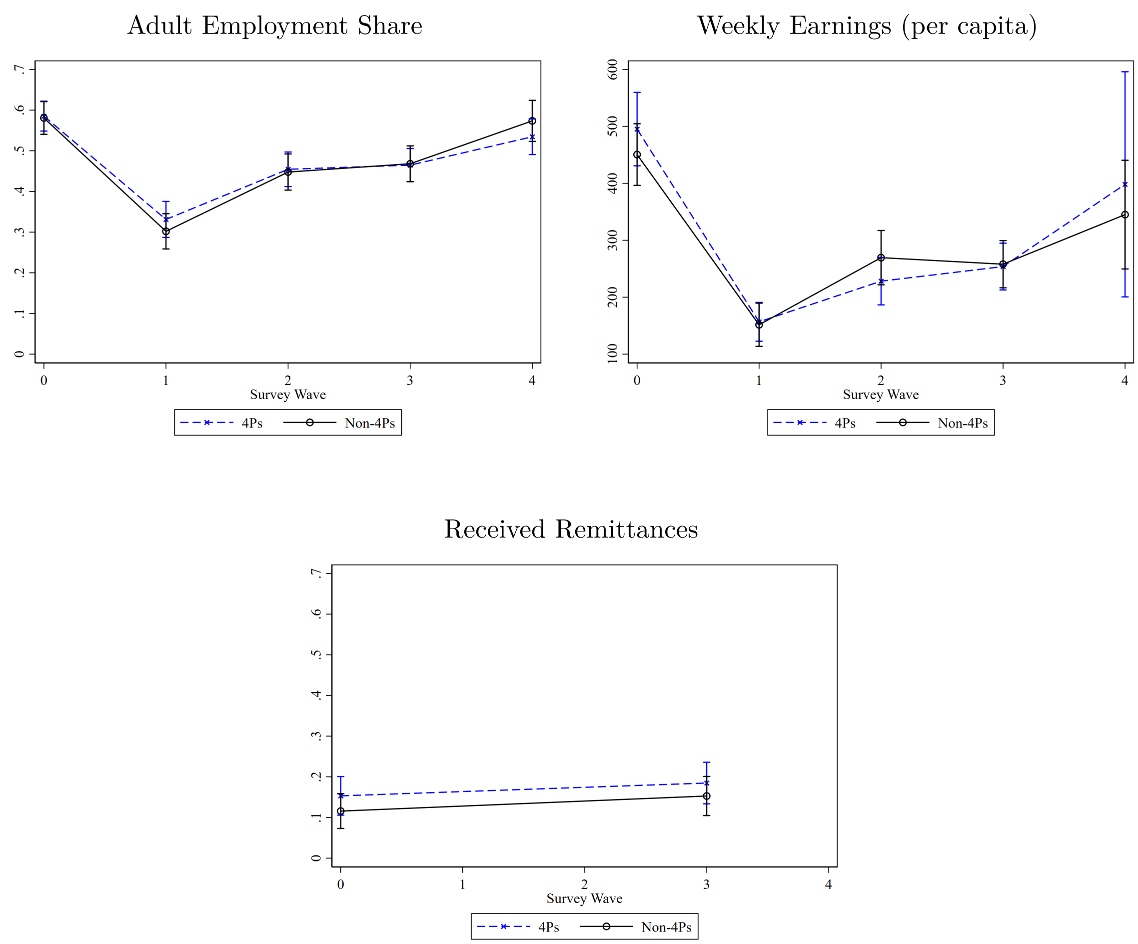
Finally, while our information about COVID-19 exposure is somewhat limited, we find no evidence that 4Ps and non-4Ps were affected differentially by the actual COVID-19 virus. Respondents are asked in wave 4 whether any household member suffered from COVID-19 symptoms, like a fever or dry cough. The share of households who responded affirmatively is similar among 4Ps (17%) and non-4Ps households (18%).

4.3 Potential Explanations

Given that we find no evidence that the effect of the unbalanced X's changed over time or that the 4Ps' and non-4Ps' economic outcomes were affected differently by the pandemic, we interpret the negative and significant β_3 as evidence that the 4Ps program matters more for mental health in crisis than in normal times.

[6] As described in section 3, we construct this variable using two questions asked in wave 3 – one question about remittances "before the lockdown in March" and another question about "after the lockdown in March."

Figure 3: Trends in Economic Variables by 4Ps Status



Notes: Figures generated from household-level data. Error bars represent 95% confidence intervals.

We next explore potential reasons for this. One natural explanation is that non-emergency social protection tools (in this case, the CCTs) have larger benefits in times of vulnerability. Another possibility is that a non-emergency social protection program might enhance the effectiveness of government programs rolled out in response to a crisis (in this setting, the SAP). In this section, we document evidence supporting both explanations.

4.3.1 Heterogeneity by Time Since CCT Receipt

We begin by exploring the importance of the actual CCTs by examining heterogeneity based on how recently the 4Ps households received their regular CCT transfer. Due to variation in survey dates and CCT receipt dates, in survey wave 3 there are some households who report having received a 4Ps transfer in the last month and some whose last transfer was received before this. We divide the 4Ps households into two groups based on this response and estimate the following regression:

$$\begin{aligned} \text{Depression}_{it} =& \delta_1 \text{Wave3}_t + \sum_k \delta_{2k} 1(\text{4Ps Receipt Category}_{j(i)} = k) + \\ & \sum_k \delta_{3k} 1(\text{4Ps Receipt Category}_{j(i)} = k) \times \text{Wave3}_t + \epsilon_{it}, \end{aligned} \tag{5}$$

where the two 4Ps transfer receipt categories are as described above.

Table 3: Severe Depression by 4Ps Transfer Receipt and Survey Wave

	(1) Severe Depression	(2) Severe Depression	(3) Severe Depression	(4) Severe Depression
Wave=3	0.33***	0.33***	0.33***	0.33***
	(0.037)	(0.037)	(0.038)	(0.037)
4Ps who received last CCT before July 2020	-0.012			
	(0.0076)			
4Ps who received last CCT in July 2020	0.0086			
	(0.012)			
Wave=3 × 4Ps who received last CCT before July 2020	-0.035	-0.031	-0.032	-0.026
	(0.094)	(0.095)	(0.097)	(0.096)
Wave=3 × 4Ps who received last CCT in July 2020	-0.12***	-0.12***	-0.11**	-0.11***
	(0.041)	(0.041)	(0.042)	(0.041)
Observations	2906	2906	2906	858
Baseline Mean Outcome	0.01	0.01	0.01	0.02
Fixed Effects	None	Household	Household	Individual
Controls	None	None	Age/Gender	N/A
Sample	All	All	All	Panel indiv.

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01.

Results are reported in Table 3. The coefficients on the indicators for the two 4Ps groups provide the difference between the non-4Ps and each 4Ps sub-group at baseline – all small in magnitude and statistically insignificant. During the pandemic, a gap emerges – but primarily for 4Ps who had received a 4Ps transfer in the last month, whose increase in depression was 12 percentage points smaller than that of the non-4Ps (a 33 percentage point increase). In other words, our main results seem to be driven by recent recipients of social protection benefits. Although the baseline wave does not ask households about their most recent receipt of the 4Ps transfer, based on variation in survey dates and expected transfer disbursement dates, we find no evidence of a similar pattern at baseline (see Appendix section A.3). Taken together, these results suggest that the continued 4Ps transfers played some role in protecting 4Ps beneficiaries from even larger increases in depression and that this form of social protection generated larger protective effects in pandemic compared to normal times.

4.3.2 Heterogeneity by SAP Receipt Timing

Another important explanation is that the 4Ps may have enhanced the effectiveness of the SAP is by allowing for more timely delivery of the emergency cash transfer. Almost all 4Ps households in our sample (those who receive their 4Ps payments through a cash card) should have had access to their SAP payment by the beginning of April, whereas the median non-4Ps household did not receive their SAP transfer until the end of April (see Figure 4 for the entire distribution of dates). In April 2020, the unemployment rate skyrocketed to 18%, more than three times higher than the pre-pandemic level, and almost 20% of total jobs were lost due to the lockdown measures (according to the Philippine Statistics Authority). Overall fear of the virus and uncertainties about employment and incomes were prevalent. In such an environment, receiving a timely cash transfer, soon after the implementation of strict quarantine rules, could have had protective effects for the mental health of 4Ps beneficiaries.

In addition, cash transfer timing may have also had important implications for food insecurity, which is well-documented to be positively correlated with mental health problems (Alloush and Bloem, 2022; Cole and Tembo, 2011; Fang et al., 2021; Jones, 2017; Pourmotabbed et al., 2020; Rahman et al., 2021). As we show in the second panel of Figure 4, unlike trends in employment, income, and remittances, trends in food insecurity do appear different for the 4Ps and non-4Ps.[7] In wave 1 (the first survey wave that included food security questions), food insecurity rates were higher for non-4Ps (0.6) compared to 4Ps households (0.52).[8] This was a period when most 4Ps households had received their SAP transfer but most non-4Ps households had

[7]We view food insecurity as a potential explanation for our results rather than a threat to identification because food insecurity is likely to have been directly affected by participation in the 4Ps program, due to the timely distribution of transfers to the 4Ps.

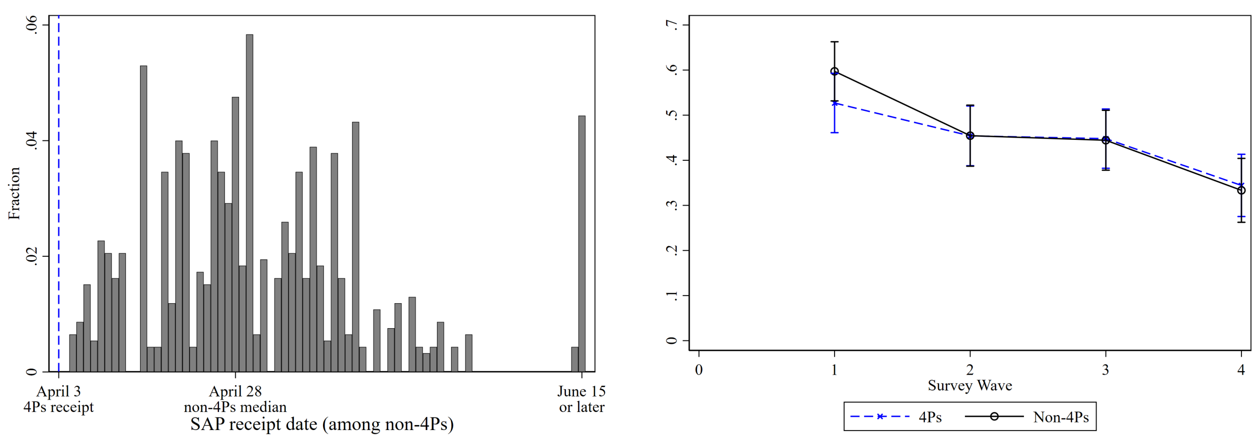
[8]In a regression that controls for wave and household fixed effects, this difference is significant at the 10% level (the last column of Appendix Table A8).

not. In subsequent waves, by the time both groups had received their SAP transfers, food insecurity rates were almost identical in the two groups, steadily trending downward for both. We unfortunately do not have food insecurity measured in the baseline wave, but given the similarities in baseline income, employment, and other variables summarized in Table 1, levels of food insecurity were likely similar for 4Ps and non-4Ps households before the pandemic began. The temporarily larger increase in food insecurity – due to the delay in SAP transfer receipt – could be one reason for the larger increases in depression for non-4Ps households. Interestingly, if this is the case, this temporary increase appears to have had persistent effects, as depression was measured in wave 3, by which point food insecurity levels were similar for 4Ps and non-4Ps.

Figure 4: SAP Receipt Dates and Food Insecurity Trends

A. SAP Receipt Date Among Non-4Ps

B. Food Insecurity by 4Ps Status and Survey Wave



Notes: Figures generated from household-level data. In panel A, the bin "June 15 or later" is comprised of households who had not received the SAP by wave 2 but who reported receiving it by wave 3 (specific date information was not collected in wave 3). In panel B, error bars represent 95% confidence intervals.

To empirically investigate the extent to which cash transfer timing can explain our main results, we use the variation in SAP receipt dates among non-4Ps and estimate the following regression:

$$\begin{aligned}\text{Depression}_{it} =& \delta_1 \text{Wave3}_t + \sum_k \delta_{2k} 1(\text{SAP Receipt Category}_{j(i)} = k) + \\ & \sum_k \delta_{3k} 1(\text{SAP Receipt Category}_{j(i)} = k) \times \text{Wave3}_t + \epsilon_{it}, \end{aligned} \tag{6}$$

where the dummy variables $1(\text{SAP Receipt Category}_{j(i)} = k)$ represent indicators for different categories of SAP receipt dates for non-4Ps: before April 21, between April 21-28, between April 29-May 9, between May 10-June 15, and after June 15, in addition to a category for non-4Ps who did not receive the SAP.[9] Because

[9]April 20, April 28, and May 9 represent the 25th, 50th, and 75th percentiles of the receipt date distribution among non-4Ps

SAP receipt dates are endogenous, this analysis should be interpreted with caution, but results are suggestive of timeliness playing a role in explaining our results.

In the first column of Table 4, we report results of specification (6) without any additional fixed effects or controls. In this specification, the coefficient on the wave 3 indicator reports the increase in depression for 4Ps households (24 percentage points). The coefficients on the indicators for the different non-4Ps timing groups provide the difference between the 4Ps and each of these non-4Ps sub-groups at baseline – all small in magnitude (though some statistically significant at the 10% level). The remaining coefficients – interactions between each sub-group indicator and the wave 3 dummy – are all positive, revealing gaps between 4Ps and non-4Ps households that emerge during the pandemic.

What we are most interested in, however, are the relative magnitudes of these interaction coefficients. Coefficients that are larger for groups with later receipt dates would be consistent with the hypothesis that cash transfer timeliness is responsible for differences in depression between 4Ps and non-4Ps during the pandemic. We find some support for this. The interaction coefficients for those who received their transfers between April 21 and May 9 are not significantly different from zero, and those for non-4Ps who received their transfers after May 9 are large in magnitude, statistically significant at the 10% level, and larger for the latest receipt group (31 percentage points) compared to the second latest receipt group (21 percentage points).

However, the coefficient on the interaction term for the non-4Ps group that received their transfers the earliest (before April 21) is also large (13 percentage points), statistically significant at the 10% level, and larger than the interaction coefficients for the next two groups (who received their transfers between April 21 and May 9). While this is inconsistent with the pattern for the remainder of the receipt date distribution, this could be due to the endogeneity of cash transfer timeliness. If the earliest group received their transfers the earliest precisely because they experienced an extremely large shock (and therefore went out of their way to apply for the SAP as soon as possible or were prioritized for SAP benefits by LGUs even before the completion of the application process), this could be the reason for their larger increase in depression. The endogeneity of SAP receipt in general could also be an explanation for the small and statistically insignificant coefficient on the interaction with the indicator for the sub-group who did not receive the SAP – perhaps these households did not make an effort to apply for the SAP because they were not as negatively affected by the onset of the pandemic.

The remaining columns of Table 4 add household fixed effects, age and gender controls, and then individual fixed effects (restricting to panel respondents). Estimates are consistent across specifications. The pattern of heterogeneity across receipt dates for all but the earliest non-4Ps recipients is consistent with the hypothesis

households who reported receiving a SAP by wave 2. June 15 is the latest SAP receipt date reported in wave 2; all respondents who had not received a SAP in wave 2 but received one between wave 2 and 3 are included in this category (no dates were recorded in this survey wave).

Table 4: Severe Depression by SAP Receipt Timing and Survey Wave

	(1) Severe Depression	(2) Severe Depression	(3) Severe Depression	(4) Severe Depression
Wave=3	0.24***	0.23***	0.24***	0.24***
	(0.037)	(0.038)	(0.039)	(0.038)
non-4Ps who received SAP before Apr 21	0.0027			
	(0.017)			
non-4Ps who received SAP between Apr 21-28	-0.016*			
	(0.0079)			
non-4Ps who received SAP between Apr 29-May 9	0.016			
	(0.034)			
non-4Ps who received SAP between May 10-Jun 15	-0.016*			
	(0.0079)			
non-4Ps who received SAP after Jun 15	-0.016*			
	(0.0079)			
non-4Ps who received no SAP	-0.0064			
	(0.012)			
Wave=3 × non-4Ps who received SAP before Apr 21	0.13*	0.13*	0.12*	0.13*
	(0.068)	(0.069)	(0.072)	(0.069)
Wave=3 × non-4Ps who received SAP between Apr 21-28	0.076	0.079	0.068	0.074
	(0.075)	(0.076)	(0.077)	(0.075)
Wave=3 × non-4Ps who received SAP between Apr 29-May 9	0.017	0.022	0.010	0.023
	(0.075)	(0.071)	(0.070)	(0.072)
Wave=3 × non-4Ps who received SAP between May 10-Jun 15	0.21*	0.21*	0.20	0.21*
	(0.12)	(0.12)	(0.12)	(0.12)
Wave=3 × non-4Ps who received SAP after Jun 15	0.31*	0.31*	0.41**	0.43**
	(0.17)	(0.17)	(0.17)	(0.21)
Wave=3 × non-4Ps who received no SAP	0.047	0.041	0.038	0.037
	(0.087)	(0.089)	(0.090)	(0.090)
Observations	2906	2906	2906	858
Baseline Mean Outcome	0.01	0.01	0.01	0.02
Fixed Effects	None	Household	Household	Individual
Controls	None	None	Age/Gender	N/A
Sample	All	All	All	Panel indiv.

Notes: Standard errors (clustered at the municipality level) are in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

that cash transfer timeliness played a role in protecting the 4Ps from even larger increases in depression.

Among the subset of households eligible for a second SAP, 4Ps beneficiaries also received their second SAP transfer earlier than non-4Ps households. Given that only 20% of households in our sample received a second SAP, this is unlikely to be a major driver of the different depression trajectories across the two groups. Indeed, when we restrict our sample to households who only received one SAP (Appendix Table A7), results are almost identical to our baseline results. In short, it seems that the timely receipt of the first transfer played a more important role than that of the second transfer in generating smaller increases in depression for 4Ps households.

5 Discussion

We compare depression rates among beneficiaries of the existing 4Ps CCT program to those of non-beneficiaries, at the end of 2019 and in July 2020. At baseline (prior to the pandemic), depression rates were extremely low and similar for both groups. During the pandemic, depression rates increased dramatically for the entire sample, but less so for 4Ps beneficiaries. After ruling out alternative explanations, we interpret this as evidence that the 4Ps program became more important for mental health during a crisis. One possible reason is that the continued CCTs provided to 4Ps beneficiaries have larger benefits in times of vulnerability. Another explanation is that the 4Ps program enhanced the effectiveness of the government's emergency cash transfer response, allowing 4Ps to receive these transfers more quickly than non-4Ps did. These results highlight that the existence of a well-functioning social protection program can yield benefits when emergencies arise, amplifying the benefits of any emergency policy response for those who are already part of the social protection system.

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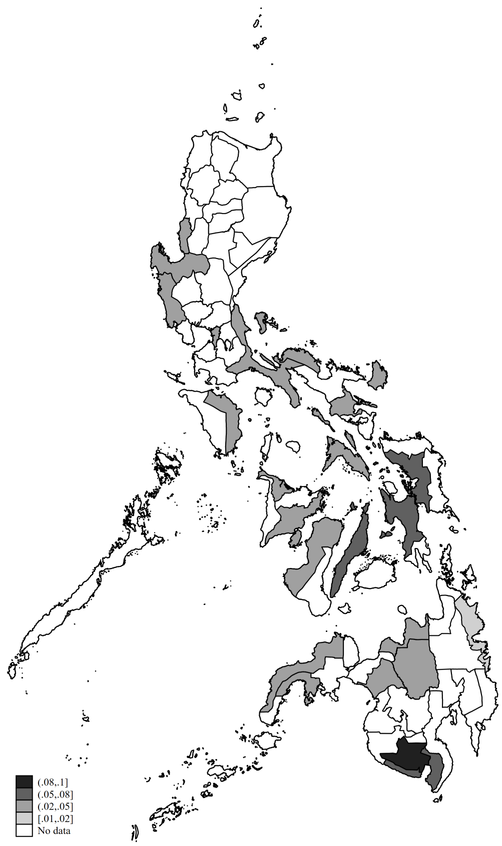
A Appendix

Figure A1: Geographic Distribution of Sample



Notes: Values in legend represent the share of the sample represented by each province.

Table A1: Distribution Across Provinces by 4Ps status

	(1) Non-4Ps	(2) 4Ps	(3) Difference
Agusan Del Sur	0.00	0.01	0.01
	(0.07)	(0.12)	(0.01)
Aklan	0.03	0.01	-0.02
	(0.16)	(0.09)	(0.01)
Albay	0.03	0.03	-0.00
	(0.16)	(0.16)	(0.02)
Bukidnon	0.04	0.04	-0.01
	(0.20)	(0.19)	(0.02)
Camarines Norte	0.04	0.03	-0.01
	(0.20)	(0.18)	(0.02)
Catanduanes	0.03	0.04	0.00
	(0.18)	(0.19)	(0.02)
Cebu	0.06	0.08	0.03
	(0.23)	(0.27)	(0.02)
Guimaras	0.00	0.00	-0.00
	(0.07)	(0.00)	(0.00)
Iloilo	0.02	0.03	0.01
	(0.14)	(0.16)	(0.01)
La Union	0.05	0.04	-0.01
	(0.21)	(0.20)	(0.02)
Lanao Del Sur	0.06	0.05	-0.01
	(0.23)	(0.22)	(0.02)
Leyte	0.08	0.09	0.01
	(0.28)	(0.29)	(0.03)
Masbate	0.03	0.03	-0.00
	(0.18)	(0.18)	(0.02)
Misamis Oriental	0.03	0.02	-0.01
	(0.18)	(0.15)	(0.02)
NCR, City of Manila, First District	0.04	0.05	0.01
	(0.20)	(0.23)	(0.02)
Negros Occidental	0.01	0.00	-0.01
	(0.10)	(0.00)	(0.01)
Oriental Mindoro	0.04	0.02	-0.01
	(0.19)	(0.15)	(0.02)
Pangasinan	0.04	0.05	0.01
	(0.19)	(0.22)	(0.02)
Quezon	0.02	0.04	0.02
	(0.14)	(0.20)	(0.02)
Samar	0.07	0.08	0.01
	(0.25)	(0.27)	(0.02)
Sarangani	0.05	0.05	0.01
	(0.21)	(0.23)	(0.02)
South Cotabato	0.11	0.10	-0.01
	(0.31)	(0.30)	(0.03)
Surigao Del Sur	0.02	0.01	-0.01
	(0.14)	(0.12)	(0.01)
Zambales	0.05	0.04	-0.01
	(0.21)	(0.20)	(0.02)
Zamboanga Del Norte	0.03	0.03	-0.01
	(0.18)	(0.16)	(0.02)
Zamboanga Sibugay	0.03	0.03	-0.01
	(0.18)	(0.16)	(0.02)
Observations	216	222	438

Notes: Standard deviations (in columns 1 and 2) and standard errors (in column 3) reported in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. Table reports the share of 4Ps and non-4Ps households residing in each province.

Table A2: Household Attrition

	(1) Household Attrited
Severe Depression (Household share)	0.22
	(0.14)
Moderate Depression (Household share)	0.029
	(0.042)
Mild Depression (Household share)	0.027
	(0.031)
4Ps	-0.018
	(0.027)
Urban	0.044
	(0.031)
Household Size	0.030
	(0.032)
N. Children	-0.032
	(0.033)
N. Adults	-0.016
	(0.032)
N. Elderly	0.0034
	(0.060)
Highest Ed Level: Primary	0.072*
	(0.042)
Highest Ed Level: Secondary	0.031
	(0.034)
Highest Ed Level: Tertiary	0.051
	(0.049)
Owns Household Business	-0.048
	(0.031)
Adult Employment Share	0.051
	(0.055)
Weekly Earnings (per capita)	-0.000014
	(0.000037)
Owns Farm	-0.049
	(0.035)
Constant	-0.0043
	(0.063)
Observations	484
Mean Attrition	0.10

Notes: Robust standard errors in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01. Sample includes all households with mental health information in the baseline wave. The outcome variable is a dummy variable equal to 1 for households who are missing mental health information in wave 3.

Table A3: Moderate or Any Depression by 4Ps Status and Survey Wave:

	(1) Moderate or Severe Dep.	(2) Moderate or Severe Dep.	(3) Moderate or Severe Dep.	(4) Moderate or Severe Dep.	(5) Any Depression	(6) Any Depression	(7) Any Depression	(8) Any Depression
4Ps	-0.00088				-0.0071			
	(0.034)				(0.036)			
Wave=3	0.37***	0.36***	0.35***	0.35***	0.18***	0.17***	0.17***	0.17***
	(0.033)	(0.034)	(0.032)	(0.033)	(0.042)	(0.042)	(0.042)	(0.042)
Wave=3 x 4Ps	-0.076	-0.056	-0.052	-0.043	-0.020	-0.0068	-0.0026	0.0038
	(0.051)	(0.049)	(0.050)	(0.050)	(0.069)	(0.067)	(0.067)	(0.066)
Observations	2906	2906	2906	858	2906	2906	2906	858
Baseline Mean Outcome	0.16	0.16	0.16	0.16	0.49	0.49	0.49	0.50
Fixed Effects	None	Household	Household	Individual	None	Household	Household	Individual
Controls	None	None	Age/Gender	N/A	None	None	Age/Gender	N/A
Sample	All	All	All	Panel indiv.	All	All	All	Panel indiv.

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01.

Table A4: Severe Depression by 4Ps Status and Survey Wave, Restricting to SAP Recipients

	(1) Severe Depression	(2) Severe Depression	(3) Severe Depression	(4) Severe Depression
4Ps	0.0024			
	(0.012)			
Wave=3	0.34***	0.34***	0.35***	0.35***
	(0.044)	(0.043)	(0.045)	(0.043)
Wave=3 x 4Ps	-0.10**	-0.10**	-0.10**	-0.11**
	(0.041)	(0.041)	(0.042)	(0.041)
Observations	2478	2478	2478	740
Baseline Mean Outcome	0.02	0.02	0.02	0.02
Fixed Effects	None	Household	Household	Individual
Controls	None	None	Age/Gender	N/A
Sample	All	All	All	Panel indiv.

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01. Regressions include non-4Ps households who reported receiving a SAP transfer by wave 3, as well as all 4Ps households.

Table A5: Severe Depression by 4Ps Status and Survey Wave, Allowing for Differential Trends by Baseline Characteristics

	(1) Severe Depression	(2) Severe Depression	(3) Severe Depression	(4) Severe Depression
4Ps	0.00053			
	(0.0090)			
Wave=3	0.37***	0.37***	0.37***	0.35***
	(0.056)	(0.055)	(0.056)	(0.055)
Wave=3 x 4Ps	-0.14***	-0.13***	-0.13**	-0.13**
	(0.045)	(0.046)	(0.047)	(0.047)
Household Size	-0.0068			
	(0.0048)			
PhilHealth Insurance	-0.015			
	(0.016)			
Has Bank Account	0.012			
	(0.0086)			
Wave=3 x Household Size	-0.0034	-0.0045	-0.0030	-0.0073
	(0.027)	(0.028)	(0.028)	(0.029)
Wave=3 x PhilHealth Insurance=1	-0.081	-0.076	-0.077	-0.060
	(0.059)	(0.059)	(0.059)	(0.062)
Wave=3 x Has Bank Account=1	0.082	0.074	0.075	0.076
	(0.049)	(0.051)	(0.052)	(0.052)
Observations	2906	2906	2906	858
Baseline Mean Outcome	0.01	0.01	0.01	0.02
Fixed Effects	None	Household	Household	Individual
Controls	None	None	Age/Gender	N/A
Sample	All	All	All	Panel indiv.

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01.

Table A6: Severe Depression by 4Ps Status and Survey Wave, Sub-Sample Regressions

	(1)	(2)	(3)	(4)
	Severe Depression	Severe Depression	Severe Depression	Severe Depression
Wave=3	0.31***	0.38***	0.30***	0.34***
	(0.039)	(0.088)	(0.072)	(0.040)
Wave=3 x 4Ps	-0.077*	-0.12	-0.023	-0.26***
	(0.042)	(0.13)	(0.078)	(0.046)
Observations	650	208	448	410
Baseline Mean Outcome	0.01	0.03	0.02	0.01
Fixed Effects	Individual	Individual	Individual	Individual
Sample	Panel indiv.	Panel indiv.	Panel indiv.	Panel indiv.
Restriction	Has PhilHealth	No PhilHealth	Has Bank Account	No Bank Account

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01.

Table A7: Severe Depression by 4Ps Status and Survey Wave, Dropping Recipients of Two SAP payments

	(1)	(2)	(3)	(4)
	Severe Depression	Severe Depression	Severe Depression	Severe Depression
4Ps	0.0095			
	(0.013)			
Wave=3	0.34***	0.34***	0.34***	0.34***
	(0.041)	(0.041)	(0.041)	(0.041)
Wave=3 x 4Ps	-0.13***	-0.14***	-0.13***	-0.13***
	(0.045)	(0.046)	(0.046)	(0.046)
Observations	2410	2410	2410	706
Baseline Mean Outcome	0.02	0.02	0.02	0.02
Fixed Effects	None	Household	Household	Individual
Controls	None	None	Age/Gender	N/A
Sample	All	All	All	Panel indiv.

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01. Regressions exclude any 4Ps or non-4Ps households who reported receiving a second SAP payment by wave 3.

Table A8: Trends in Economic Variables by 4Ps Status

	(1) Adult Employment Share	(2) Adult Employment Share	(3) Weekly Earnings (per capita)	(4) Weekly Earnings (per capita)	(5) Received Remittances	(6) Received Remittances	(7) Food Insecure	(8) Food Insecure
Wave=1 x 4Ps	0.0247	0.0247	-39.57	-43.24			-0.0811	-0.0946*
	(0.0382)	(0.0382)	(43.58)	(43.92)			(0.0528)	(0.0547)
Wave=2 x 4Ps	0.00225	0.00697	-86.02	-75.71			-0.0113	-0.0325
	(0.0395)	(0.0400)	(51.96)	(47.16)			(0.0499)	(0.0535)
Wave=3 x 4Ps	-0.00785	-0.00794	-48.90	-38.04	-0.00551	-0.00551	-0.00741	-0.0229
	(0.0365)	(0.0366)	(41.34)	(38.87)	(0.0383)	(0.0383)	(0.0435)	(0.0445)
Wave=4 x 4Ps	-0.0436	-0.0457	8.449	13.04				
	(0.0571)	(0.0548)	(128.7)	(125.6)				
4Ps	0.00452		44.74		0.0374		0.0109	
	(0.0311)		(47.02)		(0.0367)		(0.0382)	
Observations	2091	2091	2078	2078	876	876	1656	1656
Outcome Mean	0.471	0.471	298.8	298.8	0.152	0.152	0.456	0.456
Fixed Effects	None	Household	None	Household	None	Household	None	Household

Notes: Standard errors (clustered at the municipality level) are in parentheses * p< 0.1, ** p< 0.05, *** p< 0.01. In columns 1 to 6, the omitted interaction is the baseline wave. In columns 7 and 8, the omitted interaction is wave 4 because food insecurity is not measured in the baseline wave and for other outcomes, the wave most similar to baseline is wave 4 (see Figure 3).

A.1 Mental Health Questions

The baseline survey included the PHQ-9, a list of nine questions copied below.

We would like to know how you have been feeling over the last 2 weeks. Over the last 2 weeks, how often have you been bothered by any of these problems?

1. Little interest or pleasure in doing things
2. Feeling down, depressed or hopeless
3. Trouble falling or staying asleep or sleeping too much
4. Feeling tired or having little energy
5. Poor appetite or overeating
6. Feeling bad about yourself – or that you are a failure or have let yourself or family down
7. Trouble concentrating on things, such as reading the newspaper or watching television
8. Moving or speaking so slowly that other people could have noticed, or so fidgety or restless that you have been moving a lot more than usual
9. Thoughts that you would be better off dead, or thoughts of hurting yourself in some way

Respondents were asked to respond either "not at all" (for a score of 0), " several days" (1), "more than half the days" (2), or "nearly every day" (3). We use the total score across questions to categorize respondents into the following depression diagnosis groups, as in Kroenke et al. (2001):

- Severe depressive symptoms (20-27)
- Moderately severe depressive symptoms (15-19)
- Moderate depressive symptoms (10-14)
- Mild depressive symptoms (5-9)
- Minimal depressive symptoms (0-4)

In the third wave, instead of the PHQ-9, the survey included the MHI-5, which consists of the following questions:

1. During the past month, how much of the time were you a happy person?

2. How much of the time, during the past month, have you felt calm and peaceful?

3. How much of the time, during the past month, have you been a very nervous person?

4. How much of the time, during the past month, have you felt downhearted and blue?

5. How much of the time, during the past month, did you feel so down in the dumps that nothing could cheer you up?

Respondents were asked to respond either "all of the time," "most of the time," "some of the time," "a little of the time," or "none of the time." Responses to questions 1 and 2 received a score of 6 for "all of the time," 5 for "most of the time," 3 for "some of the time," 2 for "a little of the time," and 1 for "none of the time." For questions 3 to 6, scores were 1 for "all of the time," 2 for "most of the time," 4 for "some of the time," 5 for "a little of the time," and 6 for "none of the time."[10] Depression scores are calculated as a linear combination of the sum of scores – 100*(sum - 5)/25 – and used to categorize respondents into the following groups:

- Severe depression (0-52)
- Moderate depression (53-60)
- Mild depression (61-68)
- No depression (69-100)

Because the MHI-5 only has one severe category, while the PHQ-9 has both a moderately severe and a severe category, we combine the moderately severe and severe categories in the PHQ-9 (though results are similar when we do not consider the moderately severe category to be severe).

A.2 Food Security Questions

In wave 1, there is one food security question included in the survey: In the past 7 days, did you or any other family member eat fewer meals in a day because of lack of food? There are only two response options (yes/no).

In waves 2 through 4, the following questions are included.

In the last four weeks...

1. how often were you worried that your family might not have enough to eat?

[10] Note that we dropped one response option from the original MHI-5: "a good bit of the time."

2. how often were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?
3. how often did you or any household member have to eat a limited variety of foods due to a lack of resources?
4. how often did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?
5. how often did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?
6. how often did you or any other household member have to eat fewer meals in a day because there was not enough food?
7. how often was there no food to eat of any kind in your household because of lack of resources to get food?
8. how often did you or any household member go to sleep at night hungry because there was not enough food?
9. how often did you or any household member go a whole day and night without eating anything because there was not enough food?
10. 1.Never 2. Rarely (once or twice in the month) 3. Sometimes (three to ten times in the month) 4. Often (more than ten times in the month)

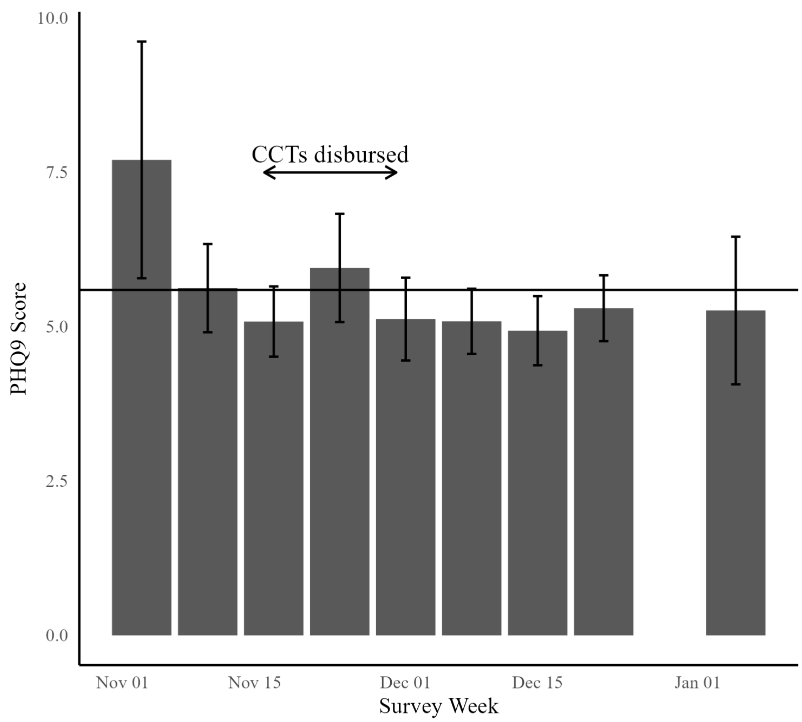
Respondents are asked to respond “never,” “rarely (once or twice in the month),” “sometimes (three to ten times in the month)”, or “often (more than ten times in the month).” Because question 6 captures the same dimension of food security as the sole question included in the baseline wave, we focus on this question in our main analysis.

The main food insecurity variable we use is a dummy equal to 1 for those who responded yes to the main food security question (in wave 1) and for those who responded “sometimes” or “often” to question 6 (for waves 2 through 4). This is because everyone in the “sometimes” or “often” groups, with the exception of those who experienced the said event three times in the month (the lower bound), would on average have experienced the event at least once in the past week (the time frame used for the binary wave 1 question).

A.3 Survey Dates and Mental Health Measures in Baseline Wave

In Table 3, we show that recent recipients of the 4Ps CCT in wave 3 had lower rates of depression than both the remaining 4Ps beneficiaries and the non-4Ps households. Unfortunately, we cannot conduct this same comparison in the baseline wave because the survey did not ask about the timing of the most recent 4Ps transfer. However, we do know each household's interview date, which spans from the beginning of November 2019 to the beginning of January 2020 in our sample. Because 4Ps transfers are usually made around the last week of each odd-numbered month, we have a rough idea of which households might have recently received their 4Ps transfer – those surveyed at the end of November and beginning of December. In Figure A2, to investigate whether household mental health might vary by time since transfer receipt, we plot average PHQ-9 scores by week of survey, restricting to 4Ps households in the baseline wave.[11]

Figure A2: 4Ps PHQ-9 Scores by Interview Date in Baseline Survey



Notes: Figure generated from individual-level data restricting to 4Ps households in the baseline wave. Error bars represent 95% confidence intervals. Horizontal line represents the average PHQ-9 score among non-4Ps households in the baseline wave.

Figure A2 provides little indication that households who were likely to be recent CCT recipients were better off than the remaining 4Ps households. Average PHQ-9 scores for 4Ps are similar to the non-4Ps average (denoted by the horizontal line) across the entire interview date distribution, with the exception

[11]We use the continuous PHQ-9 scores instead of the severe depression indicator because severe depression rates were so low at baseline that the average rate for most weeks was zero.

of those interviewed in the first week, for whom mental health is worse (indicated by higher PHQ-9 scores) though standard errors are also much larger. Households interviewed in the first week of December have better mental health (lower PHQ-9 scores) than those interviewed the week before, which would be consistent with the idea that recent recipients are better off. However, the magnitude of this difference is small relative to the standard errors. In addition, other patterns in the figure are not consistent with this idea. For example, those surveyed in the last week of November should include a subset of households who received the transfer very recently, but they appear to be worse off than those interviewed in the two weeks before (although once again there is substantial overlap in the confidence intervals). In addition, there is no clear pattern in the weeks after December 1, after which we should see a worsening of mental health but instead see a flat trend. Although there are substantial limitations to this analysis, the evidence we do have provides no indication that 4Ps transfers affected mental health at baseline – in stark contrast to the results documented in Table 3, which show lower depression rates for recent CCT recipients during the pandemic.