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Corresponding Author:	Manuela Angelucci The University of Texas at Austin Austin, TX UNITED STATES
First Author:	Manuela Angelucci
Order of Authors:	Manuela Angelucci
	Daniel Bennett
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Registered Report Stage 1: Proposal

The Long-Term Impact of Pharmacotherapy in India

Manuela Angelucci* Daniel Bennett†

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Abstract

This study evaluates the long-run impact of a single course of pharmacotherapy in Karnataka, India. Angelucci and Bennett (2024) showed that offering pharmacotherapy to depressed adults improved mental health and increased human capital investment in older children. However, the long-term effects of a single course of antidepressants are unknown. We will resurvey the original study participants to evaluate the 7-year impact of this intervention on depression severity, depression awareness and stigma, children's human capital investment, impacts in the household, and possible pathways.

Keywords: Depression, Health, Poverty

JEL Codes: I15, I18

Study pre-registration: This study is pre-registered at the AEA RCT Registry, Trial AEARCTR-0012696, https://www.socialscienceregistry.org/trials/12696.

Proposed timeline: (1) Develop and Pilot Questionnaires: January-March 2024. (2) Implement in-person surveys: April-July 2024. (3) Implement follow-up and phone surveys of missing respondents: May-August 2024. (4) Clean and analyze data: September-December 2024. (5) Write and submit paper: January-April 2025.

*Department of Economics, University of Texas at Austin, mangeluc@utexas.edu
†Center for Economic and Social Research and Department of Economics, University of Southern California, bennettd@usc.edu

1 Introduction

With a lifetime prevalence of 15-20 percent, depression is the leading cause of disability throughout the world. Depression symptoms include anhedonia (the inability to feel pleasure), impaired attention, and fatigue, which potentially have important effects on productivity, investment, and economic decision-making. Depression is more prevalent among the poor, and may contribute to poverty both contemporaneously and across generations (Ridley et al., 2020; Kessler and Bromet, 2013).

Despite the high prevalence of depression in low- and middle-income countries (LMICs) and the availability of effective treatment, most people with depression do not receive treatment (Mekonen et al., 2021). Three primary barriers contribute to the lack of effective treatment. There are an order of magnitude fewer mental health care providers in LMICs than in industrialized countries (Saxena et al., 2007), which limits the supply of depression treatment. In addition, low awareness of mental illness and pervasive stigma contribute to limited patient demand for treatment (Heim et al., 2020).

Pharmacotherapy has been shown to provide effective depression treatment in the short run (Gartlehner et al., 2017).[1] It is also a potentially important tool in LMICs because off-patent SSRIs are inexpensive and this approach requires less time from highly-trained personnel: a single psychiatrist can offer pharmacotherapy to hundreds of patients per month.

The long-term impact of a single course of pharmacotherapy on mental health is unknown. While antidepressant use is ubiquitous, and most pharmacotherapy patients receive treatment for a limited period of time (Tripathi et al., 2016), trials do not typically analyze the long-term impact of a single course of treatment. This effect is *ex ante* unclear. On one hand, the initial antidepressant-induced reduction in depression rates may fade out over time, as spontaneous recovery eventually occurs in the control group. On the other hand, the use of SSRIs causes neurochemical and physiological changes, which may affect the onset of and reaction to future spells of depression (Connor et al., 2000; Murlanova et al., 2021). These

[1] Gartlehner et al. (2017) show that Serial Serotonin Re-uptake Inhibitors (SSRIs), a commonly-prescribed class of antidepressants, reduce depression severity by 0.35 standard deviations (SD), which is comparable to the 0.22 SD impact of cognitive behavioral therapy.

effects are not well understood. In addition, a previous experience with depression treatment may change the behavioral response to future depression spells by helping the patient recognize the symptoms of depression or understand where to seek treatment. These experiences may also reduce depression stigma by teaching patients and their families that depression is a common disorder that can be treated through medication, just like many other illnesses (Henderson et al., 2014). These mechanisms suggest that, in principle, a single course of pharmacotherapy may have long-lasting effects on mental health and care-seeking through multiple pathways.

In 2016, we implemented a randomized trial to evaluate the impact of community-based provision of pharmacotherapy in Karnataka, India (Angelucci and Bennett, 2024). Around 24 percent of adults experience some depression symptoms in this context. The trial cross-randomized Psychiatric Care (PC) and Livelihoods Assistance (LA) among 1000 adults with symptoms of mild or moderate depression. We measured impacts on mental health and an array of socioeconomic outcomes in four follow-up survey rounds over 26 months. We showed that it is feasible and effective to provide pharmacotherapy to untreated low-income people in this context using the existing health care infrastructure. A single course of pharmacotherapy reduced depression severity by 0.26 SD when paired with LA and mental health impacts persisted after the interventions ended. Results also suggested a positive impact of treatment on human capital investment among older children of 0.4 SD.

This paper follows up on our original trial to study the long-run effects of pharmacotherapy on depression and socioeconomic outcomes. Seven years have now elapsed since the initial study enrollment. We plan to resurvey the original study participants and re-analyze the outcomes reported in our previous study. We have three broad objectives. First, we want to understand the long-term effects of a single course of antidepressants on depression, and whether they are related to improvements in depression awareness and stigma. While we expect benefits of pharmacotherapy along these dimensions, even null findings will expand the knowledge base regarding the role of pharmacotherapy because pharmacotherapy trials are not usually designed to measure long-term impacts of a single course of treatment. For

instance, a finding that impacts have abated in the long term may indicate that pharmacotherapy alone is inadequate to achieve lasting reductions in depression. Findings related to depression awareness and depression stigma will inform policymakers about the extent to which expanding access to care can alleviate these barriers.

Secondly, we will measure the long-term effects of depression treatment on human capital investment among older children. As in other LMICs, school attendance rates are high in primary school and drop at the transition to secondary school. Our prior results suggest that treating depressed adults increased school enrollment and attendance and reduced child labor for secondary school-aged children. We will assess whether these effects have translated into higher levels of completed schooling now that these children are young adults. We will also test whether the current cohort of children has higher human capital investment.

Finally, we will measure the long-term impacts on all the main outcomes that we considered in our initial study: work time and earnings, household consumption, durable good ownership, sanitation, cognitive performance, risk intolerance, subjective wellbeing and household decisions. Since we failed to find effects after two years for most of these outcomes, we do not expect long-term effects either.

This paper contributes to the current literature in the following ways. First, it contributes to the understanding of the long-term effects of pharmacotherapy on depression. This adds to the literature studying the long-term effects of psychotherapy on depression (Baranov et al., 2020; Bhat et al., 2022). Our earlier work finds that impacts on depression severity persist for several months after treatment concludes. This proposed study will allow us to assess whether mental health benefits persist seven years after treatment. To our knowledge, this is the first study of the long-term impacts of a single course of antidepressants. An understanding of these benefits will inform policymakers about the desirability of scaling up the provision of pharmacotherapy. Despite the widespread use of these drugs, evidence regarding long-term impacts is incomplete. As China and India develop, millions more people will likely be prescribed these drugs in the future. Therefore, the impact of these drugs on health and socioeconomic outcomes is an important development question.

Secondly, this study investigates the possible roles of depression awareness and stigma as barriers to mental health care and wellbeing. Even if pharmacotherapy *per se* does not lead to lasting mental health improvements, the experience of receiving treatment may have long-term effects through these channels. Stigma and the lack of awareness of depression are important barriers to take-up of depression treatment and more work is needed to understand ways to alleviate these constraints in LMICs.

Lastly, this study contributes to our understanding of the causal effect of adult depression treatment on child human capital investment. For example, **?** find that providing psychotherapy to women with perinatal depression increases monetary investment in children seven years later. Angelucci and Bennett (2024) find suggestive evidence of positive medium-term impacts on older children's human capital investment. Based on these findings, we anticipate long-term positive, and potentially large, impacts of community-based depression treatment on investments in child human capital, which may play an important role in breaking poverty traps and limiting the inter-generational transmission of poverty.

2 Research Design

2.1 Setting and Intervention

We conducted our prior study in a peri-urban region northwest of Bangalore, Karnataka. Our study area comprises 506 villages and wards (urban jurisdictions) with at least 40 households within the catchment area of our partner NGO in the Doddaballapur, Koratagere, and Gauribidanur districts.[2] In 2017, 24 percent of local adults aged 18 to 50 had some depression symptoms and 10 percent had symptoms of at least moderate depression.[3]

We collaborated with Grameena Abudaya Seva Samsthe (GASS), a local social service organization that has worked with people with physical and mental disabilities since 2001.

[2]Hereafter we refer to villages and wards as "localities."

[3]The prevalence of depression symptoms in our sample exceeds Sagar et al. (2020) estimate of the nationwide prevalence of 3-4 percent. This pattern may arise because our sample is relatively old and poor. Both age and poverty are positively associated with depression. This discrepancy may also reflect the difference between having depression symptoms and being depressed.

GASS aims to improve mental health and patient wellbeing by facilitating psychiatric care and providing livelihoods assistance. To support psychiatric care, GASS organizes walk-in clinics, sets up appointments, and helps transport people to health centers. It provides livelihoods assistance by counseling patients about employment and other earnings opportunities and by helping patients obtain training and small loans as appropriate.

The psychiatric care (PC) intervention provided eight months of free psychiatric care through the Shridevi Institute of Medical Sciences and Research Hospital. Shridevi is an accredited private hospital in Tumkur, Karnataka, near the study area. The facility has 750 beds, 80 percent of which are allocated for pro bono care of disadvantaged patients. The hospital sometimes receives patients from GASS. The initial visit included a diagnosis, an explanation of the significance of mental illness, and an individualized course of medical treatment. Patients returned for monthly follow-up visits. The most commonly prescribed anti-depressants were Selective Serotonin Reuptake Inhibitors (SSRIs). These drugs are generally not under patent and are available inexpensively in India. They are widely used and have relatively few well-tolerated side effects (Ferguson, 2001; Cascade, Kalali and Kennedy, 2009).

The livelihoods assistance (LA) intervention provided two group meetings and personalized livelihoods assistance during the first two months of the study. Overall, this intervention had no independent effects short or medium term. Thus, it is not the focus of our study of long-run impacts.

We used a cluster-randomized design to cross-randomize PC and LA by locality. Before starting recruitment, we stratified the randomization by district and terciles of a locality socioeconomic index based on the 2011 Census of India.[4] We screened about forty households per locality, with the target of selecting 1-2 participants per locality. Both the modal and median number of participants per locality is 2. This design minimized spillovers and cross-arm contamination. Treating few people per locality limited information leakages, protecting patient confidentiality.

[4]Socioeconomic index components include locality averages of house quality, electrification, latrine use, and durable good ownership.

We sampled participants through a door-skip pattern in which the skips were proportional to locality size. Once at the household, surveyors randomly chose an available adult to screen for eligibility. We screened people for depression symptoms with the PHQ-9 depression severity scale (Kroenke, Spitzer and Williams, 2001). This nine-item scale ranges from 0 to 27 and higher values indicate more severe symptoms. The PHQ-9 is widely validated to screen for depression and measure the response to treatment in India and throughout the world (Patel et al., 2008; Manea, Gilbody and McMillan, 2012; Indu et al., 2018). To obtain a sample of mildly or moderately depressed people, we recruited subjects with PHQ-9 scores of 9-20. In total, surveyors screened 6446 people in order to enroll a study sample of 1000 participants across 506 localities.

2.2 Hypotheses

We investigate the long-term effects of treatment with a single course of antidepressants. We are not aware of clinical studies that carry out a similar analysis. Clinical studies of the effects of pharmacotherapy typically only examine short-term effects or long-term withdrawal symptoms (Gartlehner et al., 2017; Fava et al., 2015). Results from our previous analysis suggest that impacts on depression severity may dissipate because many control participants also eventually experience remission. Nonetheless, depression treatment could have long-term effects by altering the frequency or severity of future depression spells or by changing the way that people respond to these spells due to information or stigma. Thus, we formulate the following hypotheses.

Primary Hypothesis: Depression. The intervention reduces depression severity after seven years.

Secondary Hypothesis 1.a: Depression Awareness. The intervention increases participants' (i) awareness of the symptoms of depression and (ii) knowledge of how and where to seek depression treatment after seven years.

Secondary Hypothesis 1.b: Stigma. The intervention reduces participants' experiences and perceptions of depression stigma after seven years.

Our previous study uncovered suggestive evidence that reducing depression may increases investment, both in human capital of children aged 13-18, and in preventing negative shocks. However, it is unclear if the effect on these outcomes is long-lasting. Thus, we formulate the following hypotheses:

Secondary Hypothesis 2a: Young Adults' Completed Schooling. The intervention increases the educational attainment of children aged 13 to 18 *at the time of the intervention*.

Secondary Hypothesis 2.b: Older Children's Human Capital Investment. The intervention increases human capital investment for children *currently* aged 13 to 18.[5]

Secondary Hypothesis 2.c: Shocks. The intervention reduces the current incidence of negative socioeconomic shocks.

Our previous analysis showed no positive medium-term effects on participants' work time and earnings, household consumption, durable good ownership, or hygiene/sanitation. Therefore, we hypothesize that there are also no long-term effects on these outcomes.

Secondary Hypothesis 3: Effects in the Household. The intervention has no long-term positive effects on the above outcomes.

Similarly, we do not expect positive long-term effects on risk tolerance, cognitive performance, subjective wellbeing, and household decisions because we did not observe medium-term impacts on these outcomes previously.

Secondary Hypothesis 4: Pathways. The intervention has no long-term positive effects on the above outcomes.

2.3 Primary and Secondary Outcomes

We intend to estimate the long-term effects of all the outcomes for which we measured medium-term effects. In addition, we want to study the long-term effects on depression awareness and stigma.

[5]To examine all the outcomes in Angelucci and Bennett (2024), we will also consider the effects on human capital investment for children *currently* aged 12 and under. However, we do not expect long-term effects on these outcomes, since there were no medium-term impacts.

Primary Outcome: Depression

- **Depression:** we will consider the standardized PHQ-9 score as our main outcome to measure the contemporaneous severity of depression symptoms. In addition, we will consider the self-reported depression history and compute the total number of months in which the respondent has been depressed since 2018 (summing up multiple spells of depression).

Secondary Outcomes: Depression Awareness and Stigma

- **Depression Awareness:** we measure participants' knowledge of (i) the symptoms of depression and (ii) how and where to seek depression treatment.
- **Stigma:** we measure participants' perceptions and experiences of depression stigma.

Secondary Outcome: Investment

- **Educational attainment for children aged 13-18 at baseline:** We measure educational attainment for household members who were aged 13-18 at the study baseline. These individuals are now 20-25 years old.
- **Human capital investment among current children:** We measure current human capital investment as the first principal component of school enrollment, school attendance, homework time, and child labor for children currently aged 5 to 12 and 13 to 18 separately.
- **Shocks:** We will measure the household socioeconomic shocks in the previous six months. A lower prevalence of shocks can be the consequence of higher investment in the prevention of negative events.

Secondary Outcomes: Effects in the Household

- **Work Time and Earnings:** We measure work time – the time spent on productive activities – from a 24-hour time diary and then convert responses into weekly values.

Productive activities include primary and secondary jobs, agricultural work, child care, cooking, cleaning, doing laundry, and fetching water.[6] We measure weekly earnings from primary and secondary jobs.

- **Household consumption:** Per-capita consumption is the sum of household food consumption in the past week (across 23 food groups that are common locally) and expenditures on 13 non-durable non-food commodities (converted into weekly values from 1 or 2 month recalls) divided by household size.[7]

- **Durable good ownership:** We measure durable goods ownership according to indicators for household ownership of nine goods.[8]

- **Hygiene/sanitation:** We measure hygiene and sanitation by observing whether there is open defecation or visible garbage at the respondent's home, whether the cooking area is clean, and whether the respondent has visibly dirty hands and fingernails.

Secondary Outcomes: Pathways

- **Risk intolerance**: We elicit risk intolerance through items from the Blais and Weber (2006) DOSPERT scale, a generalized risk self-assessment (Dohmen et al. (2011)), and the Eckel and Grossman (2008) incentivized lottery game.

- **Cognitive performance**: We assess cognitive performance through three incentivized tests: Raven's Progressive Matrices, which estimates fluid intelligence, and forward and backward digit spans, which measure verbal short-term and working memory.

- **Subjective wellbeing**: We use the five-item Satisfaction with Life Scale to measure subjective wellbeing (Kobau et al. (2010)).

[6] In addition, we elicit the time devoted to primary and secondary jobs and domestic work in the past seven days. We prefer the time diary approach because it includes time spent on productive tasks that the respondent may not define as work.

[7] We include foods that were purchased, produced at home, or received from others. To compute the value of non-purchased food, we multiply the quantity consumed by median unit values.

[8] These goods are a chair, a bed, a table, an electric fan, a television, a refrigerator, a bicycle, a motorcycle or scooter, and a car.

- **Participation in household decisions**: As a measure of participation in household decisions, respondents indicate whether they make household financial and employment decisions alone, with other household members, or not at all.

3 Data

3.1 Data collection and processing

We will resurvey participants of 2016 RCT that provided pharmacotherapy to low-income adults with depression in Karnataka, India. We will track individuals from their origin localities and implement both in-person and telephone surveys to reach as many people as possible. We will consider a person missing if we fail to contact them in person up to three times and on the phone up to four times, pending confirmation of our surveying firm. We expect the data collection process to start in 3-4 months and take up to 4 months, including personnel training and survey piloting.

3.2 Variations from the intended sample size

Following DiNardo et al. (2021), we will randomize a subset of unreachable subjects for additional intensive followup. If the baseline characteristics of the original study participants we will be able to re-survey are unbalanced, we will apply entropy weights are report the unweighted and weighted estimated treatment effects.

3.3 Pilot Data

Our original trial provides a rich source of preliminary data for this analysis. Data from this trial are available from the AEA Data and Code Repository (Angelucci and Bennett, 2023). Where possible, we will reproduce the variable definitions used in the previous analysis.

Tables 1-3 reproduce the key results from Angelucci and Bennett (2024). Table 1 shows that the PC and PC/LA interventions have statistically significant effects on depression

severity in both the short term and the medium term (at which time the PC intervention has concluded). Table 2 shows that the interventions do not have significant positive impacts on work time or earnings, which contributes to our hypothesis that we will not find significant long-term impacts on these outcomes. However Table 3 shows strong positive effects of the pharmacotherapy interventions on child human capital investment among older children. We do not find strong positive impacts on most other socioeconomic outcomes in our previous analysis. These patterns motivate our hypotheses above.

4 Analysis

4.1 Statistical methods and model

We will estimate "intent-to-treat" effects by including all respondents within an intervention arm regardless of compliance. We will estimate the equations below by OLS and cluster standard errors by locality in all specifications.

We will estimate the parameters of the following equation for respondent i in locality j:

$$Y_{ij} = \beta_1[PC_j] + \beta_2[LA_j] + \beta_3[PC/LA_j] + \beta_4 X_{ij} + \epsilon_{ij} \quad (1)$$

The variables PC, LA, and PC/LA are indicators for the arms that receive PC only, LA only, or both PC and LA. X_{ij} is a vector of predetermined covariates. To select these covariates, we will alternatively use an ANCOVA specification (in which case, we will control for the baseline dependent variable and strata indicators) or a double-selection LASSO (Belloni, Chernozhukov and Hansen, 2014). The parameters β_1 to β_4 identify the Average Intent to Treat (AIT) effects of each intervention arm under the assumptions that potential outcomes of each treated person are unaffected by the treatment status of other people and that treatment assignment is independent of potential outcomes. Assigning treatment by locality minimizes instances of violations of the first assumption through spillovers such as social interactions, while treating 1-2 people per locality minimizes locality-specific equilibrium

effects. Random assignment should ensure that the second assumption holds.

In our previous analysis, a Young (2019) omnibus test failed to reject the hypothesis of no effect of LA on the study outcomes. Based on this finding, we will also pool the PC and PC/LA arms in order to increase precision, as the following equation shows:

$$Y_{ij} = \rho_1[LA_j] + \rho_2[PC_j^{pooled}] + \rho_3 X_{ij} + \mu_{ij} \tag{2}$$

The variables PC^{pooled} is an indicator for arms either receives PC only or both PC and LA. Other variables are defined as the same as equation 1.

- **Attrition**: We expect the attrition rate to be around 10%, based on piloting. We will track individuals from their origin localities and implement both in-person and telephone surveys to reach as many people as possible. Following DiNardo et al. (2021), we will randomize a subset of hard-to-reach subjects for additional intensive followup. If attrition in unbalanced by arm, we will use entropy weights.

- **Missing Values**: Our existing data have few missing values for outcome variables among non-attriters. We will use the same approach as in Angelucci and Bennett (2024), which was to include all available observations for a given outcome.

- **Outliers**: We follow Tukey et al. (1977) and winsorize observation outside 1.5 times the interquartile range. We will also assess the sensitivity of our estimates to including or excluding outliers.

4.2 Sample and Statistical power

In the original survey, we enrolled 395 participants (from 204 localities) in the control arm, 207 participants (from 99 localities) in the PC arm, 205 participants (from 102 localities) in the LA arm, and 193 participants (from 101 localities) in the PC/LA arm.

Assuming a 10% attrition rate for each arm in the follow-up survey, the minimum detectable effect (MDE) for the comparison of any of the intervention arms with the control

arm (e.g. PC/LA vs. control) is 0.20 SD. This calculation is based on the assumptions of 80 percent power and 95 percent confidence. For a comparison of pooled PC arms with the control arm (e.g. PC/LA and PC vs. control), the MDE is 0.17 SD. With 20% attrition, the two MDEs are 0.21 SD and 0.17 SD. With 30% attrition, the two MDEs are 0.23 SD and 0.19 SD.

4.3 Multiple Hypothesis Testing

We will correct for multiple hypothesis testing within families of outcomes. To do that, we will create indices for each family of outcomes whenever applicable: child human capital investment and sanitation, durable goods, risk intolerance, negative shocks, cognition and subjective wellbeing include multiple component variables. If we show individual index components, we will report the q-values. This approach is also consistent with how we dealt with multiple hypothesis testing in our previous analysis.

4.4 Heterogeneous Effects

Angelucci and Bennett (2024) did not find any short- and medium-term heterogeneous effects for a list of pre-specified subgroup. Thus, we do not expect long-term heterogeneous effect and we do not plan to test for them.

5 Interpreting Results

Resources to treat depression are scarce in India and other LMICs. Pharmacotherapy is a plausible approach to provide treatment in settings with limited resources, however there is little evidence about the mental health and economic impacts of this approach. The preponderance of depression research focuses on clinical settings in industrialized countries. This research makes an important contribution to closing this knowledge gap by providing rigorous estimates of the long-run impacts of pharmacotherapy in poor communities in India.

An understanding of these benefits helps inform policymakers about the desirability of scaling up the provision of pharmacotherapy.

In addition, the long-term impacts of a single course of antidepressants are not well-understood, in developing countries or elsewhere. If this medication induces permanent physiological changes, it is possible that it will continue to impact the relapse and recurrence of depression. If so, there may be future benefits from it even after the treatment itself has been discontinued. The single course of medication can have additional long-term impacts unmediated by biological changes: exposing people to treatment can increase depression awareness, making people more aware of the symptoms of depression, the available treatment, and how to seek it. If so, a single course of treatment can have lasting impacts by teaching people how to recognize symptoms and seek care. This channel can also reduce the duration of future spells of depression, as people in relapse or recurrence can take action to seek care. Lastly, increased familiarity with depression symptoms and treatment can also dispel harmful beliefs about people with depression, contribute to normalize the condition, and thus alleviate self sigma and stigma in the household. This channel can also have lasting beneficial impacts within the household.

6 Administrative Information

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Table 1: Impact on Depression Severity (Table 2 from Angelucci and Bennett (2024))

	PHQ-9 (std.)	
	(1)	(2)
A: During the PC Intervention		
PC/LA	-0.26	-0.26
	(0.081)	(0.080)
PC	-0.14	-0.15
	(0.083)	(0.079)
LA	-0.079	-0.063
	(0.087)	(0.079)
H_0: $PC/LA = PC$	0.21	0.23
H_0: $PC/LA = PC + LA$	0.76	0.70
H_0: $PC = LA$	0.55	0.36
H_0: $PC/LA = LA$	0.07	0.04
H_0: $PC/LA = PC = LA$	0.17	0.11
Control mean of outcome	0	0
B: After the PC Intervention		
PC/LA	-0.24	-0.24
	(0.086)	(0.087)
PC	-0.039	-0.067
	(0.077)	(0.075)
LA	0.0058	0.016
	(0.081)	(0.079)
H_0: $PC/LA = PC$	0.04	0.06
H_0: $PC/LA = PC + LA$	0.10	0.12
H_0: $PC = LA$	0.62	0.35
H_0: $PC/LA = LA$	0.01	0.01
H_0: $PC/LA = PC = LA$	0.03	0.03
Control mean of outcome	0	0
Baseline outcome coefficient	0.151	0.095
	(0.026)	(0.023)
Specification	ANCOVA	LASSO
Observations	3476	3476

Note: The table reports AIT effects following Equation (1). Column 1 uses an ANCOVA specification that controls for time indicators, strata indicators, and the baseline dependent variable. Column 2 uses the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 24 explains this approach in more detail. Locality-clustered standard errors appear in parentheses. "During" and "after" estimates are based on a common regression. The outcome is the standardized PHQ-9 depression severity score.

Table 2: Impact on Weekly Work Time and Earnings (Table 3 from Angelucci and Bennett (2024))

	Hours		Earnings	
	(1)	(2)	(3)	(4)
A: During the PC Intervention				
PC/LA	1.07	1.48	37.9	22.4
	(1.66)	(1.60)	(61.3)	(57.7)
PC	-5.40	-4.92	-65.4	-82.9
	(1.70)	(1.64)	(54.2)	(53.1)
LA	-1.02	-0.50	-32.8	-38.0
	(1.68)	(1.61)	(61.8)	(58.1)
H_0: $PC/LA = PC$	0.00	0.00	0.12	0.10
H_0: $PC/LA = PC + LA$	0.00	0.01	0.14	0.10
H_0: $PC = LA$	0.03	0.02	0.63	0.48
H_0: $PC/LA = LA$	0.29	0.30	0.33	0.38
H_0: $PC/LA = PC = LA$	0.00	0.00	0.30	0.26
Control mean of outcome	58.7	58.7	577.1	577.1
B: After the PC Intervention				
PC/LA	-3.31	-2.84	38.7	20.8
	(1.77)	(1.74)	(67.3)	(65.9)
PC	-1.18	-0.84	-52.8	-63.6
	(1.98)	(1.89)	(61.0)	(57.5)
LA	-1.52	-1.04	47.9	45.1
	(1.95)	(1.93)	(62.2)	(60.0)
H_0: $PC/LA = PC$	0.34	0.35	0.22	0.24
H_0: $PC/LA = PC + LA$	0.84	0.74	0.65	0.68
H_0: $PC = LA$	0.89	0.93	0.15	0.10
H_0: $PC/LA = LA$	0.42	0.41	0.90	0.74
H_0: $PC/LA = PC = LA$	0.58	0.58	0.29	0.23
Control mean of outcome	60.4	60.4	639.2	639.2
Baseline outcome coefficient	0.208	0.131	0.188	0.095
	(0.023)	(0.020)	(0.028)	(0.028)
Specification	ANCOVA	LASSO	ANCOVA	LASSO
Observations	3476	3476	3476	3476

Note: The table reports AIT effects following Equation (1). Columns 1 and 3 use an ANCOVA specification that controls for time indicators, strata indicators, and the baseline dependent variable. Columns 2 and 4 use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 24 explains this approach in more detail. Locality-clustered standard errors appear in parentheses. "During" and "after" estimates are based on a common regression. The outcome in Columns 1 and 2 is weekly productive time, which is the sum of time spent on primary and secondary jobs, agriculture, child care, cooking, cleaning, laundry, and fetching water. The outcome in Columns 3 and 4 is weekly earnings from primary and secondary jobs.

Table 3: Impact on Child Human Capital Investment (Table 4 from Angelucci and Bennett (2024))

	Child Human Capital Investment Index					
	Full Sample		Child Age ≤ 12		Child Age > 12	
	(1)	(2)	(3)	(4)	(5)	(6)
A: During the PC Intervention						
PC/LA	-0.14	-0.12	-0.065	-0.065	-0.23	-0.22
	(0.090)	(0.090)	(0.059)	(0.060)	(0.17)	(0.17)
PC	0.11	0.13	0.00027	0.00065	0.17	0.19
	(0.073)	(0.077)	(0.056)	(0.059)	(0.12)	(0.13)
LA	0.036	0.042	-0.061	-0.061	0.12	0.12
	(0.065)	(0.067)	(0.059)	(0.059)	(0.10)	(0.12)
H_0: $PC/LA = PC$	0.01	0.01	0.35	0.35	0.03	0.03
H_0: $PC/LA = PC + LA$	0.02	0.04	0.96	0.96	0.01	0.02
H_0: $PC = LA$	0.34	0.23	0.38	0.36	0.67	0.57
H_0: $PC/LA = LA$	0.06	0.08	0.95	0.96	0.04	0.05
H_0: $PC/LA = PC = LA$	0.05	0.09	0.57	0.56	0.07	0.08
Control mean of outcome	0	0	0.22	0.22	-0.20	-0.20
B: After the PC Intervention						
PC/LA	0.12	0.12	-0.083	-0.073	0.40	0.30
	(0.13)	(0.13)	(0.13)	(0.13)	(0.24)	(0.27)
PC	0.18	0.21	-0.012	-0.0014	0.44	0.44
	(0.099)	(0.10)	(0.11)	(0.11)	(0.16)	(0.17)
LA	0.11	0.11	-0.025	-0.019	0.32	0.30
	(0.12)	(0.11)	(0.11)	(0.11)	(0.19)	(0.20)
H_0: $PC/LA = PC$	0.61	0.45	0.62	0.62	0.87	0.56
H_0: $PC/LA = PC + LA$	0.30	0.21	0.80	0.77	0.21	0.16
H_0: $PC = LA$	0.53	0.33	0.92	0.89	0.53	0.40
H_0: $PC/LA = LA$	0.97	0.92	0.69	0.71	0.76	0.99
H_0: $PC/LA = PC = LA$	0.78	0.56	0.88	0.88	0.82	0.63
Control mean of outcome	0	0	0.21	0.21	-0.27	-0.27
Baseline outcome coefficient	0.40	0.32	0.15	–	0.47	0.49
	(0.045)	(0.056)	(0.045)		(0.049)	(0.054)
Specification	ANCOVA	LASSO	ANCOVA	LASSO	ANCOVA	LASSO
Observations	2232	2232	1244	1244	988	988

Note: The table reports AIT effects following Equation (1). Locality-clustered standard errors appear in parentheses. The "during" period in Panel A includes Rounds 2-3 and the "after" period in Panel B includes Round 4 because child human capital data are not available in Round 5. "During" and "after" estimates are based on a common regression. All estimates are weighted by the inverse number of school-aged children in the household. We test whether treatment effects are equal for younger and older children in the "after" period and report the following p-values: Columns 3 and 5: $p = 0.09$ for PC/LA, $p = 0.02$ for PC, and $p = 0.19$ for LA; Columns 4 and 6: $p = 0.10$ for PC/LA, $p = 0.04$ for PC, and $p = 0.21$ for LA.