The Economic Impact of Depression Treatment in India: Evidence from Community-Based Provision of Pharmacotherapy

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Abstract

This study evaluates the impact of depression treatment on economic behavior in Karnataka, India. We cross-randomized pharmacotherapy and livelihoods assistance among 1000 depressed adults and evaluated impacts on depression severity, socioeconomic outcomes, and several potential pathways over 26 months. Pharmacotherapy reduces depression severity, especially when paired with a light-touch livelihoods intervention, with benefits that persist after treatment concludes. The treatments increase child human capital investment, particularly for older children, and decrease risk tolerance and the incidence of negative shocks. These findings suggest two pathways through which treating depression may reduce the intergenerational transmission of poverty.

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1 Introduction

Depression is a pervasive and costly illness with a lifetime prevalence of 15-20 percent (Moussavi et al. 2007, Ferrari et al. 2013, Hasin et al. 2018). It is the fourth largest contributor to the global burden of disease and the third largest source of years lost to disability (James et al. 2018). Depression symptoms include anhedonia (the inability to feel pleasure), pessimism, and disrupted sleep and nutrition. These symptoms may lower productivity (Beck et al. 2011), reduce the willingness or ability to invest in child human capital (Cummings and Davies 1994), and affect participation in household decisions (Baranov et al. 2020), thereby impacting socioeconomic outcomes throughout the household. By addressing these symptoms, depression treatment may have health benefits and improve socioeconomic outcomes.

For developing countries, it is particularly important to understand the economic impact of depression and find effective and scalable treatments: depression is more prevalent among the poor and may contribute to poverty and poverty traps (Ridley et al. 2020, Kessler and Bromet 2013, Haushofer and Fehr 2014). Despite a high need for treatment, the supply of mental health care is constrained by a shortage of providers in low-income countries (Saxena et al. 2007).

Pharmacotherapy may be a useful tool to treat depression in developing countries. Clinical studies demonstrate the effectiveness of this approach in industrialized countries (Gartlehner et al. 2017). However, we lack evidence of the feasibility and effectiveness of community-based provision of pharmacotherapy in developing countries, as well as evidence of the long-term effects of pharmacotherapy in general. We also lack knowledge of how mental health care may affect outcomes such as time use, earnings, and investment, and the pathways through which these effects may occur.

This paper studies the effects of pharmacotherapy on depression, socioeconomic outcomes, and possible pathways that may link mental health and economic behavior. We implemented a community-based cluster cross-randomized trial offering Psychiatric Care (PC) and Livelihoods Assistance (LA) to 1000 adults (86 percent of whom are female) with symptoms of mild or moderate depression in a peri-urban region near Bangalore, India. PC and LA are two commonly available services to treat depression both in this setting and elsewhere. Some mental health care providers believe that livelihoods assistance may increase the effectiveness of pharmacotherapy.

The PC intervention provided eight months of personalized pharmacotherapy with the diagnosis and oversight of a psychiatrist from a local research hospital. The LA intervention consisted of two group meetings to address work-related challenges, followed by personalized support to help participants find employment or other income-generating opportunities. We delivered both interventions using the existing local infrastructure: we partnered with a local NGO that offers these programs to people with mental illness. We measured impacts on the mental health, time use, and earnings of participants, human capital investment in children, and consumption, durable goods ownership, and hygiene/sanitation of households, as well as several potential pathways that could link depression to these outcomes. Forty-four percent of participants complied with the PC intervention and 68 percent complied with LA. This level of participation suggests that it is possible to surmount barriers to mental health treatment such as a lack of awareness and high stigma. We assessed impacts while the PC intervention was ongoing (our "during" period) and 16-26 months after it began (our "after" period). The follow-up data allow us to measure the longer-term effects of pharmacotherapy on mental health and other outcomes, which are largely unknown.

Both pharmacotherapy arms reduce depression severity. While effect sizes are comparable to the literature, the effect of PC/LA is larger and more persistent. The effect of PC on depression severity is -0.14 SD (-0.28/-0.001) while PC is ongoing and -0.04 SD (-0.17/0.09) after PC concludes. The effect of PC/LA is -0.26 SD (-0.39/-0.12) during the PC intervention and -0.24 SD (-0.38/-0.10) afterward.[1,2] PC/LA is also more cost effective because the cost of adding LA to PC is relatively small.

Neither PC nor LA increases work time or earnings. PC *reduces* work time by 5.4 hours per week (2.6/8.2) during the PC intervention but this effect dissipates afterward. By contrast, PC/LA does not reduce work time during the PC intervention.[3] Household

[1]We report average intent to treat effects and provide lower and upper bounds based on 90 percent confidence intervals in parentheses throughout the paper.

[2]The impact of LA on depression severity is -0.08 SD (-0.22/0.06) during the intervention and 0.01 SD (-0.13/0.14) after. The short term impact translates into a decline of 7 percentage points (0.03/13) in the probability of moderate or severe depression.

[3]Despite the intention behind the program, LA alone does not have labor market impacts. The lack of an impact suggests that the LA intervention alone is not sufficient to overcome the barriers to market work

consumption follows a similar pattern: PC significantly reduces consumption during the intervention but PC/LA does not. The effects of PC and PC/LA on work time and consumption are statistically different during the PC intervention but not afterward. Therefore, bundling LA with PC has the additional benefit of protecting against some temporary negative effects of PC. None of the interventions has a statistically significant effect on earnings, hygiene/sanitation, or durable goods ownership.

We find large benefits of depression treatment on child human capital investment after the PC intervention. PC increases investment by 0.18 SD (0.02/0.34) and PC/LA increases investment by 0.12 SD (-0.09/0.33). Effects are larger and more significant for older children. Among children who are 12 or older (the age of transition to secondary school), PC increases investment by 0.44 SD (0.17/0.70) and PC/LA increases investment by 0.40 SD (0.01/0.79). These results complement Baranov et al.'s (2020) findings that offering psychotherapy to low-income Pakistani women with perinatal depression increases subsequent child human capital investment. Effect sizes are comparable to the impact of conditional cash transfers (Baird et al. 2014), as well as other initiatives to increase student enrollment and attendance (Evans and Yuan 2020).[4]

We consider possible pathways through which depression treatment may affect behavior and find evidence consistent with a preference pathway, as the treatments increase risk intolerance and reduce the incidence of negative shocks. Finding that depression treatment changes preferences is consistent with Bhat et al. (2022), although the specific impact on preferences varies. Conversely, we can rule out improved cognition and participation in household decisions as pathways through which depression treatment fosters socioeconomic improvements in our sample.

This paper advances several areas of research. We contribute to the studies of the effectiveness of pharmacotherapy in three ways. First, we establish that a community-based pharmacotherapy intervention in a developing country is feasible and effective at reducing symptoms of depression. Therefore, pharmacotherapy may be an additional tool to address the unmet mental health care needs of the global poor. Secondly, we study the medium-term

among study participants.

[4]LA also increases child human capital investment. This effect could arise through a small effect of LA on mental health or through an effect of the interventions on human capital investment via other channels.

effects of a single course of pharmacotherapy, while most studies look at its contemporaneous effects only. Thirdly, we show that adding LA to PC enhances the effects on mental health and protects against temporary negative impacts, suggesting that pairing pharmacotherapy with additional light-touch programs may be cost-effective (Wiles et al. 2016).

We contribute to the literature on child development, which correlates parental depression with impaired child development (Cummings and Davies 1994) and lower human capital investment (Claessens et al. 2015, Dahlen 2016, Shen et al. 2016). While most papers in this area are descriptive, our study points toward a causal effect of depression on these outcomes. This finding also contributes to the literature that studies effective interventions to promote children's education by identifying an additional demand-side barrier to human capital accumulation.

Lastly, we contribute to the literature on the psychology of poverty by exploring the link between mental health and poverty (Mani et al. 2013, Mullainathan and Shafir 2013, Haushofer and Shapiro 2016). We do not find evidence that depression treatment increases productivity, work time, or earnings. While this result is initially surprising, it aligns with findings by Baranov et al. (2020) and Bhat et al. (2022), who also focus on women in South Asia. However, we find that depression may reduce investment in child human capital, increase risk tolerance, and thereby expose households to additional negative economic shocks. These behaviors reduce the future consumption of children and interfere with wealth accumulation (Lybbert et al. 2004, Carter and Barrett 2006), suggesting an intergenerational link between depression and poverty. A related literature establishes that childhood poverty leads to adult mental illness (e.g. Persson and Rossin-Slater 2018, Adhvaryu et al. 2019). Our findings highlight the bi-directional causal relationship between depression and poverty (Ridley et al. 2020) by showing that adult depression may contribute to future poverty in children.

2 Setting and Interventions

We conducted this 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, Korategere, and Gauribidanur districts. To measure the prevalence and correlates of depression in this area, we concurrently surveyed a representative sample of adults in an adjacent non-study district. In this setting, 24 percent of adults aged 18 to 50 have some depression symptoms and 10 percent have symptoms of at least moderate depression.[5] Symptoms are more severe for women, older people, and people with low socioeconomic status, as studies document elsewhere (Gilman et al. 2002). We elaborate on these patterns in Appendix A.1.

We study the effects of community-based provision of pharmacotherapy among adults who screen positive for depression. 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. 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 PC intervention provided eight months of free psychiatric care through the Shridevi Institute of Medical Sciences and Research Hospital. Shridevi is a local private hospital that offers pro bono care to some patients and 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 et al. 2009).[6] Appendix A.2 discusses ethical considerations. In

[5]The prevalence of depression in our sample exceeds Sagar et al.'s (2020) estimate of the nationwide prevalence of 3-4 percent. In part, this pattern may reflect higher depression prevalence in Karnataka than elsewhere. Moreover, national estimates include a representative share of young people, who have lower rates of depression than adults.

[6]Unlike in a clinical trial, participants were aware of their participation in the PC intervention. A portion of the treatment effect on mental health may arise through a placebo effect. This non-blinded arrangement realistically characterizes depression treatment in practice. A meta-analysis by Arroll et al. (2005) shows that treatment with SSRIs is more effective than a placebo in primary care, where the characteristics of patients

addition to treating depression, the PC intervention may raise awareness and salience of depression in the household, which could lead to additional effects.

The LA intervention provided two group meetings and personalized livelihoods assistance. The meetings, which lasted three hours each, discussed ways to earn income and deal with on-the-job challenges. Each meeting had about 30 participants. In the first meeting, participants had group discussions of their experiences working and earning income, as well as the challenges they perceived in the labor market. In the second group meeting, facilitators sought to identify suitable livelihoods activities for participants. In subsequent weeks, staff provided one-on-one assistance to help participants pursue income-generating activities through job placements, small loans, or training, according to participants' individual needs and circumstances. This intervention took place during the first two months of the study. Although the program was intended to facilitate economic opportunities, the group meetings may have fostered informal support by bringing participants together (Pfeiffer et al. 2011).

3 Design, Sampling, and Recruitment

The study design and analysis follow the analysis plan that we pre-specified and registered before collecting follow-up data. Table A1 itemizes and explains our minor deviations from the analysis plan. We used a cluster-randomized design to cross-randomize psychiatric care (PC) and livelihoods assistance (LA) by village or ward (urban jurisdiction).[7] Figure 1 provides a CONSORT chart for this study. Before starting the recruitment, we stratified the randomization by district and terciles of a village socioeconomic index based on the 2011 Census of India, for a total of nine strata.[8] We then selected 1-2 participants per village. This

and the manifestations of depression often differ from inpatient psychiatric settings. A meta-analysis by De Maat et al. (2006) shows that pharmacotherapy and psychotherapy are similarly effective on average, and that pharmacotherapy is effective for treatment of both mild and moderate depression. Around 20 percent of patients who abruptly discontinue SSRIs experience antidepressant discontinuation syndrome. Symptoms such as dizziness, fatigue, nausea, and irritability may last for 1-2 weeks (Fava et al. 2015, Gabriel and Sharma 2017), although evidence regarding this phenomenon continues to evolve (Davies and Read 2019). Discontinuation symptoms are milder and occur less frequently for patients who receive shorter courses of treatment (Warner et al. 2006, Eveleigh et al. 2018). GASS organized all visits, transported participants to their appointments, and monitored patient welfare via home visits throughout the intervention.

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

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

design minimized spillovers and cross-arm contamination. Treating few people per village limited information leakages, protecting patient confidentiality.

Our partner NGO had limited capacity for both the PC and LA interventions. To increase statistical power given this constraint, we allocated twice as many participants to the control arm as to each of the other intervention arms. We ultimately enrolled 395 participants (from 204 villages) in the control arm, 207 participants (from 99 villages) in the PC arm, 205 participants (from 102 villages) in the LA arm, and 195 participants (from 101 villages) in the PC/LA arm. With these sample sizes, the minimum detectable effect (MDE) for the comparison of any of the interventions with the control group (e.g. PC/LA vs. Control) is 0.16 SD in either the "during" or "after" periods. This calculation is based on the assumptions of 80 percent power and 5 percent significance. For a comparison of two interventions (e.g. PC/LA vs. PC), the MDE is 0.19 SD. For a test of the complementarity between the interventions (whether PC/LA = PC + LA), the MDE is 0.28 SD.[9] Appendix A.3 discusses these calculations further.

We began recruitment in December 2016. We sampled participants through a door-skip pattern in which the skips were proportional to village 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 et al. 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 (e.g., Patel et al. 2008, Manea et al. 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.[10] In total, surveyors screened 6446 people in order to enroll a study sample of 1000 participants across 506 villages.

[9]The difference in sample size across arms and periods is small enough that it has negligible influence on the MDE.

[10]We initially used a minimum PHQ-9 threshold of 7 before revising the threshold to 9 based on our success with recruitment. As a result, 8 percent of participants have baseline PHQ-9 scores of 7 or 8. Following our IRB protocol, we referred people with PHQ-9 scores of 21 or more (indicating severe depression) for immediate treatment and did not enroll them in the study. To select the people most likely to benefit from the livelihoods intervention, we did not recruit people who had disabilities that prevented them from working, who were currently earning more than Rs. 6000 per month, or whose child care duties required them to remain at home throughout the day. We also excluded pregnant women due the additional risks of pharmacotherapy during pregnancy.

We did not stratify by gender during recruitment, and 86 percent of participants are female. This gender ratio is common in other depression studies (e.g. Patel et al. 2017) and reflects the higher prevalence of depression among women.

4 Data and Measurement

We surveyed respondents five times over 26 months. Round 1 took place at recruitment, before the start of the interventions. Round 2 occurred four months after recruitment, midway through the PC intervention and at the end of the LA intervention, and Round 3 occurred eight months after recruitment, around the end of the PC intervention. Round 4 occurred 16 months after recruitment and Round 5 occurred 26 months after recruitment. We refer to Rounds 2 and 3 as "during the PC intervention" and Round 4 and 5 as "after the PC intervention" in our analysis below. Figure A2 illustrates the study timeline.

We study four categories of outcomes: (1) primary outcomes, including depression severity, work hours, and earnings for participants; (2) child human capital investment; (3) household consumption, wealth, and hygiene/sanitation; (4) and potential pathways that link depression to the other outcomes. We winsorize monetary values at 5 percent and convert to 2017 values using the Indian consumer price index.

We measure depression severity using the PHQ-9 scale. The PHQ-9 is not a diagnostic tool. However, scores of 5-9 roughly correspond to mild depression and scores of 10-20 roughly correspond to moderate or moderately-severe depression, with 88 percent sensitivity and specificity (Kroenke et al. 2001). Patients with PHQ-9 scores of 10 or more are likely to have major depressive disorder and are generally referred for medical treatment. We examine impacts on standardized PHQ-9 scores.

We measure work time – the time spent on productive activities – from a 24-hour time diary, which we convert into a weekly value. Productive activities include primary and secondary jobs, agricultural work, as well as child care, cooking, cleaning, doing laundry, and fetching water.[11] We measure weekly earnings from primary and secondary jobs.

[11] In addition, we elicit the time devoted to primary and secondary jobs and domestic work in the past seven days. Estimates using this definition of work time yield similar results. We prefer the time diary approach because it includes time spent on productive tasks that the respondent may not define as work.

We measure child human capital investment for all children within the household aged 5-18. Outcomes include current school enrollment, days of attendance, hours of homework, and whether the child currently works for pay. We do not observe any of these variables in Round 5. We use child-level data for these estimates but we weight by the inverse number of children per household so that estimates are comparable to other results in the paper.[12]

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.[13] We measure durable goods ownership according to indicators for household ownership of nine goods.[14] 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.

To identify several potential pathways for the socioeconomic impacts of depression treatment, we measure cognitive performance, risk intolerance, subjective wellbeing, and participation in household decisions. 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. 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.[15] We use the five-item Satisfaction with Life Scale to measure subjective wellbeing (Kobau et al. 2010). As a measure of participation in household decisions, participants indicate whether they make household financial and employment decisions alone, with other

[12] Estimates based on household averages yield similar results. 54 percent of study participants live with school-aged children and treatment effects on depression are similar regardless of whether school-aged children are present.

[13] 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.

[14] 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.

[15] We measure these variables in Rounds 1-4 only. For the DOSPERT scale items, participants indicate their willingness to ride a motorbike without a helmet, leave their children unattended for 30 minutes, lend money to a neighbor, invest 10 percent of annual income in a new business venture, eat spoiled food, and delay a child's health care. The first four items are from the original DOSPERT scale and the last two items are customized to our setting. The incentivized lottery exercise asks participants to choose from a menu of binary lotteries with payoffs that differ in variance and expected value.

household members, or not at all.

Since each family of outcomes has multiple variables, we create family-specific indices by computing the first principal component of the outcomes within each family. This approach accounts for multiple inference within families. We define the sign of the components within each group so that larger values have a common interpretation. We also standardize these indices to ease interpretation. As exceptions to this approach, total consumption is defined as the sum of food and non-food consumption. For participation in household decisions, we count the number of decisions (across financial and employment decisions) that the respondent participates in.

5 Treatment Compliance

Across the three arms that received either PC or LA, 65 percent of participants had at least one psychiatric meeting (for PC) or livelihoods-related interaction (for LA) within the interventions. Similar proportions of PC and PC/LA participants (45 and 43 percent) attended at least one psychiatric visit ($p = 0.51$ for this comparison) according to psychiatrist records. Similar proportions of LA and PC/LA participants (66 and 71 percent) attended at least one livelihoods assistance meeting ($p = 0.36$ for this comparison). Within PC/LA, 31 percent of participants took up both interventions. Figures A3 and A4 further illustrate intervention compliance.

91 percent of people who met with a psychiatrist were diagnosed with depression. Patients who were diagnosed with depression received SSRIs for a median of four months. When asked in Round 4 to recall drug usage during the PC intervention, 91 percent of participants report that they took medications either "every day" or "every other day" and 13 percent of patients continued to take SSRIs after the PC intervention ended. Medication adherence is 8 percentage points higher in the PC/LA arm ($p = 0.07$). This difference suggests that the LA treatment may have enabled participants to plan or follow through.[16] Among LA compliers, 81 percent attended at least one livelihoods workshop and 47 percent received personalized

[16]Some patients were also diagnosed with anxiety, pain and high blood pressure, which are common depression comorbidities (Hirschfeld 2001, Bair et al. 2003, Meng et al. 2012). These patients received appropriate treatment for these comorbidities (e.g., pain relievers or beta blockers).

livelihoods assistance.[17] Appendix A.4 considers the correlates of intervention compliance. PC and PC/LA compliers are more likely to be men than non-compliers, while LA compliers are more likely to have better mental health than non-compliers. However, these differences are not large and compliers and non-compliers do not differ along most dimensions, including SES and household economic circumstances. Moreover, aside from better mental health in LA, complier characteristics do not differ across arms. Because the compliance rate and the characteristics of compliers are similar in PC and PC/LA, differential impacts of PC/LA relative to PC are unlikely to arise because of differences in intervention participation.

6 Identification and Estimation

We estimate the parameters of the following equation for respondent i in village j and in round t:

$$\begin{aligned} Y_{ijt} = {} & \beta_1[PC_j \cdot D_t] \ + \ \beta_2[LA_j \cdot D_t] \ + \ \beta_3[PC/LA_j \cdot D_t] \ + \\ & \beta_4[PC_j \cdot A_t] \ + \ \beta_5[LA_j \cdot A_t] \ + \ \beta_6[PC/LA_j \cdot A_t] \ + \\ & X'_{ij}\beta_7 \ + \ \varepsilon_{ijt} \end{aligned} \tag{1}$$

The variables PC, LA, and PC/LA are indicators for the arms that receive PC only, LA only, or both PC and LA. D ("during") and A ("after") are indicators for Rounds 2 and 3 (while PC was ongoing or had just concluded) and Rounds 4 and 5 (up to 26 months after the start of the PC intervention). X is a vector of predetermined covariates. The parameters β_1 to β_6 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 treatment assignment is independent of potential outcomes. Assigning treatment by village minimizes instances of violations of the first assumption through spillovers such as social interactions, while treating 1-2 people per village minimizes village-level general equilibrium effects. Random assignment should ensure that the second assumption holds.

[17] Nobody in the control group sought treatment through GASS. It is possible but unlikely that control participants sought treatment elsewhere; most people with mental disorders go untreated in this setting.

We test whether PC and PC/LA have the same effects ($\beta_1 = \beta_3$ and $\beta_4 = \beta_6$) and whether there are no complementarities between PC and LA ($\beta_3 - \beta_1 - \beta_2 = 0$ and $\beta_6 - \beta_4 - \beta_5 = 0$). Moreover, we test that the treatment effects do not differ by arm ($\beta_1 = \beta_2 = \beta_3$ and $\beta_4 = \beta_5 = \beta_6$) and that the other pairwise effects are identical (e.g., $\beta_1 = \beta_2$, and $\beta_3 = \beta_2$). We use OLS and cluster standard errors by village.

We estimate ANCOVA and LASSO versions of this specification for all outcomes. Under ANCOVA, X includes the baseline dependent variable and strata and time dummies.[18] The LASSO approach uses the post-double-selection method of Belloni et al. (2014) to choose covariates. When these approaches yield similar estimates (the majority of cases), the text describes the ANCOVA estimates. Otherwise, we note the discrepancy between the two estimates.[19]

Table 1 shows baseline summary statistics of key outcome variables and covariates by intervention arm. Columns 2-3 show the control mean and standard deviation of each variable. Columns 4-9 show the mean difference between each intervention arm and the control arm, along with p-values (based on village-clustered standard errors) that indicate the statistical significance of these differences. Finally, Column 10 provides the p-value for the joint test of significance of the three intervention arms relative to control. Most outcomes are balanced across intervention arms in Round 1, and we cannot reject that the variables in the table are

[18]Our analysis plan prescribes using an ANCOVA specification for outcomes with low serial correlation and a difference-in-difference specification for outcomes with high serial correlation (McKenzie 2012). In practice, all outcomes have serial correlations below 0.3, except for the durable goods index, which has serial correlation of 0.53. Therefore, we use ANCOVA to streamline the analysis. Difference-in-difference estimates closely resemble ANCOVA estimates and are available from the authors.

[19]For the lasso regression, we allow the estimator to select from the following list of baseline covariates: strata indicators, round indicators, gender, marital status, education, scheduled caste/tribe, literacy, household size, PHQ-9 score and components, PHQ-9 $<$ 10 indicator, PHQ-9 $<$ 5 indicator, GAD-7 (anxiety) score and components, activities of daily living index and components, time use (all work, paid work, unpaid work, sleep, leisure, and job search hours), per capita household non-durable consumption and expenditures (total, food, non-food, clothes for children, medical), sanitation/hygiene index and components, older child human capital index and components, young child health index and components, per capita net savings and components, durable goods index and components, risk intolerance index and components, negative shock index and components, cognition index and components, subjective wellbeing index and components, participation in household decision and components. This list includes the baseline values of all outcomes in our analysis. Child human capital regressions also include child-level covariates: an indicator that the individual is the child of the study participant, the baseline human capital index and components, and age and gender dummies. To avoid dropping observations, we include indicators for missing values of all covariates and then set missing values to zero. The algorithm chooses the baseline dependent variable or some of its components in 76 percent of cases. All specifications choose at least some time dummies and 36 percent of specifications select at least some strata dummies. The algorithm selects a median of nine covariates.

jointly balanced ($p = 0.21$). However, the table shows that PHQ-9 scores are imbalanced, which could contribute to follow-up differences in this or other outcomes. To address this concern, we also estimate a version of all regressions that uses entropy weights to impose balance across arms in the first three moments of the PHQ-9 distribution (Hainmueller 2012, Hainmueller and Xu 2013). Estimates are robust to weighting, and weighted estimates (available from the authors) are generally similar to unweighted estimates.

The last row of Table 1 shows that, overall, attrition does not vary systematically by arm. However, when we examine attrition by arm, we find a higher attrition rate in the PC arm for Round 5. Appendix A.5 considers this issue and concludes that differential attrition does not affect the results we present below.

7 Impacts on Participants

7.1 Depression Symptoms

Table 2 shows treatment effects on depression symptoms. Both pharmacotherapy arms improve mental health to some extent. However, the impact of PC/LA is significantly larger and more durable: PC/LA reduces the PHQ-9 score by 0.26 SD (-0.39/-0.12) during the PC intervention and by 0.24 SD (-0.38/-0.10) afterward, while PC alone reduces the PHQ-9 score by 0.14 SD (-0.27/-0.001) during the PC intervention and by 0.04 SD (-0.17/0.09) afterward. These effect sizes are consistent with the literature, as we discuss in Appendix A.6.

Tests of coefficient equality confirm that the impact of PC/LA is significantly larger than the impact of PC or LA alone, and fail to reject that PC and LA have similar effects. The impact of PC/LA is generally larger than the sum of the impacts of PC and LA, consistent with a complementarity between these interventions. However, this difference is generally statistically insignificant ($0.10 \leq p < 0.28$). LA has smaller effects than the other arms: -0.08 SD (-0.22/0.06) during the PC intervention and 0.01 SD (-0.13/0.14) afterward. The differences between the effects of LA and PC are not statistically significant.

To quantify the differential impact of PC/LA over PC, we compute the total reduction in PHQ-9 $\times$ months over the study period for each arm.[20] Under this metric, PC/LA is 3.5 times more effective than PC. Since PC/LA costs just 5 percent more than PC alone ($232 versus $221 per study participant), bundling PC and LA improves the cost effectiveness in terms of reducing depression symptoms. Appendix A.7 describes this exercise in more detail.

Two figures provide more information about the treatment effects on mental health. Figure 2 plots the PHQ-9 densities by arm during and after the PC intervention. Depression symptoms decrease throughout the support both during and (to a lesser extent) after the intervention. As noted, impacts are largest for PC/LA participants. Figure 3 plots average PHQ-9 scores by arm and round. The gap between treatment and control is largest for the PC/LA arm in every round and smaller, but still positive, for the other arms. It gradually decreases over time as mental health improves in the control group. This pattern is consistent Spijker et al.'s (2002) finding that depression symptoms diminish over 1-2 years for most people but persist for 10-30 percent of patients.

Appendix A.8 provides effects on the probability of no moderate or severe depression (PHQ-9 $<$ 10) and no depression (PHQ-9 $<$ 5). These estimates are helpful for comparative purposes since they are commonly reported in the literature. Table A2 and Figure A5 show that the results for these outcomes are qualitatively similar to our main results: both PC and PC/LA reduce the frequency of mild and moderate depression, but PC/LA has bigger and more long-lasting impacts. We also find that LA has a modest impact on the frequency of moderate or severe depression.

Appendix A.9 estimates heterogeneity in the impact on mental health by baseline gender, age, socioeconomic status, PHQ-9 score, physical health, cognition, and exposure to negative shocks during childhood. These estimates appear in Figure A6. Both PC/LA and PC have larger effects for people with worse physical health. PC/LA is more effective for people with many childhood shocks. We do not find significant heterogeneity in the impact of LA or in the impacts of any of the interventions along other dimensions.

Figure A7 in Appendix A.10 estimates impacts on the GAD-7 anxiety score and an index of activities of daily living (ADL). The PC/LA intervention significantly reduces anxiety

[20] We multiply the "during" period estimates in Column 1 of Table 2 by eight months and the "after" period estimates in Column 1 by eighteen months.

while the other interventions do not have statistically significant effects. The impact on activities of daily living varies by arm: PC/LA statistically increases the ADL index, PC decreases it during the intervention, and LA does not have statistically significant effects.

7.2 Work Time and Earnings

Table 3 shows that PC/LA and PC have different treatment effects on weekly work time and earnings while the PC intervention is ongoing. The effect of PC on work time is -5.4 hours per week (-8.2/-2.6) and the effect on earnings is -65 rupees per week (-155/24), a 10 percent decrease in both outcomes. By contrast, the effect of PC/LA on work time is 1.1 hours per week (-1.7/3.8) and the effect of PC/LA on earnings is 38 rupees per week (-63/139). The difference between the effects of PC/LA and PC in the "during" period is significant for work time ($p = 0.001$) but not for earnings ($p = 0.12$). Figure A8 shows that there is a concurrent increase in sleep and leisure time in the PC arm, as we discuss in Appendix A.11. This pattern suggests that PC may reduce work time by increasing the marginal utility of leisure or self-care. Alternatively, mental health stigma might reduce either labor supply or demand (Corrigan et al. 2001, Bharadwaj et al. 2017). The significant negative impact of PC and the significant difference between PC and PC/LA are not present at follow-up, at which point the effects are negative for both arms, but closer to zero and statistically insignificant.[21]

In sum, our results suggest that pharmacotherapy does not increase the time spent on productive activities in our sample. 86 percent of our study participants are female, and low female labor force participation in India may weaken the labor market impacts in this setting. Baranov et al. (2015) and Bhat et al. (2022) also find no long-term effects of psychotherapy on labor market outcomes among all or mostly female samples in South Asia. By contrast, Patel and Kleinman (2003) and Patel et al. (2017) find that mental health care reduces self-reported work absenteeism and Lund et al. (2018) find that various mental health interventions have positive effects on employment.

The LA intervention has no statistically or economically significant effects on work time

[21] PC/LA reduces work time under the ANCOVA specification (-6.2/-0.4) but has a statistically insignificant effect under LASSO (-6.3/0.6).

and earnings. In the "during" period, the effect of LA on work time is -1.0 hours per week (-3.8/1.8) and the effect on earnings is -33 rupees per week (-135/69). In the "after" period, the effect of LA on work time is -1.5 hours per week (-4.7/1.7) and the effect on earnings is 48 rupees per week (-55/150). There are likely multiple barriers to increasing work time and earnings for our sample. Our findings suggest that neither mental health care nor livelihoods assistance are sufficient to overcome these barriers.

8 Impacts on Children and the Household

Impacts on child human capital investment appear in Table 4. Most effects are not statistically significant in the "during" period, although PC increases investment by 0.13 SD (0.01/0.26) under the LASSO specification.[22] Effects of PC/LA and PC are significantly different from each other, consistent with patterns for several other outcomes. In the "after" period, all coefficients are positive and are not significantly different from one another. However, only the impact of PC is statistically significant under both specifications. Under ANCOVA, PC has an effect of 0.18 SD (0.02/0.34), while PC/LA has an effect of 0.12 SD (-0.09/0.33) and LA has an effect of 0.11 SD (-0.08/0.30).[23] We also collected health and anthropometric data for children under age five. However, only 85 study participants resided with young children who provided measurements. Estimates for these outcomes (available from the authors) are imprecise but align with the positive impacts on child human capital discussed here. Finding that the LA arm, which had minimal mental health improvements, also increases child human capital suggests that the treatments may affect human capital investment also through channels other than improved mental health. For example, the interventions may raise awareness of mental health within the household or lead the household to reconsider important economic choices.

Next, we examine heterogeneity by the median age of 12, which corresponds to the

[22]The impact on child human capital investment may occur with a lag because enrollment typically occurs at the beginning of the academic year. In addition, school attendance and homework time are likely to be inelastic among non-enrolled students and among all students during periods when school is not in session. Enrollment, attendance, and homework maybe unresponsive in Round 2 because it occurred during the same academic year as Round 1. In addition, attendance and homework may be unresponsive in Round 3 because school was not in session for many students at that time.

[23]Figure A9 shows impacts on the components of the child human capital investment index.

transition to secondary school. Estimates are small and statistically insignificant for younger children. For older children, PC/LA has an impact of 0.40 SD (0.01/0.79), PC has an impact of 0.44 SD (0.17/0.70), and LA has an impact of 0.32 SD (0.01/0.64) in the "after" period, with slightly larger estimates under LASSO. The effects differ significantly by child age for PC/LA ($p = 0.09$) and for PC ($p = 0.02$), but not for LA ($p = 0.18$). This pattern may reflect a ceiling on the potential impact for younger children. For example, for children who are 12 or younger in the control group, 94 percent are enrolled and 0.5 percent work for pay across Rounds 1-4. By comparison, 85 percent of children over 12 are enrolled and 11 percent work for pay.

To benchmark these impacts, we compare our estimates for enrollment with the impacts of both educational interventions on enrollment from Evans and Yuan (2020) and conditional and unconditional cash transfers from the meta-analysis by Baird et al. (2014). We find that our estimates are within the range of both sets of outcomes, suggesting that these effects are economically relevant.

Figure 4 shows treatment effect heterogeneity in the "after" period by several additional characteristics, including the child's gender, relation to the study participant and baseline human capital, as well as the study participant's baseline depression severity and gender. There is a significantly larger effect of PC/LA for boys and children with high baseline human capital investment, but other differential effects are statistically insignificant.

Figure 5 shows that the interventions have no statistically significant impacts on hygiene/ sanitation, durable good ownership, or household consumption. An exception to this pattern is that PC significantly reduces per capita household consumption in the "during" period. A concurrent decline in per capita household income for the PC arm may be responsible for this effect.[24] Appendix A.13 shows impacts on the components of these indices.

[24] PC reduces per capita household income by Rs. 44 (5/83) and reduces per capita household consumption by Rs. 59 (20/96) in the "during" period. No other arms have statistically significant effects on this outcome either during or after the PC intervention.

9 Potential Pathways

This section considers four pathways that may link depression and depression treatment to socioeconomic outcomes: risk intolerance, subjective wellbeing, cognitive performance, and participation in household decisions. Figure 6 shows treatment effects on these outcomes.

The interventions increase risk intolerance, although the timing and significance of the effects vary across arms. PC increases risk intolerance by 0.25 SD (0.05/0.43) and PC/LA increases risk intolerance by 0.18 SD (-0.01/0.38) in the "after" period, while LA increases risk intolerance by 0.16 SD (0.01/0.26) in the "during" period. This pattern is consistent with a preferences pathway in which treatment reduces anhedonia and pessimism. These common depression symptoms reduce the actual and expected marginal utility of consumption, which may decrease the perceived return on human capital investment, as well as the desire to minimize the incidence of negative shocks.[25] This pathway is also consistent with the relationship between chronic illness and the marginal utility of consumption (Finkelstein et al. 2013), as well as the negative association between poverty and the enjoyment of various activities (Schofield and Venkataramani 2021).

Consistent with this interpretation, we find that the pharmacotherapy interventions reduce the incidence of negative shocks. Figure A16 shows that PC/LA reduces the incidence of negative shocks by 0.14 SD (0.01/0.28) and PC reduces the incidence of negative shocks by 0.11 SD (0.02/0.24) in the "after" period.[26] These findings suggest that, in addition to suppressing human capital investment, depression may also perpetuate poverty by exposing people to additional shocks that prevent wealth accumulation (Lybbert et al. 2004, Carter and Barrett 2006).

Next, we consider the impacts on subjective wellbeing, which is a proxy for utility. Since depression is emotionally painful, we may expect depression treatment to improve wellbeing

[25] This logic is commonly applied to mortality risk in order to elicit the value of statistical life (e.g. León and Miguel 2017). For a reduction in the marginal utility of consumption to have this effect, the cost of taking action must not decrease commensurately. Fatigue and impaired cognition, which are also depression symptoms, likely increase the cost of taking action.

[26] Since "an illness lasting at least one month" is an element of the negative shock index, the interventions could mechanically improve the index by reducing the incidence of depression. We investigate this possibility by excluding the illness component and find results that are robust and very similar to the estimates in Figure A16. Estimates are available upon request.

(Smith et al. 2020). However we find that the interventions reduce subjective wellbeing. The effect size varies by intervention arm but ranges from -0.18 to 0 SD, despite the observed improvements in mental health in Table 2. This pattern suggests that the interventions may change aspirations, expectations, or reference points, which is consistent with findings by Adhvaryu et al. (2020) that objective improvements in circumstances that fall short of expectations reduce life satisfaction.

Depression could also change behavior by affecting cognition. Figure 6 shows an impact of PC/LA on cognitive performance of -0.16 SD (-0.30/-0.02) and an impact of PC on cognitive performance of -0.19 SD (-0.32/-0.06) in the "after" period. The lack of a positive effect rules out that improved cognition is a pathway through which better mental health can lead to improved socioeconomic outcomes for our sample. Appendix A.14 discusses possible explanations for this finding.

Finally, we consider impacts on participation in household decisions. We do not find evidence for this channel: most estimates are small and statistically insignificant both during and after the PC intervention. An examination of the components of this index in Figure A18 suggests a shift toward joint rather than individual decision-making under PC.

10 Joint Significance and Treatment Complementarities

This section tests whether the interventions have effects that are jointly significant across the eleven main outcomes of our analysis.[27] We use the "omnibus" test proposed by Young (2019) to examine whether the interventions have significant. We reject the null hypothesis that the three interventions are jointly insignificant ($p < 0.001$). Implementing this test separately by intervention arm, we reject the hypothesis of no effect of PC/LA ($p = 0.001$) and of PC ($p = 0.001$) but fail to reject the hypothesis of no effect of LA ($p = 0.22$). Therefore we conclude that both pharmacotherapy interventions have significant effects.

Next, we re-estimate the effects on these eleven outcomes as a system of seemingly unrelated regressions (SUR) to test the additional hypotheses described in Section 6 jointly

[27] These outcomes are the PHQ-9 score, weekly work time, weekly earnings, child human capital investment, hygiene/sanitation, durable goods ownership, per-capita consumption, risk intolerance, subjective wellbeing cognitive performance, and participation in household decisions.

across outcomes. When comparing the effects of PC and PC/LA ($H_0 : PC = PC/LA$), we reject equivalence in the "during" period ($p = 0.001$) but not in the "after" period ($p = 0.37$). We reject equivalence if we pool time periods ($p = 0.001$). When testing for "no complementarity" in the effects of PC and LA ($H_0 : PC/LA = PC + LA$), we find evidence of complementarity in the "during" period ($p = 0.001$) but not in the "after" period ($p = 0.74$). We reject this hypothesis if we pool time periods ($p = 0.02$). These findings reaffirm our conclusions that pairing LA with PC leads to significantly different outcomes and that LA appears to temper several transitory negative effects of PC in the "during" period.[28]

11 Discussion

There is an urgent need for mental health care in India and other developing countries. In a representative survey we conducted adjacent to the study area, 24 percent of adults had at least mild depression symptoms and depression was strongly correlated with low socioeconomic status. Although the Mental Health Care Act of 2017 creates a legally-binding right to mental health care in India (Duffy and Kelly 2019), only 15 percent of people with depression in India receive care (Gautham et al. 2020). Evidence regarding the effectiveness of depression treatment in low-income settings is limited (Patel et al. 2007). The impact of treatment may differ across developed and developing countries due to disparities in health care access and quality, the severity of depression, the prevalence of different types of depression (Harald and Gordon 2012), awareness of mental illness, stigma, and treatment compliance.

Psychotherapy and pharmacotherapy are the leading approaches to depression treatment. While studies have shown the utility of psychotherapy as a way to provide depression care to poor people in developing countries (Baranov et al. 2020, Haushofer et al. 2020, Patel et al. 2017, Barker et al. 2021), research has not explored the effectiveness of community-based pharmacotherapy. Since it requires fewer personnel than psychotherapy, pharma-

[28]The SUR approach allows us to test the remaining Section 6 hypotheses jointly. We fail to reject the hypothesis that the effects of PC and LA are equal ($p = 0.16$ overall, $p = 0.35$ in the "during" period, $p = 0.29$ in the "after" period). We reject the hypothesis that the effects of PC/LA and LA are equal overall ($p = 0.07$) and in the "during" period ($p = 0.03$) but not in the "after" period ($p = 0.26$). We reject the hypothesis that the three interventions have equal effects overall ($p < 0.001$) and in the "during" period ($p < 0.001$) but not in the "after" period ($p = 0.19$).

cotherapy may be a valuable tool to treat depression in low and middle income countries, where mental health specialists are scarce (Saxena et al. 2007).

In our trial, we find effects on depression symptoms that align with the clinical literature (Gartlehner et al. 2017). While treating depressed adults increases child human capital investment, it also has some negative impacts, most of which are transitory. Pairing livelihoods assistance with pharmacotherapy increases the size and duration of the mental health benefit, preserves the positive effect on child human capital investment, and safeguards people against several of these negative effects. Adding livelihoods assistance increases intervention costs by only 5 percent.

Future research should investigate the complementarity between pharmacotherapy and livelihoods assistance and whether other inexpensive light-touch interventions enhance the benefit of mental health care in a similar way. Since LA does not directly increase work time or earnings, features other than job-related benefits of LA may impact mental health. The group and individual social interactions that occur under LA may have enabled participants to receive emotional support from like-minded peers. Higher medication adherence among the PC/LA participants also suggests that LA may have improved the ability of participants to plan or follow through. Moreover, LA may have helped participants overcome the stigma of receiving mental health care by supplying a "reason" for participating without admitting to mental illness.

Finding that treating adult depression increases child human capital investment suggests that the well-known correlation between parental depression and child development is at least partially causal. The magnitude of this impact is large. Therefore, this finding shows that adult mental health may be an important demand-side constraint on child human capital accumulation.

Finally, our study suggests that depression treatment may change preferences by increasing risk intolerance, consistent with an increase in the marginal utility of consumption. This finding of an impact on preferences is broadly consistent with the evidence from Bhat et al. (2022), although they find effects on altruism and patience, rather than risk tolerance. This divergence between our findings could reflect a difference between psychotherapy and pharmacotherapy.

A central question for the study of the psychology of poverty is the extent to which depression contributes to poverty by changing economic behavior. A methodological challenge is that both psychotherapy and pharmacotherapy RCTs induce random variation in depression treatment, rather than depression itself. Both therapeutic approaches may have effects through channels other than improved mental health. For example, psychotherapy may enhance someone's ability to solve problems and may improve self efficacy irrespective of its effects on depression, while the side effects of antidepressants could directly affect productivity. While it is impossible to rule out additional effects of treatment, finding common impacts of psychotherapy and pharmacotherapy suggests that these impacts may be due to improved mental health.

To our knowledge, Baranov et al. (2020) and Bhat et al. (2022) are the only large-scale RCTs that study the long-term impact of psychotherapy on socioeconomic outcomes for people with depression. A comparison of our study with these studies shows important commonalities. Like Baranov et al. (2020), we find that child human capital investment increases when treatment enables people with depression to recover. Like Bhat et al. (2022), we find that depression treatment may change economic preferences.[29] As the evidence base grows, our understanding of the linkages between depression and poverty will continue to improve.

[29]Baranov et al. (2020) do not measure preferences and Bhat et al. (2022) do not measure child human capital investment. Haushofer et al. (2020) find that a psychotherapy intervention that has no impact on adult depression after one year also does not cause any changes to children's education. This finding also suggests that the changes in education discussed above are due to reductions in depression.

Table 1: Baseline Summary Statistics

	N	Control		PC/LA		PC		LA		Joint
		Mean	St. Dev.	Diff.	P-Value	Diff.	P-Value	Diff.	P-Value	P-Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A: Respondent, Child, and Household Characteristics										
Age	1,000	35.6	7.6	-0.32	0.65	-0.53	0.46	-0.69	0.32	0.76
Female	1,000	0.90	0.30	-0.06	0.04	-0.06	0.06	-0.05	0.09	0.07
Married	1,000	0.78	0.41	0.00	0.94	0.00	0.96	-0.03	0.38	0.82
Schooling (years)	995	4.95	4.27	0.32	0.39	-0.22	0.57	0.08	0.83	0.65
Scheduled Caste/Tribe	999	0.50	0.50	0.02	0.76	0.06	0.25	0.05	0.31	0.61
Literacy (1-3)	999	1.9	0.92	0.06	0.55	-0.05	0.54	-0.01	0.94	0.78
Household size	1,000	4.17	1.62	0.07	0.63	001	0.94	-0.19	0.18	0.38
Exposure to early-life shocks	1,000	92.5	96.6	-1.8	0.83	7.5	0.39	-7.0	0.43	0.57
Housing quality index	743	0	1	0.02	0.88	0.06	0.57	0.01	0.94	0.95
B: Primary Outcomes										
PHQ-9 depression scale (0-27)	1,000	14.4	3.3	-0.83	0.03	-0.5	0.21	-0.8	0.03	0.08
Weekly paid and unpaid work hours	1,000	57.1	28.1	-1.75	0.51	-2.0	0.35	-0.19	0.94	0.76
Weekly earnings (Rs.)	1,000	308	668	103	0.14	57	0.37	7	0.9	0.44
C: Household Socioeconomic Outcomes										
Hygiene and sanitation	974	0	1	-0.13	0.23	0.00	0.98	0.09	0.37	0.36
Durable goods	983	0	1	0.03	0.78	0.06	0.51	-0.08	0.40	0.62
Total per capita consumption (Rs.)	1,000	463	251	-18	0.46	21	0.36	18	0.53	0.46
D: Child Outcomes										
Human Capital Investment Index	902	-0.03	1.01	-0.09	0.47	-0.02	0.86	0.12	0.24	0.41
E: Potential Mechanisms										
Prevention and risk intolerance	971	0	1	-0.26	0.02	-0.05	0.63	-0.21	0.05	0.04
Cognitive performance	1,000	0	1	0.05	0.62	-0.12	0.22	-0.06	0.47	0.43
Subjective wellbeing	974	0	1	-0.01	0.91	0.11	0.25	0.08	0.43	0.52
Participation in household decisions	997	1.24	0.93	0.12	0.16	0.05	0.57	0.17	0.04	0.16
Number of rounds present (1-5)	1,000	4.5	1.1	-0.05	0.62	-0.2	0.06	0.07	0.46	0.12

Note: PC = psychiatric care, LA = livelihoods assistance, C = control. All statistics are computed at baseline. Column 1 shows the sample size across all arms. Columns 2-3 show the mean and standard deviation in the control arm. Columns 4, 6, and 8 show the difference between the PC/LA, PC, and LA arms and the control arm. Columns 5, 7, and 9 show the p-values for these differences based on regressions with village-clustered standard errors. Column 10 reports the p-value for the joint significance of the parameters in Columns 4, 6, and 8. The housing quality index is the first principal component of four measures of the quality of the flooring, roof, and walls of the dwelling as observed by the surveyor. Exposure to early life shocks is based on the Holmes and Rahe (1967) scale. All other variables are self explanatory or are described in the text.

Table 2: Impact on Depression Severity

	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
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 19 explains this approach in more detail. Village-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Impact on Weekly Work Time and Earnings

	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
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 19 explains this approach in more detail. Village-clustered standard errors appear in parentheses. “During” and “after” estimates are based on a common regression. The outcome in Columns 1 and 3 is weekly productive time, the sum of time spent on primary and secondary jobs, agriculture, child care, cooking, cleaning, laundry, and fetching water. The outcome in Columns 2 and 4 is weekly earnings from primary and secondary jobs. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Impact on Child Human Capital Investment

	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	-0.19
	(0.090)	(0.090)	(0.059)	(0.060)	(0.17)	(0.17)
PC	0.11	0.13*	0.00027	0.00065	0.17	0.21
	(0.073)	(0.075)	(0.056)	(0.059)	(0.12)	(0.13)
LA	0.036	0.041	-0.061	-0.061	0.12	0.12
	(0.065)	(0.066)	(0.059)	(0.059)	(0.10)	(0.11)
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	0.01
H_0: $PC = LA$	0.34	0.23	0.38	0.36	0.67	0.51
H_0: $PC/LA = LA$	0.06	0.08	0.95	0.96	0.04	0.07
H_0: $PC/LA = PC = LA$	0.05	0.09	0.57	0.56	0.07	0.09
Control mean of outcome	0	0	0.22	0.22	-0.20	-0.20
B: After the PC Intervention						
PC/LA	0.12	0.13	-0.083	-0.073	0.40*	0.44
	(0.13)	(0.13)	(0.13)	(0.13)	(0.24)	(0.27)
PC	0.18*	0.22**	-0.012	-0.0014	0.44***	0.54***
	(0.099)	(0.10)	(0.11)	(0.11)	(0.16)	(0.17)
LA	0.11	0.12	-0.025	-0.019	0.32*	0.36*
	(0.12)	(0.12)	(0.11)	(0.11)	(0.19)	(0.19)
H_0: $PC/LA = PC$	0.61	0.45	0.62	0.62	0.87	0.69
H_0: $PC/LA = PC + LA$	0.30	0.21	0.80	0.77	0.21	0.14
H_0: $PC = LA$	0.53	0.33	0.92	0.89	0.53	0.29
H_0: $PC/LA = LA$	0.97	0.92	0.69	0.71	0.76	0.78
H_0: $PC/LA = PC = LA$	0.78	0.56	0.88	0.88	0.82	0.57
Control mean of outcome	0	0	0.21	0.21	-0.27	-0.27
Specification	ANCOVA	LASSO	ANCOVA	LASSO	ANCOVA	LASSO
Observations	2232	2232	1244	1244	988	988

Note: The table reports AIT effects following Equation (1). 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 the impact of each treatment is equal across subgroups 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

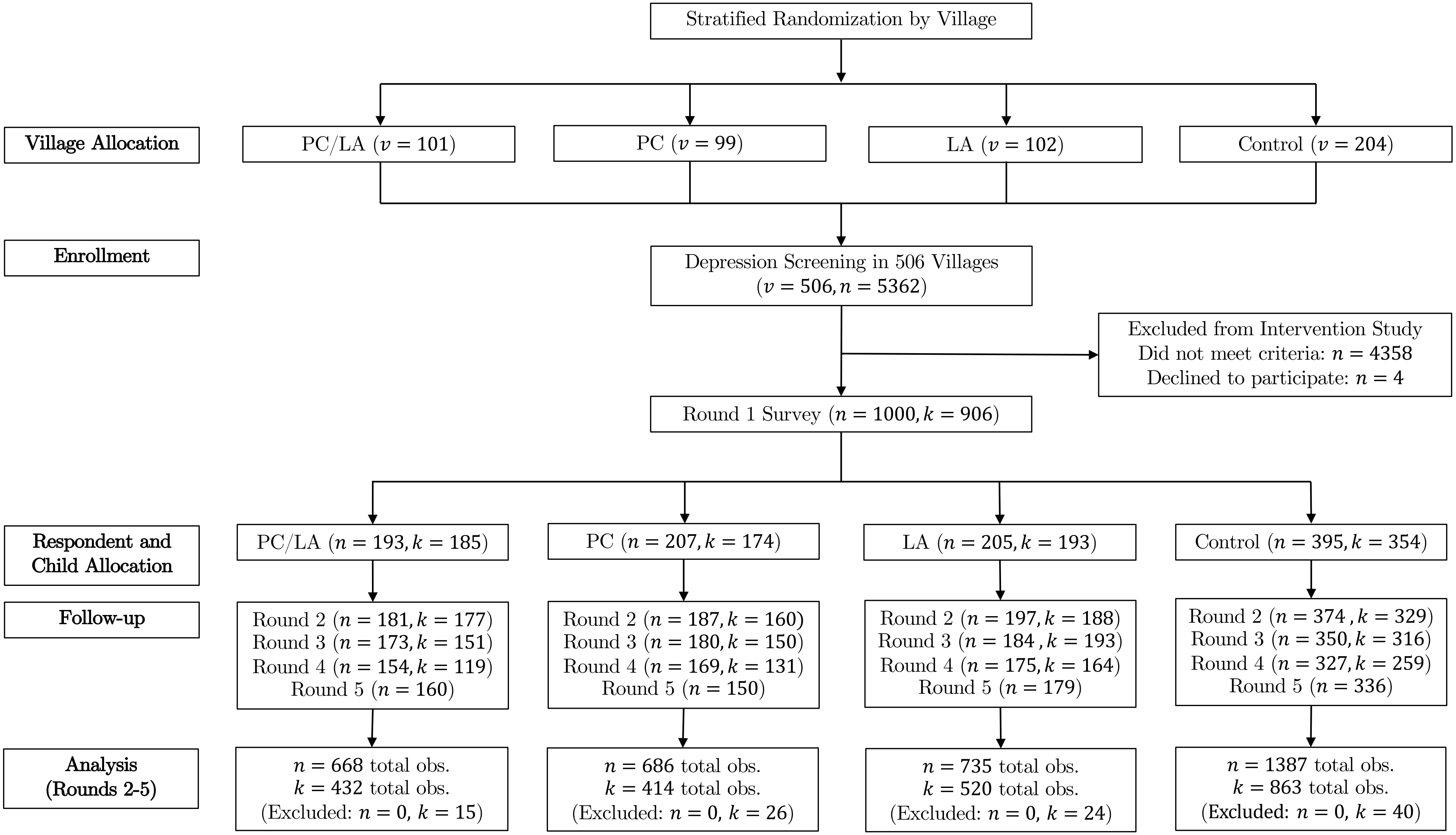

Figure 1: CONSORT Flow Diagram

Note: the chart shows trial design and the allocation of villages, respondents, and household children to intervention arms. v indicates the number of villages, n the respondents, and k the children. We randomized villages across intervention arms and then recruited participants through depression screening within the community. Participants immediately completed the Round 1 ("Baseline") survey. Participants in the PC/LA and PC arms received the PC intervention. Participants in the PC/LA and LA arms received the LA intervention. Figure A2 illustrates the study timeline in more detail.

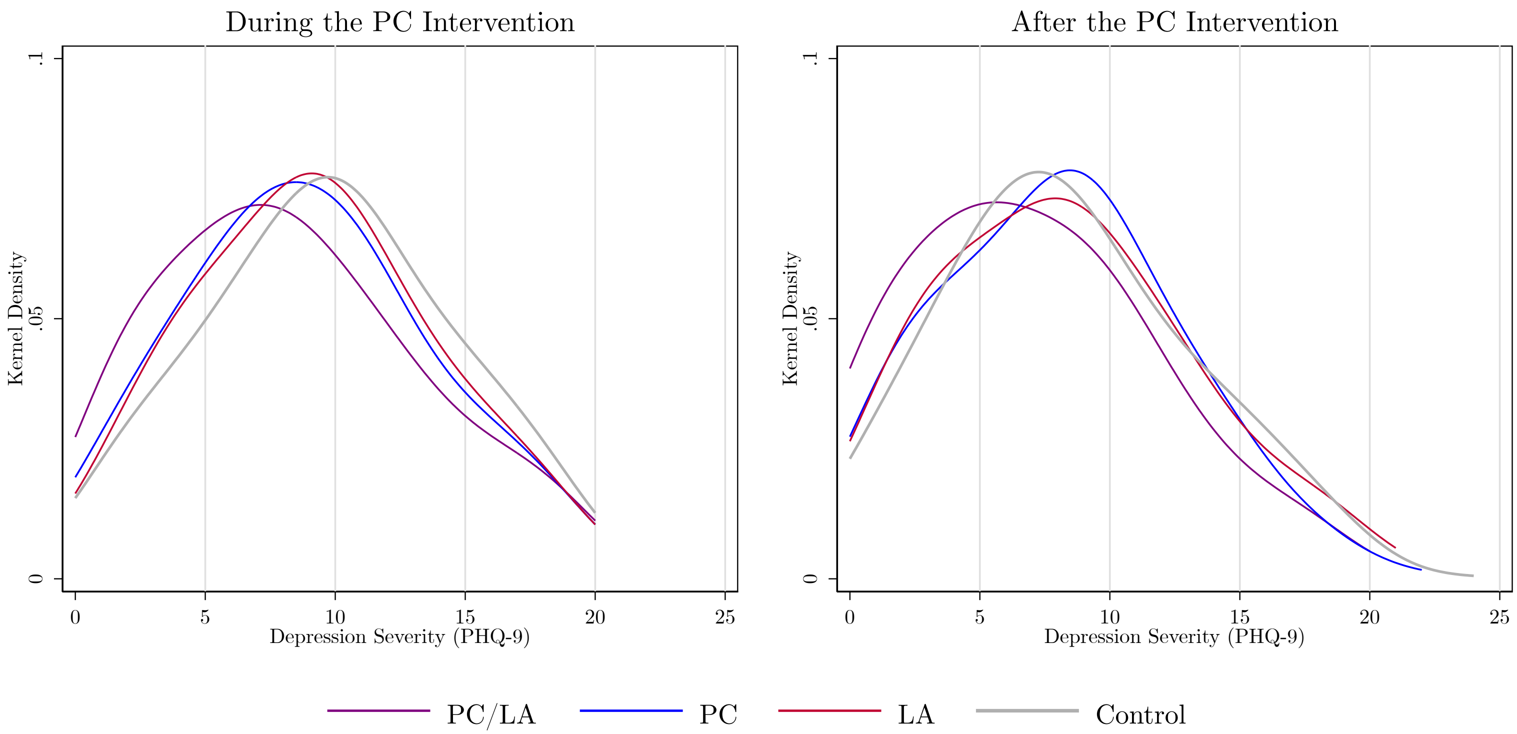

Figure 2: Density of PHQ-9 Scores by Arm

Note: The figure shows the density of PHQ-9 scores by intervention arm during the PC intervention (left panel) and after the PC intervention (right panel).

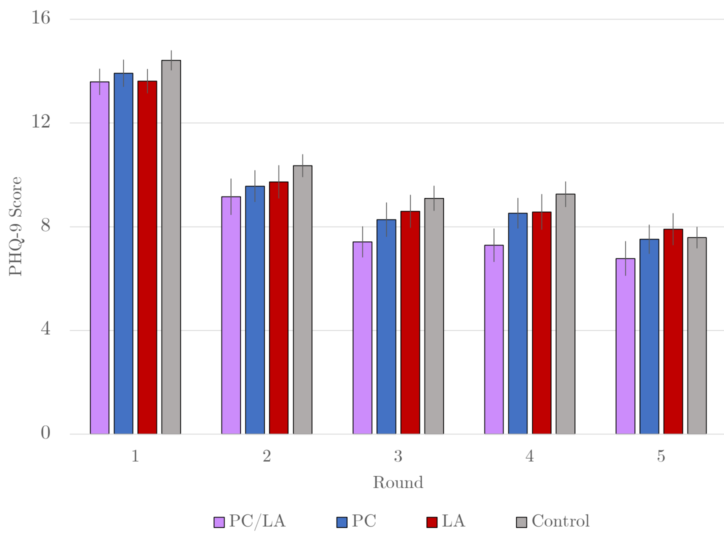

Figure 3: Depression Severity by Round and Intervention Arm

Note: The figure shows the average PHQ-9 score by survey round. Error bars show 90 percent confidence intervals based on village-clustered standard errors.

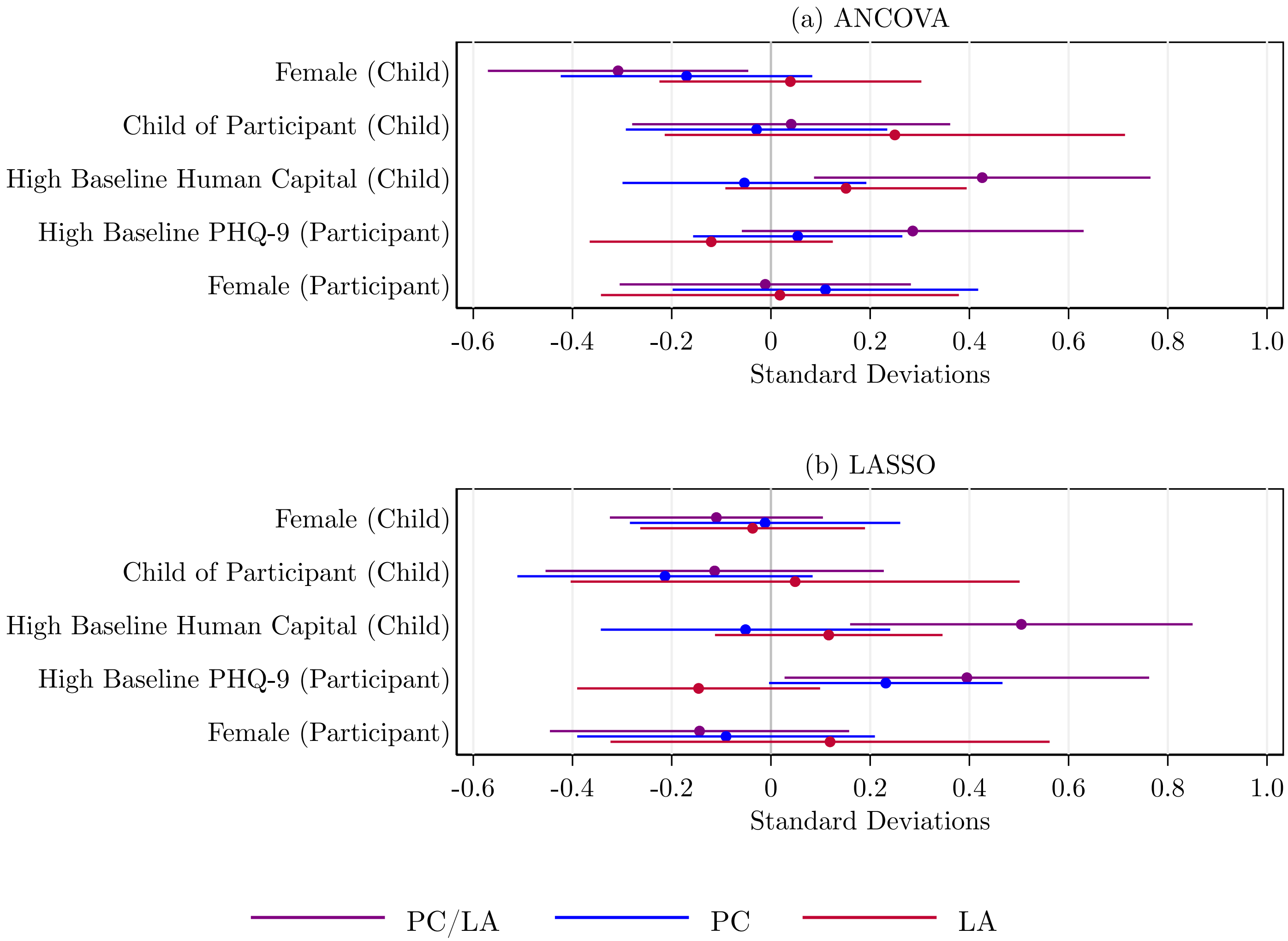

Figure 4: Heterogeneous Impacts on Child Human Capital Investment in Round 4

Note: The figure shows impacts by subgroup on the child human capital index in Round 4. Error bars indicate 90 percent confidence intervals. All estimates modify Equation (1) to include designated interaction terms. Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. All estimates are weighted by the inverse number of school-aged children in the household. We examine heterogeneity according to the child's gender, relation to the study participant, and baseline human capital investment, as well as the participant's baseline PHQ-9 score and the participant's gender. We divide at the median for baseline child human capital investment (0.24 SD) and baseline participant PHQ-9 score (15).

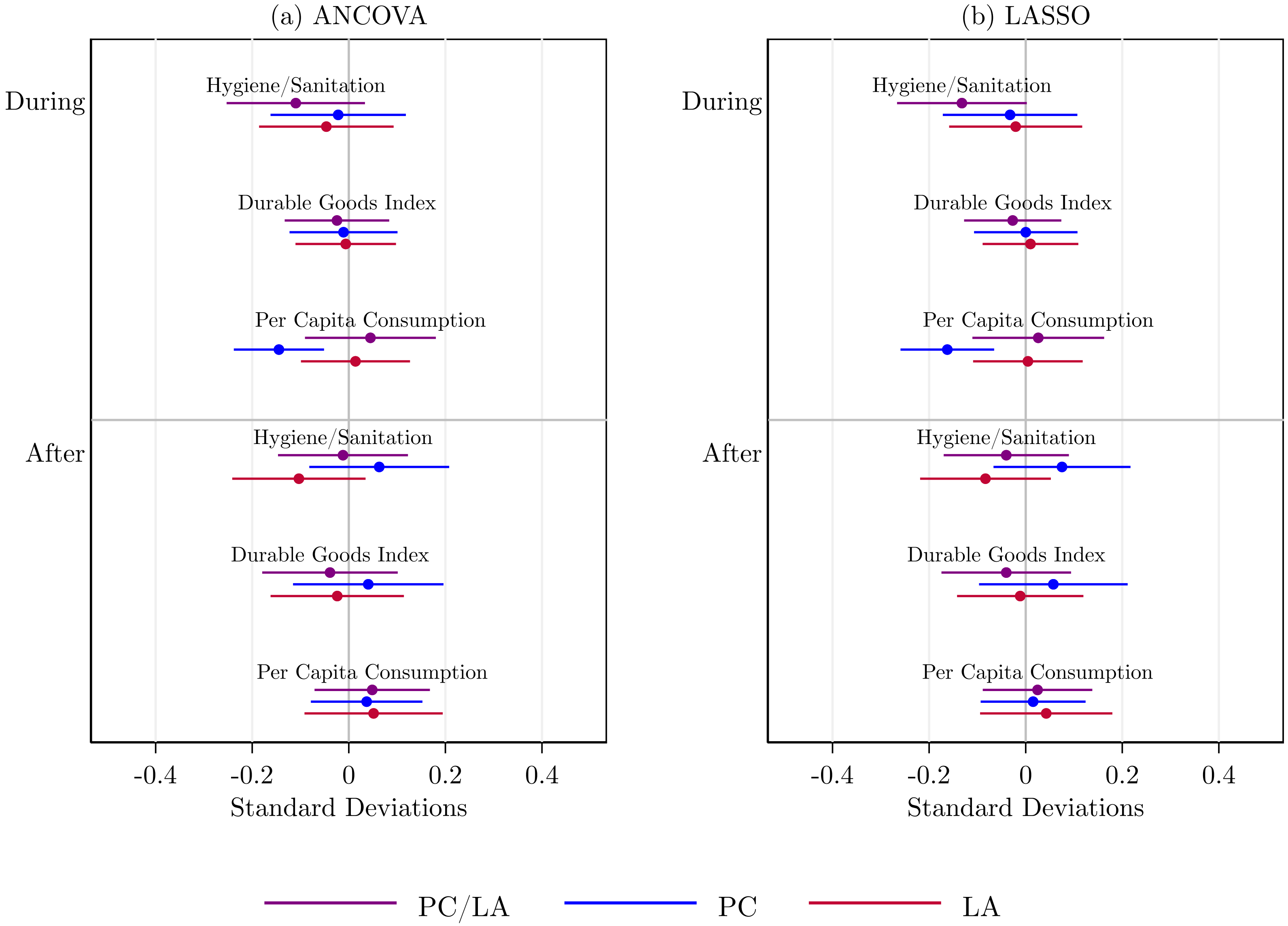

Figure 5: Standardized Impacts on Socioeconomic Outcomes

Note: The figure shows standardized impacts and 90 percent confidence intervals for socioeconomic outcomes, as explained in the text. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention.

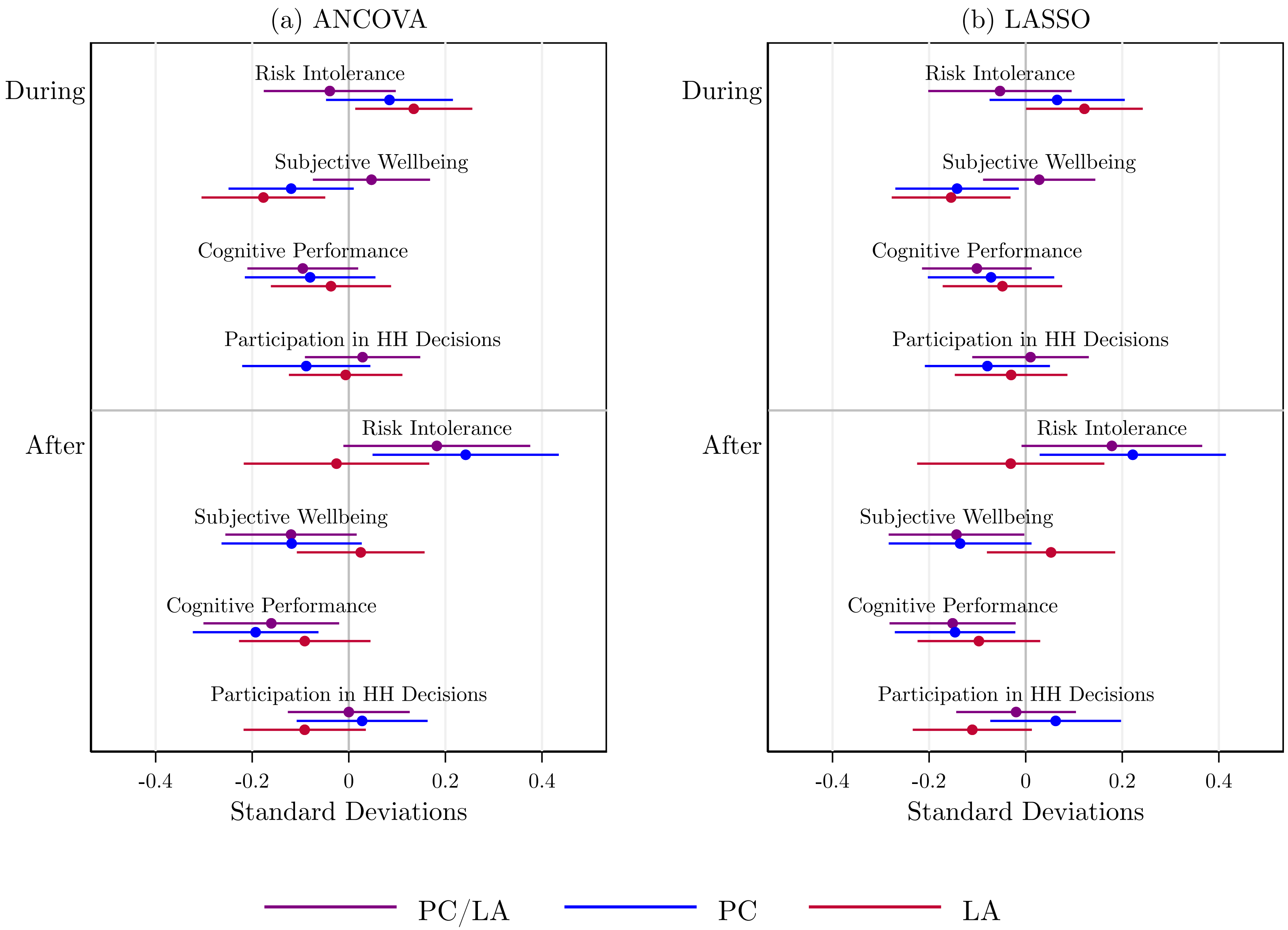

Figure 6: Standardized Impacts on Possible Pathways

Note: The figure shows standardized impacts and 90 percent confidence intervals for potential mechanisms through which depression treatment may improve socioeconomic outcomes, as explained in the text. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention.

A Appendix: For Online Publication

A.1 Depression Prevalence and Correlates in the Community

The global prevalence of major depressive disorder (MDD) is around 5 percent (Ferrari et al. 2013). A much larger fraction of people have minor depression, which also impacts quality of life and is a leading risk factor for developing more severe illness (Cuijpers et al. 2004). Depression is higher for women (Piccinelli and Wilkinson 2000) and people with lower socioeconomic status (Sareen et al. 2011).

Although these general patterns are clear, the prevalence of depression and the association between depression and economic circumstances may vary across settings. To gauge the impact of depression in the study context, we measured depression symptoms in a representative sample of adults in Madhugiri District, Karnataka, which is adjacent to the study area and has similar demographic characteristics.[30] A comparison to the 2011 Census of India shows that our sample is representative of the caste, gender, and religious composition of Madhugiri. Estimates in this section are weighted to match the gender, religion, caste, and literacy composition of Madhugiri, although this step does not alter any results.

Figure A1 illustrates the main findings of the depression prevalence survey. The top panel shows the cumulative distribution function of PHQ-9 scores. 76.3 percent of respondents had scores below 5, indicating no depression, 14.5 percent had scores of 5-9, indicating mild depression, and 9.2 had scores of 10 or more, indicating moderate or severe depression. The PHQ-9 threshold for moderate depression corresponds loosely with an MDD diagnosis, although the PHQ-9 scale is not a diagnostic instrument. These findings suggest that depression is more prevalent in this setting than elsewhere in the world. Madhugiri is a poor area, and the elevated prevalence of depression in our sample suggests that poverty may contribute to depression. To investigate further, we created a socioeconomic status (SES) index by computing the first principal component of caste, literacy, education, savings, and home size. The bottom panel of Figure A1 documents a strong negative correlation between SES and depression severity. The figure shows a monotonic decline in average PHQ-9 scores as SES increases. People in the bottom quartile of the SES distribution have average PHQ-9 scores of 4.55 while those in the top quartile of the SES distribution have scores of 2.00 ($p < 0.001$ for this comparison). Table A3 shows how socioeconomic and demographic variables correlate with depression in the community. Age, female gender, low literacy and education, and recent exposure to negative shocks are positively correlated with depression, which aligns with existing evidence (Gilman et al. 2002).

A.2 Ethics and IRB Oversight

This appendix describes the ethical considerations for this study. This study received approval from multiple IRBs in India and the United States. The Institutional Ethical Commit-

[30] We randomly chose 120 villages and sampled a number of household per village that was proportional to the village's population in the 2011 census. Within each household, we attempted to survey up to two adults. Surveyors made up to three attempts over several weeks to reach each respondent and attempted to measure depression consistently with the intervention study.

tee of the Shridevi Institute of Medical Sciences and Research Hospital in Tumkur, Karnataka provided primary oversight of the PC intervention. We also received IRB approval for the full study, including the interventions and data collection, from the University of Chicago, the University of Michigan, the University of Southern California, the University of Texas at Austin, and the Institute for Financial Management and Research (IFMR), which led the data collection.

The PC intervention facilitated the provision of mental health care that was otherwise available in the community. For example, each subdivision operates a public hospital with weekly psychiatric office hours for drop-in treatment. SSRIs are also available for free through these consultations. In practice, access may be difficult for many people because hours are limited and patients must arrange transportation to the hospital.

The IRB protocol for this study delineated practices to ensure the safety and protection of study participants. Subjects gave written informed consent before participating in the initial screening to identify people with depression symptoms who were eligible for the study. Eligible participants provided consent again before joining the study and completing the Round 1 survey. Informed consent scripts were customized to each intervention arm. When seeking consent for screening or intervention participation, surveyors always informed subjects that they could obtain free health care from the local hospital during the weekly clinics.

Staff monitored the wellbeing of all study participants throughout the study. Subjects were ineligible to join the study if they had PHQ-9 scores greater than 20, indicating severe depression. According to the protocol, anyone with a PHQ-9 score of 21 or more would be referred for immediate treatment for free at Shridevi Hospital. GASS personnel also monitored all study participants on a monthly basis throughout the PC intervention. Anyone whose symptoms worsened into severe depression would be referred for immediate treatment for free at Shridevi Hospital. In practice, we did not encounter anyone with a PHQ-9 score greater than 20 during screening. One individual developed severe depression in Round 4 and three individuals developed severe depression in Round 5.

This study evaluates the socioeconomic impact of pharmacotherapy using SSRIs. A psychiatrist worked with patients to establish individualized courses of treatment. The research team did not play a role in determining courses of treatment. Participants with depression received escitalopram, fluoxetine, paroxetine, or setraline, which are off-patent SSRIs, based on the determinations of psychiatrists. These FDA-approved medications have been widely used since 1988 to treat depression (Hillhouse and Porter 2015). Side effects for these drugs include nausea, nervousness, dizziness, reduced sexual desire, drowsiness, insomnia, weight gain or loss, headache, dry mouth, vomiting, and diarrhea. Reduced sexual desire, weight gain, and sleep disturbance are the most common side effects. However, side effects are generally mild, and can usually be addressed by changing drugs or adjusting the dosage (Ferguson 2001). In practice, 12 percent of PC compliers (n = 15) reported experiencing any side effects after the intervention.

A.3 Power Calculations

Our power calculations assume an intraclass correlation of 0.2, a within-respondent autocorrelation of 0.7, and power of 0.8, and consider a 5 percent significance in two-tailed tests. Since the ex-ante and ex-post sample sizes are similar, ex-post minimum detectable effects (MDEs) are at most 0.005 SD larger than ex-ante MDEs. We describe ex-ante MDEs below.

In the "during" period, the study has power to detect an effect of 0.16 SD (PC/LA vs. C, PC vs. C, LA vs. C).[31] For pairwise comparisons of the interventions (PC/LA vs. PC, PC/LA vs. LA, PC vs. LA), the trial has power to detect a difference of 0.185 SD. We also assess the power to test whether PC and LA are complements, so that the impact of PC/LA is greater than the sum of the impacts of PC and LA. For this power calculation, we assume that the sum of the PC and LA effects has a standard deviation of $\sqrt{2}$. The study is powered to detect a complementarity if the PC/LA mean is at least 0.275 SD larger than the sum of the PC and LA means. Attrition slightly reduces the sample size in the "after" period. This change increases the MDEs by 0.005SD. These minimum effects sizes are in line with Gartlehner et al.'s (2017) meta-analysis of the effects of pharmacotherapy, which we describe in Appendix A.6.

In the child sample, which we use to estimate impacts on child human capital investment, the MDE for the comparison to the control arm is 0.23 SD in the "during" period and 0.31 SD in the "after" period. The MDE for the pairwise comparison of intervention arms is 0.29 SD in the "during" period and 0.37 SD in the "after" period. The MDE for the test of whether PC and LA are complements is 0.37 SD in the "during" period and 0.43 SD in the "after" period.

A.4 Selection and Intervention Compliance

This section investigates which variables may be correlated with intervention compliance. For this exercise, we define compliance with the PC intervention as attending at least one meeting with a psychiatrist and compliance with the LA intervention as attending a livelihoods workshop or obtaining a job or other livelihoods opportunity from the NGO. We investigate differences between compliers and non-compliers along five dimensions: age, gender, mental health, SES, and economic circumstances. For mental health, we compute the first principal component of the baseline PHQ-9, the GAD-7 anxiety scale, prior experiences of depression, and health and happiness as a child (which are risk factors for depression). For SES, we compute the first principal component of baseline literacy, education, caste, earnings, savings, and house size. For economic circumstances, we compute the first principal component of recent negative shocks, net worth, and consumption.

In Table A4, Columns 1-3 show the differences between compliers and non-compliers in each intervention arm. Compliers and non-compliers do not differ across most characteristics, with the exception of PC compliers, who are more likely to be female than PC non-compliers, and LA compliers, who have better baseline mental health than LA non-compliers. Columns 4 and 5 test whether these compliance differentials vary significantly across PC/LA, PC, and LA. We find no significant differences in compliance selection across PC/LA and PC. This

[31] The larger sample size in the control group helps to improve power for these comparisons.

finding suggests that the stronger mental health impact of PC/LA does not arise through a difference in the types of participants who received the PC intervention. The comparison of PC/LA and LA shows that LA compliance is more strongly associated with mental health than PC/LA compliance.

A.5 Attrition

Survey participation is balanced across arms during Rounds 2-4, but falls differentially for PC in Round 5. In Round 5, participation is 83% for PC/LA, 72% for PC, 87% for LA, and 85% for control. We note that the effects on child human capital investment and risk intolerance cannot be affected by this, since these variables are not available in Round 5. Therefore, any differential attrition in Round 5 cannot confound those estimates.

To understand who attrits, we select the correlates of attrition through LASSO (from the list in footnote 18 of the manuscript). The most notable variables in this list are marital status, education, and durable goods ownership. Attriters are 10 percentage points less likely to be married at baseline than non-attriters ($p = 0.002$), they have 0.8 more years of education ($p = 0.02$), and they have 0.15 SD lower scores for the durable goods index. The baseline PHQ-9 score is not correlated with subsequent attrition ($p = 0.95$).

As an additional robustness test, we use the set of baseline covariates included in the LASSO specification to estimate the propensity score for subsequent attrition. These covariates are jointly significant and explain 18 percent of the variation in attrition. We re-estimate the specifications in the paper using entropy weights (Hainmueller 2012) to impose balance in the attrition propensity across arms. Estimates (available upon request) are very similar to the results in the paper, which provides reassurance that selective attrition is not a serious concern in practice.

A.6 Mental Health Impacts Compared to the Literature

To compare our estimates to the literature, we focus on our "during" estimates, since most trials in the literature measure impacts over just a few months. Table 2 shows that the effect of PC on depression severity is -0.14 SD (-0.27/-0.001) and the effect of PC/LA on depression severity is -0.26 SD (-0.39/-0.12) during the PC intervention.

Gartlehner et al. (2017) provide a comprehensive review of over 140 studies of depression treatment with SSRIs and cognitive-behavioral therapy (CBT). The authors find that SSRIs reduce depression severity by 0.35 SD and that CBT reduces depression severity by 0.22 SD. A challenge for this exercise is that most studies of depression treatment are conducted in clinical settings with very high patient participation. By contrast, only 45 percent of PC participants and 43 percent of PC/LA participants attend at least one psychiatric visit in our study. Therefore, we multiply Gartlehner et al.'s (2017) estimates by our compliance rate to make a like-to-like comparison.[32] This approach assumes that assignment to treatment does not affect the mental health of non-compliers. After this adjustment, Gartlehner et

[32] To be conservative, we use the PC compliance rate of 43 percent rather than the rate of joint compliance with PC and LA, which is 31 percent.

al.'s (2017) findings imply an intent-to-treat effect of -0.15 SD (-0.13/-0.17) for SSRIs and -0.09 SD (-0.02/-0.16) for CBT, which are comparable to our findings.

Most mental health trials are conducted in developed countries (Patel et al. 2007), and we are not aware of a meta-analysis of pharmacotherapy in poor countries. Our estimates are similar to the average impacts of *psychotherapy* in low-income and middle-income countries in the meta-analysis by Singla et al. (2017). Studies of the long-term impacts of depression treatment in developing countries are even more scarce.[33]

A.7 Intervention Costs

Table A5 shows the implementation costs for the study interventions. Panel A describes the actual costs, Panel B disaggregates intervention components, and Panel C estimates costs under several hypothetical scenarios. Costs were incurred in Indian rupees from 2017-2019. To convert figures into 2017 US dollars, we adjust for inflation using the Indian consumer price index and convert to dollars using the January 2017 exchange rate of 67.4 rupees per dollar.

Panel A reports that the cost per person for PC is \$221 while the cost of PC/LA is \$232. These costs are similar because the LA intervention is inexpensive (\$11 per person). A back-of-the-envelope calculation to compare the relative cost-effectiveness of the PC and PC/LA arms computes the cost of improving mental health by 0.1SD on the PHQ9 scale for each month for which we have data. This method accounts for the larger and more durable mental health impacts in the PC/LA intervention. We consider the "during" period, which lasts 8 months, and the "after" period, which lasts 18 months. Over the 26-month time horizon in our data, Table A5 indicates that PC/LA costs \$8.90 per month per person while PC costs \$8.50 per month per person. According to the PC/LA estimates in Table 2 (-0.26 SD in the "during" period and -0.24 SD in the "after" period), the cost to reduce the PHQ-9 by 0.1 SD per person per month is 8.9/2.6 = \$3.4 in the "during" period and 8.9/2.4 = \$3.7 in the "after" period. According to Table 2, PC alone reduces depression symptoms by 0.14 SD in the "during" period and by 0.04 SD in the "after" period (an estimate that is not statistically significant). Therefore, the cost to reduce the PHQ-9 by 0.1 SD per person per month is 8.5/1.4 = \$6.1 in the "during" period and 8.5/0.4 = \$21.3 in the "after" period. In sum, PC/LA is more cost effective in terms of improving mental health because it costs only slightly more than PC, but it has larger and more persistent effects.

The intervention would be cheaper under alternative implementation scenarios. Since recruitment is a substantial cost (\$43 per participant), interventions in clinical settings could reduce or eliminate this cost by treating people who have already been diagnosed with depression, reducing the cost of PC/LA by 18 percent (\$191 versus \$232). Alternatively, an intervention might reduce costs by asking psychiatrists to donate their time. Eliminating

[33] While we are not aware of comparable meta-analyses, four individual studies report heterogeneous results. In two studies set in Goa, India, Patel et al. (2003) find no effects of pharmacotherapy or psychotherapy over 12 months and Haushofer et al. (2020) find no effects of psychotherapy over 12 months. However, a third study in Goa finds an ATT effect of psychotherapy of -0.32 SD over 12 months (Weobong et al. 2017), which corresponds to a -0.14 SD effect with 43% compliance. Rahman et al. (2008) find that psychotherapy reduces perinatal depression by 0.82 SD after one year in Pakistan (corresponding to a -0.35 SD AIT with 43% compliance).

psychiatrist salaries would reduce the cost of PC/LA by 17 percent ($192 versus $232). Many pharmacotherapy interventions have shorter durations than the eight-month PC intervention. Reducing the duration of the PC intervention to four months would reduce the cost of PC/LA by 38 percent ($144 versus $232).

A.8 Impacts on Depression Indicators

Table A2 provides estimates of the AIT effects on two depression indicators, based on the PHQ-9 score, while Figure A5 shows means by arms and rounds. Scores of 5 and 10 correspond to mild and moderate depression (Kroenke et al. 2001). In Table A2, Columns 1-2 show impacts on the frequency of no moderate depression (PHQ-9 $<$ 10). In the "during" period, PC/LA reduces the frequency by 15 percentage points (9/21), PC reduces the frequency by 7 percentage points (1/13), and LA reduces the frequency by 7 percentage points (0.5/15). In the "after" period, PC/LA reduces the frequency of moderate depression by 8 percentage points (1/15) and PC and LA have no effect. In Columns 3-4, results for the frequency of no depression (PHQ-9 $<$ 5) are qualitatively similar. The results for PHQ-9$<$5 are qualitatively similar.

A.9 Heterogeneous Impacts on Mental Health

In this section, we assess possible heterogeneity in the mental health impact of the interventions. We modify Equation (1) to interact each intervention with indicators for these subgroups in order to obtain subgroup-specific estimates. Figure A6 shows impacts on the standardized PHQ-9 score along these margins. The figure plots the difference in the standardized treatment effect between groups and shows 90 percent confidence intervals. A negative and significant effect means that the first listed group has a larger reduction in depression symptoms. We do not find statistically significant differences between subgroup-specific impacts in most dimensions, including gender, SES, baseline depression severity, and exposure to recent negative shocks. The figure suggests that participants above the median age of 36, in worse physical health at baseline, and who experienced above median childhood shocks have larger mental health benefits.

A.10 Impacts on Anxiety and Activities of Daily Living

We measure impacts on the GAD-7 anxiety scale (Spitzer et al. 2006), a common depression comorbidity, and on several activities of daily living (ADL) in all survey rounds. The GAD-7 is a seven-item scale in which respondents indicate how frequently they have experienced anxiety symptoms in the past two weeks. Scores range from 0-21: scores of 4 or less indicate no anxiety, and scores of 9 or less indicate less than moderate anxiety. The ADL outcomes we measure are: the ability to do vigorous and moderate physical activities, to bathe and dress without help, and to carry a 10-kilogram object for 500 meters; the number of kilometers the respondent can walk without getting tired, the amount of physical pain the respondent has experienced in the past month, and whether pain has made it difficult to carry out daily activities. We scale these components so that larger values indicate better health and construct an ADL index from the standardized first principal component of these variables.

Figure A7 shows treatment effects on the standardized GAD-7 score and on the ADL index. Consistent with the depression findings in Table 2, the PC/LA intervention has the largest effect on anxiety symptoms, reducing anxiety by 0.18 SD (-0.30/-0.06) during the PC intervention and by 0.23 SD (-0.38/-0.09) afterward. When offered separately, PC and LA do not significantly affect anxiety.

The figure also shows that PC/LA improves activities of daily living in both the “during” and “after” periods. The ADL index increases by 0.15 SD (0.00/0.24) during and by 0.18 SD (0.05/0.32) after. Conversely, PC alone *reduces* the ADL index by 0.19 SD (-0.33/-0.05) in the “during” period. Patel and Kleinman (2003) find similar effects. This pattern is consistent with the transitory negative effect of PC on consumption and productive time use. The lack of this negative effect for PC/LA suggests that supplementing PC with LA may be protective.

A.11 Impacts on Time Use

In Table 3, Columns 1-2 report impacts on the number of productive hours per week, which is the sum of time spent on primary and secondary jobs, agriculture, child care, cooking, cleaning, laundry, and fetching water. Here, we disaggregate this variable and also show effects on sleep, leisure, and job search. These variables are based on 24-hour time diaries and are scaled up to represent weekly values.

Figure A8 shows these estimates. In the “during” period, PC reduces time spent on primary and secondary jobs and agriculture by 0.12 SD (-0.23/-0.01), which represents a decline of 3.1 hours per week. It concurrently increases time spent on sleep by 0.11 SD (0.01/0.21) and leisure by 0.14 SD (0.03/0.25), which represents an increase of 1.9 hours and 2.7 hours per week. The PC/LA and LA interventions do not have statistically significant effects on time use in the “during” period. In the “after” period, PC continues to reduce time spent on primary and secondary jobs and agriculture, although the estimate is statistically significant only under the LASSO specification. Rather than shift toward sleep and leisure, PC participants increase time spent on domestic work. These impacts appear to cancel out in Table 3, which aggregates both measures. In addition, LA may reduce sleep time in the “after” period, although the estimate is only statistically significant in the LASSO specification.

A.12 Impacts on the Human Capital Index Components

Figure A9 shows impacts on the components of the child human capital investment index, including enrollment, attendance, homework time, and whether the child works for pay. The negative effect of PC/LA on attendance in the “during” period becomes positive in the “after” period. The figure shows that enrollment and attendance increase, while child labor decreases, although most of the effects are not individually statistically significant.

A.13 Impacts on Components of Consumption, Wealth, and Sanitation/Hygiene

Figures A10 and A11 show estimates for the components of the hygiene/sanitation and durable goods indices, while Figure A12 shows estimates for components of total consumption. Household food and non-food consumption decrease in the PC arm during the intervention. These households also experience a drop in income of similar magnitude in the same time period, which could explain the consumption drop.[34] In Figure A10 most estimates are not statistically significant, which is consistent with the lack of an effect of the interventions on the overall index in Figure 5. Figure A11 also shows few significant estimates, with the exception of large effects of PC and PC/LA on car ownership in the "after" period. However only 12 households in the sample own cars. This effect arises because there are 7 households with cars in PC and 3 households with cars in PC in the "after" period, compared to one household in the control arm.

Our analysis plan identifies durable goods as our primary measure of household wealth. Table A6 also shows estimates for net savings, which includes gross savings, credit (loans by the household to others), and debt. We find a reduction in indebtedness in the during period in the PC and LA arms, and in the after period in the LA arm.

This difference is driven by few households in the PC and LA arms who refrain from taking out relatively large loans. For example, in the "during" period, the 75th percentile for per capita loans is 8-9,000 rupees in all arms. However, the 90th percentile is 35,000 rupees in the control group and 19,000-28,000 rupees in the treatment arms.

A.14 Impact on Cognitive Performance

Evidence on the effect of pharmacotherapy (typically involving SSRIs) on cognition is mixed. Meta-analyses by Cowen and Sherwood (2013) and Prado et al. (2018) indicate mild positive effects of SSRIs on cognition. However, Moraros et al. (2017) finds a negative association between prior use of antidepressants and cognitive impairment, and Han et al. (2020) find no relationship.

Figure A13 shows that there are negative treatment effects for each of the index components. We investigate two possible explanations for the negative effect we estimate in our sample. Cognitive performance could appear to decline if participants exert less effort or focus less intensively on the cognition exercises. However, we do not find significant impacts on the mean or the distribution of completion times for cognitive exercises, suggesting that participants do not change their approach to completing these exercises (estimates available from the authors). Secondly, lower cognitive performance could be related to antidepressant discontinuation syndrome (Davies and Read 2019), which may cause symptoms such as lethargy and fatigue. This explanation is unlikely because only 12 percent of PC compliers report any side effects of treatment. The broader question of the causal effects of pharmacotherapy on cognitive performance remains unresolved.

[34] PC reduces per capita household income by Rs. 44 (5/83) and reduces per capita household consumption by Rs. 59 (20/96) in the "during" period. No other arms have significant effects on this outcome either during or after the PC intervention.

A.15 Impact on Status Within the Household

We examine impacts on proxies for status within the household. In Round 5, we collected data on physical autonomy and participation in communal meals to proxy for status (Palriwala 1993). Physical autonomy measures include whether the respondent has left the house alone in the past seven days and whether the respondent requires permission to leave the house. Communal meal variables include whether the respondent consumes meals at home, at different times than others, alone, or while cooking, and well as whether he or she eats food leftover by other family members. We aggregate these variables into a status index by computing the first principal component of these variables and standardizing this measure.

Estimates for intra-household status appear in Figure A14. Since these data are only available in Round 5, we cannot control for the baseline dependent variable or show estimates for the "during" period. The table shows no statistically significant impacts on status within the household.

A.16 Impact on Incidence of Negative Shocks

To measure the incidence of negative shocks, all survey rounds record whether anyone in the household experienced any of eight shocks in the past four months. These shocks are: an illness lasting at least one month, a death, an unemployment spell of at least one month, the loss of a business, a natural disaster (e.g. a fire or flood), incarceration, a divorce or separation, or another serious loss. We aggregate these shocks according to the Holmes and Rahe (1967) scale, which assigns severity scores to the shocks, and standardize this index.

Figure A16 shows estimates for the negative shock index. The PC and PC/LA interventions reduce the incidence of negative shocks by around 0.1 SD in the "after" period while LA does not have a significant effect on this outcome. This finding is consistent with the reduction in risk intolerance that we observe in Figure 6. Since "an illness lasting at least one month" is an element of the index, the interventions could mechanically improve the index by reducing the incidence of depression. We investigate this possibility by excluding the illness component and find results that are robust and very similar to the estimates in Figure A16. Estimates are available upon request.

Table A1: Deviations from the Pre-Analysis Plan

Pre-Specified Approach	Deviation	Rationale
Use an ANCOVA specification for outcomes with low serial correlation and a differences-in-differences specification for outcomes with high serial correlation.	Use ANCOVA and LASSO specifications for all outcomes.	We do not use differences-in-differences because serial correlation is low for all outcomes and therefore ANCOVA is efficient. Referees suggested incorporating the LASSO specification.
Estimate the impact of PC/LA relative to PC and LA.	Estimate the impact of PC/LA relative to C.	This approach eases the interpretation of our estimates.
Use the Romano and Wolf (2005) step-down procedure control for the false discovery rate (FDR) across index components.	Use Benjamini et al. (2006) sharpened q-values to control for the FDR.	The Benjamini et al. (2006) approach is more straightforward to implement.
No pre-specified way to assess joint significance and treatment complementarities	Use the Young (2019) "omnibus" test to test joint significance and estimate a system of seemingly unrelated regressions to jointly test for treatment complementarities.	These methods are appropriate to address these additional inquiries.
The follow-up period includes Rounds 2 and 3.	Add Rounds 4 and 5. Delineate between the "during" period (Rounds 2 and 3) and the "after" period (Rounds 4 and 5).	Most mental health studies focus on immediate impacts. Additional funding allowed us to measure treatment effects over a longer horizon.
Elicit earnings in the past month and in the past week.	Only elicit earnings in the past week.	Surveys do not include a monthly earnings question.
Use the Convex Time Budget (CTB) method to elicit time preferences.	Omit from the analysis.	The data are unreliable because many responses are inconsistent with a downward sloping demand for leisure.
Estimate impacts on the variance in the prevention and risk intolerance index.	Omit from the analysis.	We find that the treatments reduce the variance in the risk intolerance index in the "after" period. Estimates are available from the authors.
Estimate the impact of treatment on the adoption of liquid hand sanitizer.	Omit from the analysis.	We are pursuing this study in another paper.
No pre-specified way to deal with outlying monetary values.	Winsorize monetary values at 5 percent.	Winsorizing increases the precision of these estimates without qualitatively changing the results
Do not estimate the impact on exposure to negative shocks.	Include these estimates.	Prevention and risk intolerance results suggest that the interventions may lead people exert more effort to avoid negative shocks, and therefore experience fewer negative shocks. These estimates allow us to test this prediction.
Assess baseline balance on presence of open defecation, presence of garbage, and cleanliness of the cooking area.	Assess balance on the hygiene and sanitation index instead.	These variables are components of the hygiene and sanitation index. We show that this index is balanced in Table 1.

Note: The table lists and provides an explanation for all deviations from our analysis plan. The analysis plan is available through entry AEACTR-0001067 on the AEA RCT Registry.

Table A2: Impact on Depression Indicators

	No Moderate/Severe Depression		No Depression	
	(1)	(2)	(3)	(4)
A: During the PC Intervention				
PC/LA	0.15***	0.14***	0.095***	0.085***
	(0.039)	(0.038)	(0.028)	(0.028)
PC	0.071*	0.067*	0.043	0.041
	(0.039)	(0.037)	(0.028)	(0.026)
LA	0.069*	0.052	0.028	0.019
	(0.040)	(0.037)	(0.030)	(0.028)
H_0: $PC/LA = PC$	0.07	0.10	0.10	0.17
H_0: $PC/LA = PC + LA$	0.87	0.73	0.59	0.56
H_0: $PC = LA$	0.97	0.73	0.67	0.48
H_0: $PC/LA = LA$	0.08	0.04	0.05	0.04
H_0: $PC/LA = PC = LA$	0.12	0.11	0.11	0.12
Control mean of outcome	0.48	0.48	0.15	0.15
B: After the PC Intervention				
PC/LA	0.078*	0.069*	0.12***	0.11***
	(0.041)	(0.040)	(0.035)	(0.036)
PC	0.0030	0.0085	0.027	0.034
	(0.037)	(0.036)	(0.030)	(0.029)
LA	-0.012	-0.026	0.031	0.024
	(0.037)	(0.036)	(0.031)	(0.029)
H_0: $PC/LA = PC$	0.10	0.17	0.02	0.05
H_0: $PC/LA = PC + LA$	0.14	0.13	0.24	0.28
H_0: $PC = LA$	0.72	0.38	0.91	0.78
H_0: $PC/LA = LA$	0.05	0.03	0.03	0.03
H_0: $PC/LA = PC = LA$	0.12	0.09	0.05	0.07
Control mean of outcome	0.63	0.63	0.22	0.22
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 19 explains this approach in more detail. Village-clustered standard errors appear in parentheses. "During" and "after" estimates are based on a common regression. The outcome in Columns 1-2 is an indicator for PHQ-9$<$ 10, which is consistent with less than moderate depression. The outcome in Columns 3-4 is an indicator for PHQ-9$<$ 5, which is consistent with no depression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Healthy and Depressed Adults in the Community Compared to the Intervention Sample

	Community Sample		Intervention	Significance	
	Healthy	Depressed	Sample	(1) vs. (2)	(2) vs. (3)
	(1)	(2)	(3)	(4)	(5)
PHQ-9 depression scale	1.29	11.29	13.99	***	***
Age	34.5	37.0	35.3	***	***
Female	0.48	0.61	0.86	***	***
Scheduled caste/tribe	0.24	0.26	0.64		***
Schooling (years)	7.7	4.7	5.0	***	
Literacy (1-3)	2.3	1.8	1.9	***	
Any household savings	0.52	0.47	0.30		***
Bedrooms (number)	1.5	1.5	1.5		
Negative life event scale	39	54	95	***	***
Observations	1249	256	1000	–	–

Note: the intervention sample includes baseline observations for all trial participants, while the community sample is a representative sample of adults (aged 18-50) from the adjacent taluk (Madhugiri). Estimates in Columns 1 and 2 are weighted to match the available demographic characteristics (percent literate, Hindu, Muslim, and scheduled caste/tribe) of Madhugiri according to the 2011 Census of India. The healthy subsample in Column 1 includes community respondents for whom PHQ-9 < 7, which matches the trial eligibility threshold. The depressed subsample in Column 2 includes community respondents for whom PHQ-9 ≥ 7. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Selection into Intervention Compliance

	Compliers − Non-Compliers			P-Value	
	PC/LA	PC	LA	PC/LA − PC	PC/LA − LA
	(1)	(2)	(3)	(4)	(5)
Age	-0.667	-0.499	-1.839	0.92	0.52
	(1.318)	(1.150)	(1.186)		
Female	-0.0338	-0.130**	0.0218	0.24	0.51
	(0.0646)	(0.0505)	(0.0552)		
Mental Health Index	-0.262	0.0825	0.385***	0.12	0.00***
	(0.179)	(0.139)	(0.144)		
SES Index	0.0345	0.224	0.0968	0.41	0.79
	(0.180)	(0.146)	(0.152)		
Economic Circumstances Index	0.251	0.159	-0.135	0.69	0.11
	(0.173)	(0.136)	(0.169)		
Observations	186	202	201	589	589

Note: Columns 1-3 show the differences in characteristics between compliers and non-compliers for each intervention arm. PC compliance is defined as attending at least psychiatric consultation. LA compliance is defined as attending at least one livelihoods workshop or obtaining employment (or another livelihoods opportunity) from the NGO. The mental health index is the standardized first principal component of PHQ-9, GAD-7 anxiety scale, prior experiences of depression, and health and happiness as a child, all of which are measured at baseline. The SES Index is the standardized first principal component of baseline literacy, education, caste, earnings, savings, and house size. The Economic Circumstances Index is the the first principal component of recent negative life events, net worth, and consumption. Standard errors and p-values are based on univariate regressions of the characteristics on a compliance indicator. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Intervention Costs Per Participant Under Alternative Scenarios

	Cost (USD)	Unit
	(1)	(2)
A: Actual Costs		
PC/LA	232	per person
PC	221	per person
LA	11	per person
B: Intervention Components		
Recruitment	43	per person
Home Visits	2	per person-month
Medicine and transportation	15	per person-month
Psychiatrist salaries	5	per person-month
Livelihoods services	11	per person
C: Alternative Hypothetical Scenarios		
PC/LA with psychiatrists working for free	192	per person
PC/LA w/o recruitment costs	191	per person
4-month PC/LA intervention	144	per person
4-month PC/LA intervention w/o recruitment costs	102	per person

Note: Expenses were incurred in 2019 Indian rupees. The table converts these values to 2017 US dollars using the Indian consumer price index and the January 2017 exchange rate of 67.4 rupees per dollar.

Table A6: Impacts on Net Savings and Components

	Net Savings		Savings		Credit		Debt	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: During the PC Intervention								
PC/LA	1194	1239	-88*	-94**	-5.5	-33	-1417	-1434
	(1322)	(1262)	(46)	(47)	(91)	(91)	(1283)	(1251)
PC	1986*	1967*	-29	-50	53	25	-1923*	-2034*
	(1130)	(1152)	(58)	(58)	(105)	(104)	(1122)	(1148)
LA	2553**	2504**	-60	-71	-59	-6	-2642**	-2686**
	(1159)	(1141)	(50)	(49)	(77)	(73)	(1146)	(1128)
H_0: $PC/LA = PC$	0.57	0.60	0.33	0.45	0.60	0.62	0.71	0.66
H_0: $PC/LA = PC + LA$	0.07	0.07	0.98	0.74	0.99	0.98	0.08	0.06
H_0: $PC = LA$	0.65	0.67	0.63	0.73	0.27	0.39	0.56	0.60
H_0: $PC/LA = LA$	0.34	0.35	0.60	0.64	0.54	0.74	0.37	0.35
H_0: $PC/LA = PC = LA$	0.63	0.65	0.61	0.74	0.52	0.69	0.66	0.64
Control mean of outcome	-9640	-9640	400	400	184	184	10,280	10,280
B: After the PC Intervention								
PC/LA	-2222	-2234	-62	-77	-270***	-297***	1848	1840
	(1540)	(1506)	(55)	(56)	(82)	(88)	(1544)	(1505)
PC	-777	-784	-45	-64	-52	-72	701	560
	(1457)	(1426)	(51)	(51)	(123)	(128)	(1418)	(1390)
LA	3087***	3016***	13	1.4	-75	-78	-3077***	-3102***
	(1064)	(1057)	(59)	(57)	(121)	(123)	(1058)	(1049)
H_0: $PC/LA = PC$	0.43	0.41	0.77	0.83	0.03	0.02	0.53	0.47
H_0: $PC/LA = PC + LA$	0.03	0.03	0.72	0.86	0.35	0.35	0.04	0.03
H_0: $PC = LA$	0.01	0.01	0.38	0.29	0.86	0.96	0.01	0.01
H_0: $PC/LA = LA$	0.00	0.00	0.27	0.23	0.04	0.02	0.00	0.00
H_0: $PC/LA = PC = LA$	0.00	0.00	0.52	0.43	0.01	0.01	0.00	0.00
Control mean of outcome	-9610	-9610	411	411	351	351	10,374	10,374
Observations	3455	3455	3465	3465	3466	3466	3462	3462
Specification	ANCOVA	LASSO	ANCOVA	LASSO	ANCOVA	LASSO	ANCOVA	LASSO

Note: The table reports AIT effects following Equation (1). Columns 1, 3, and 5 use an ANCOVA specification that controls for time indicators, strata indicators, and the baseline dependent variable. Columns 2, 4, and 6 use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. Village-clustered standard errors appear in parentheses. "During" and "after" estimates are based on a common regression. "Savings" in Columns 3-4 is the household's gross monetary savings, "credit" in Columns 5-6 is the value of credit that the household has extended to others, and "debt" in Columns 7-8 is the value of debt that the household owes to others. "Net savings" in Columns 1-2 equals savings plus credit minus debt. All variables are measured in 2017 rupees and winsorized at 5 percent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

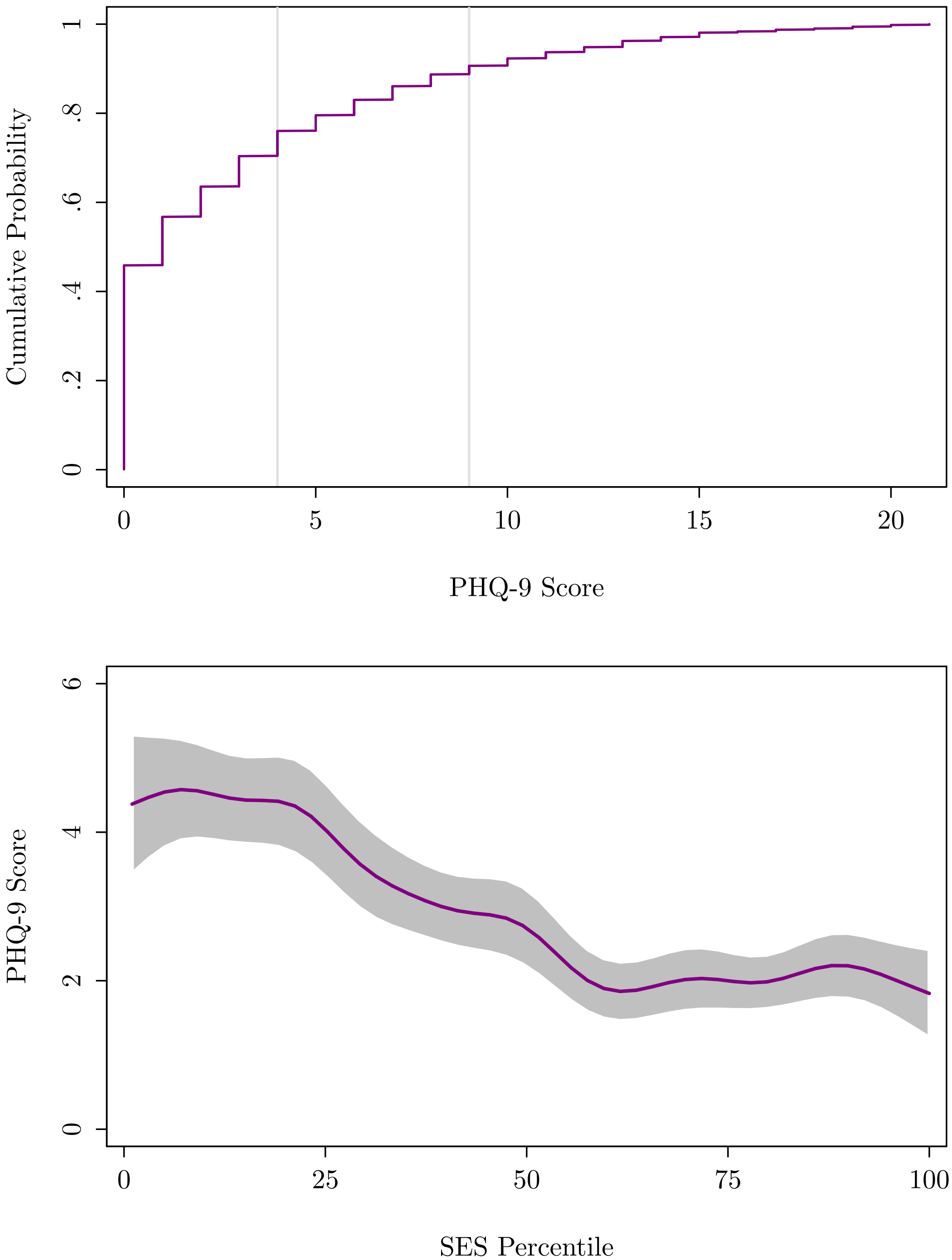

Figure A1: Community Depression Prevalence (Panel A) and Association with SES (Panel B)

Note: Data are from a representative sample of adults from Madhugiri District. Estimates are weighted to match the age, gender, religion, and caste distribution of the district in the 2011 Census of India. Panel A shows the cumulative density of PHQ-9 scores. Gray vertical bars indicate thresholds for mild and moderate depression. In Panel B, we construct an SES index according to the first principal component of caste, education, literacy, savings, and house size, which we convert into percentiles. The figure shows estimates from a locally-weighted polynomial regression of PHQ9 scores on the SES percentile.

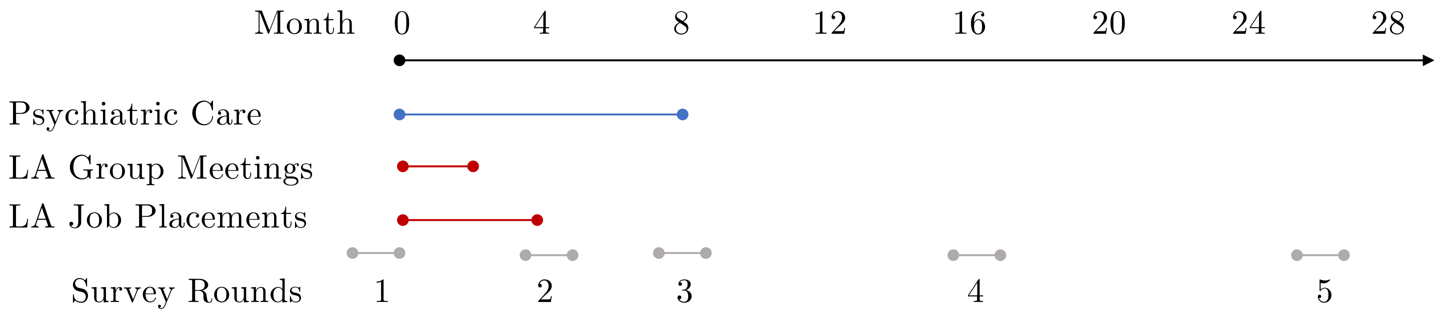

Figure A2: Study Timeline

Note: the figure shows the timing of the study components. PC components appear in red, LA components appear in blue, and survey rounds appear in gray.

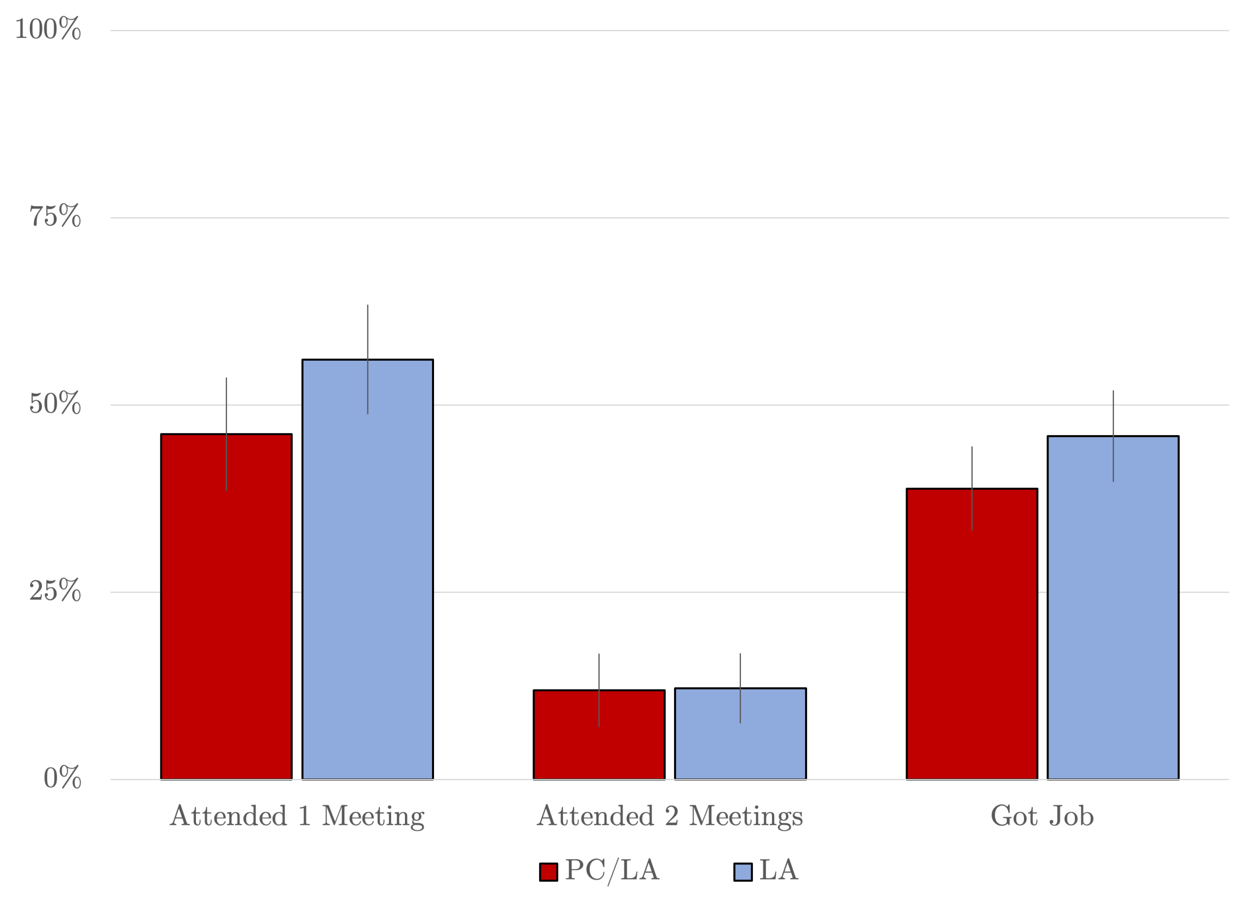

Figure A3: Participation in the LA Intervention

Note: the figure shows the percent of participants in the LA and PC/LA interventions who attended one meeting, attended two meetings, and who received a job or other livelihoods activity.

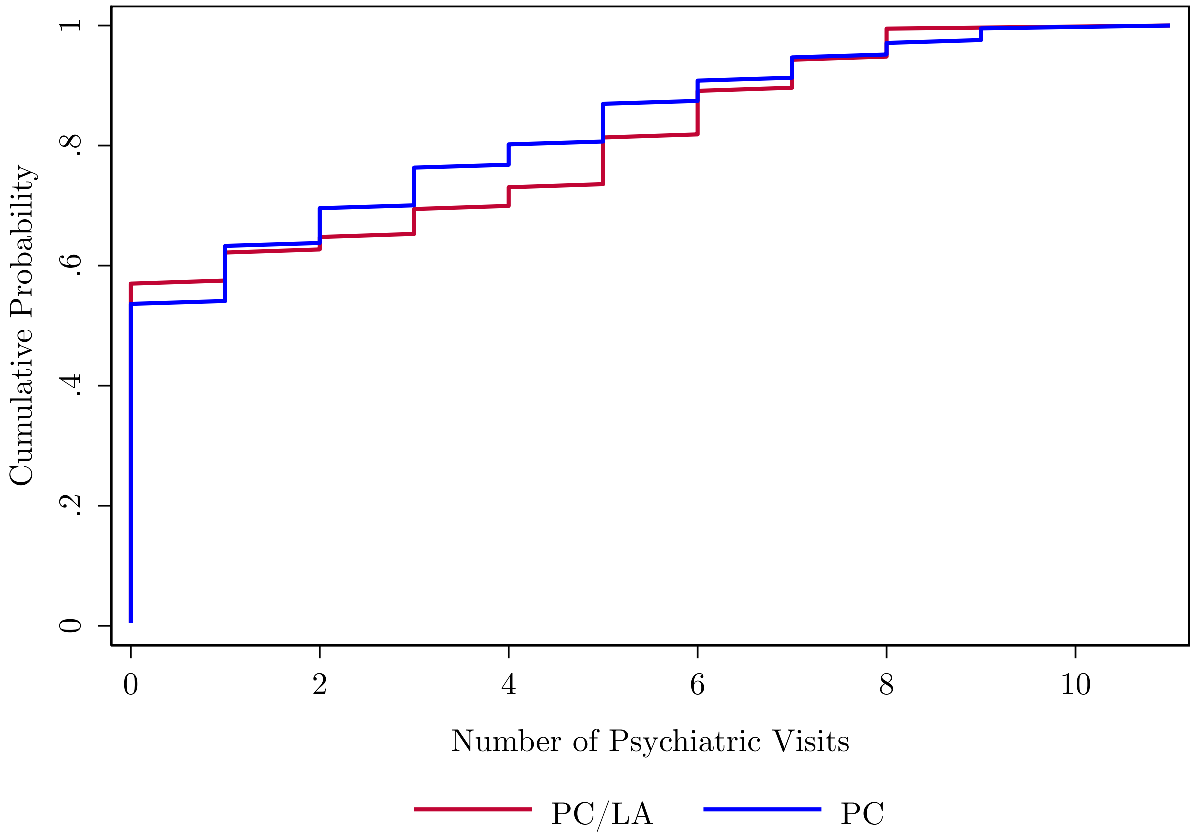

Figure A4: Participation in the PC Intervention

Note: the figure shows the cumulative density function for the number of psychiatric visits received by participants in the PC and PC/LA arms.

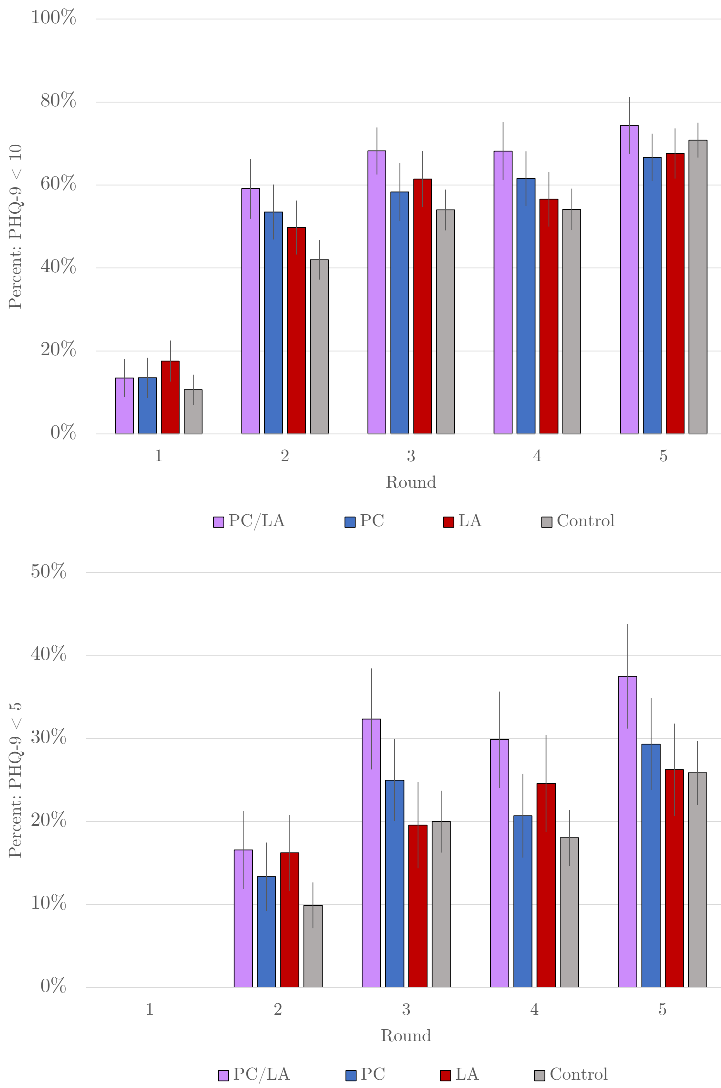

Figure A5: Depression Indicators by Round and Intervention Arm

Note: Panel A shows the percent of participants with PHQ-9 scores below 10, which is consistent with no moderate or severe depression, and Panel B shows the percent of participants with PHQ-9 scores below 5, which is consistent with no depression. All participants have PHQ-9 scores that are greater than 5 in Round 1 because people were required to have initial PHQ-9 scores above 7 to participate in the study. Error bars show 90 percent confidence intervals based on village-clustered standard errors.

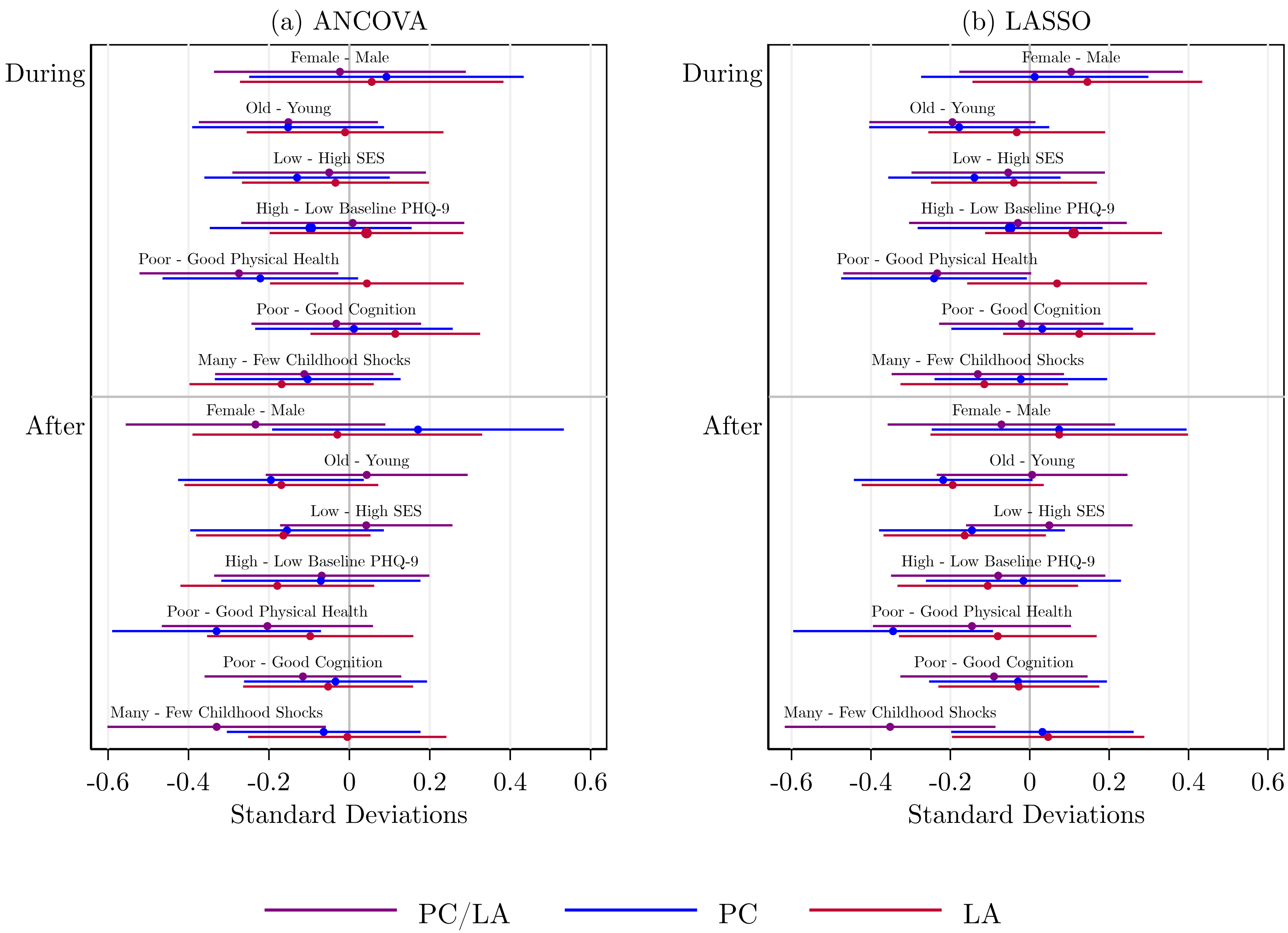

Figure A6: Heterogeneous Impacts on Depression Severity (PHQ-9)

Note: the figure follows Equation (1) and shows the difference in impacts across subgroups. Panel (a) shows estimates under the ANCOVA specification and Panel (b) shows estimates under the LASSO specification. A negative and significant effect means that the first listed group has a larger reduction in depression symptoms. SES is the first principal component of education, caste, earnings, savings, and house size. Physical health is the first principal component of five activities of daily living and recent levels of pain. Cognition is the first principal component of scores for the Raven's Progressive Matrices and forward and backward digit spans. Childhood shocks is an index of follows the Holmes and Rahe (1967) index of childhood negative life events. All variables are measured at baseline. We divide the sample at the median in each case, aside from gender.

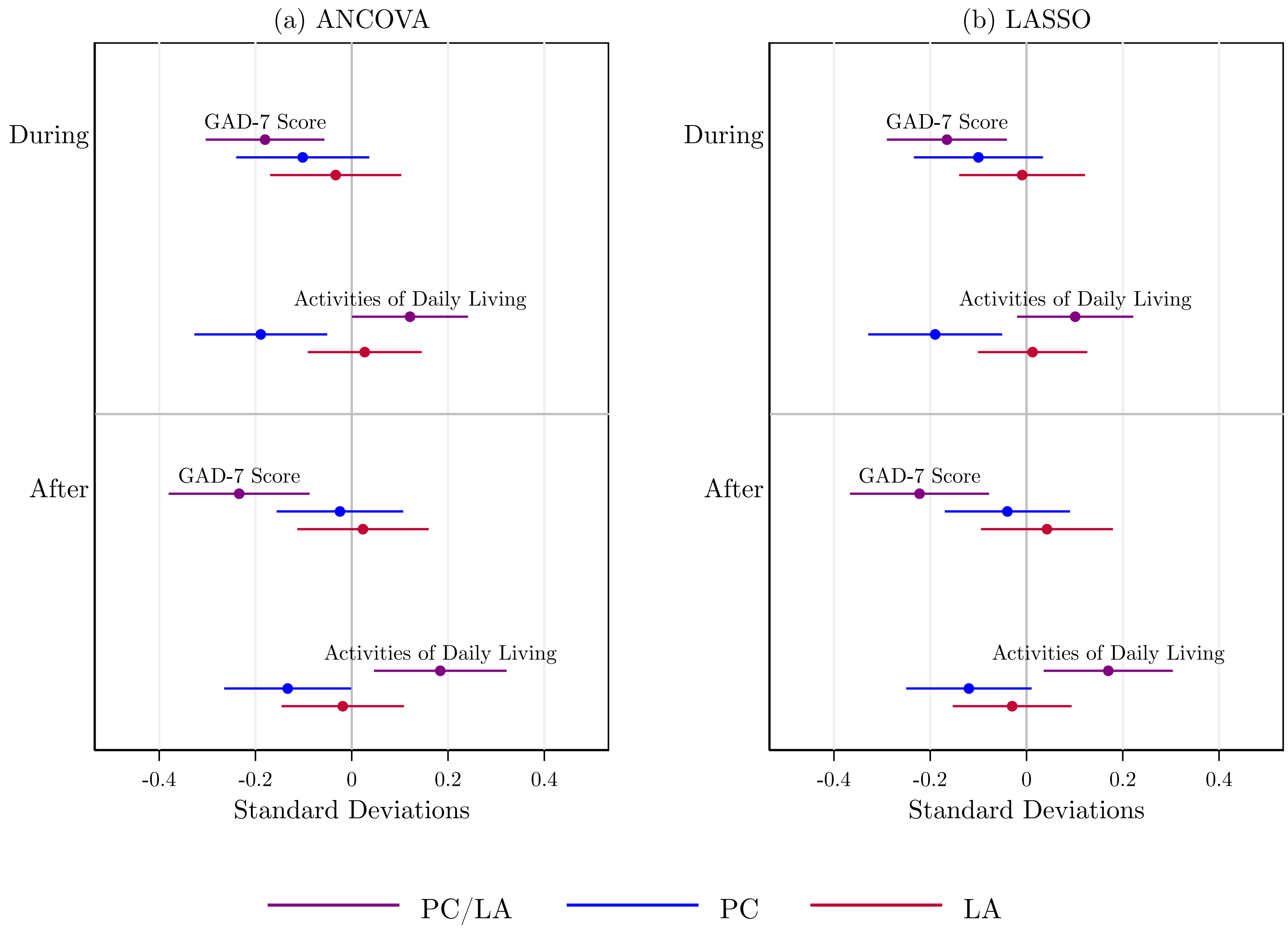

Figure A7: Impacts on Additional Health Outcomes

Note: The figure shows standardized impacts and 90 percent confidence intervals for the GAD-7 anxiety scale and activities of daily living (ADL) index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. The following estimates are statistically significant after this adjustment: impact of PC/LA on both outcomes in the "during" period under ANCOVA ($q = 0.04$ for GAD-7 and $q = 0.05$ for ADL) and LASSO ($q = 0.06$ for GAD-7 and $q = 0.09$ for ADL), and in the "after" period under ANCOVA ($q = 0.02$ for GAD-7 and $q = 0.02$ for ADL) and LASSO ($q = 0.02$ for GAD-7 and $q = 0.02$ for ADL). ADL impact of PC in the "during" period ($q = 0.05$ for both ANCOVA and LASSO). All other estimates are statistically insignificant after adjustment.

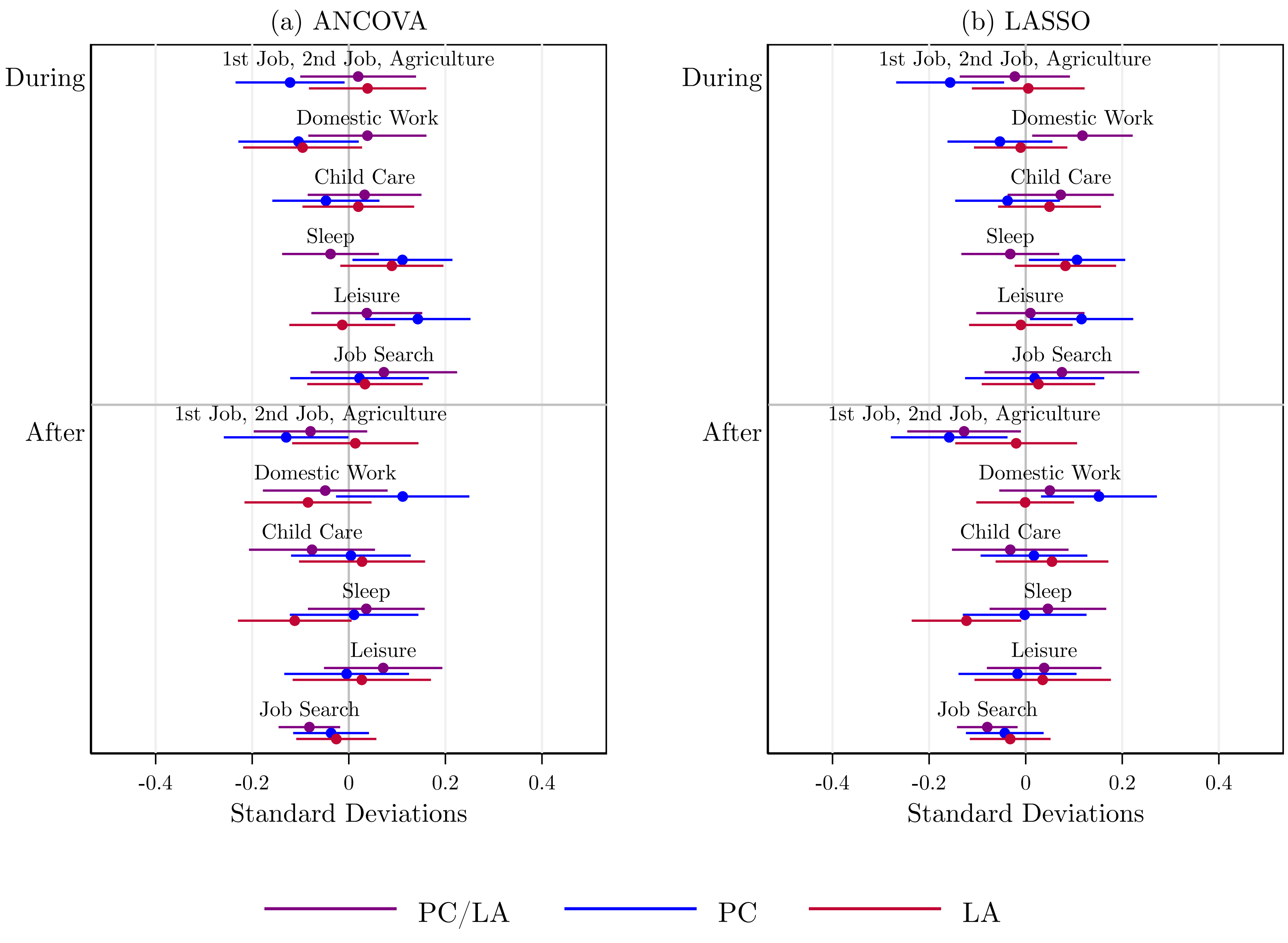

Figure A8: Impacts on Time Use

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the subjective wellbeing index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. All estimates are statistically insignificant after adjustment.

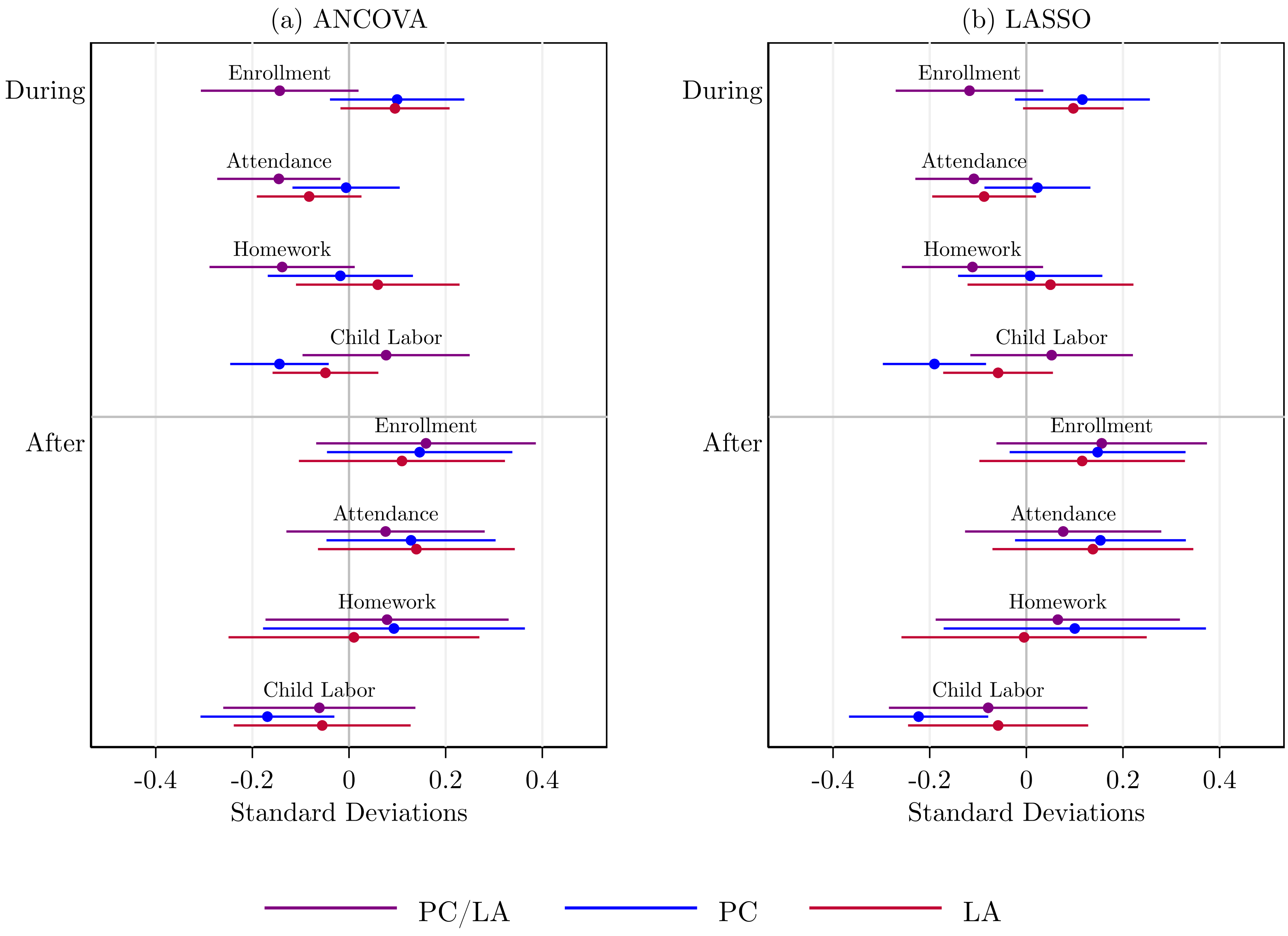

Figure A9: Impacts on Components of the Education Index

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the child human capital investment index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. The following estimates are statistically significant after this adjustment: "work for pay" impact of PC in the "during" period under ANCOVA ($q = 0.09$) and under LASSO ($q = 0.01$) and in the "after" period under LASSO ($q = 0.05$). All other estimates are not statistically significant after the adjustment.

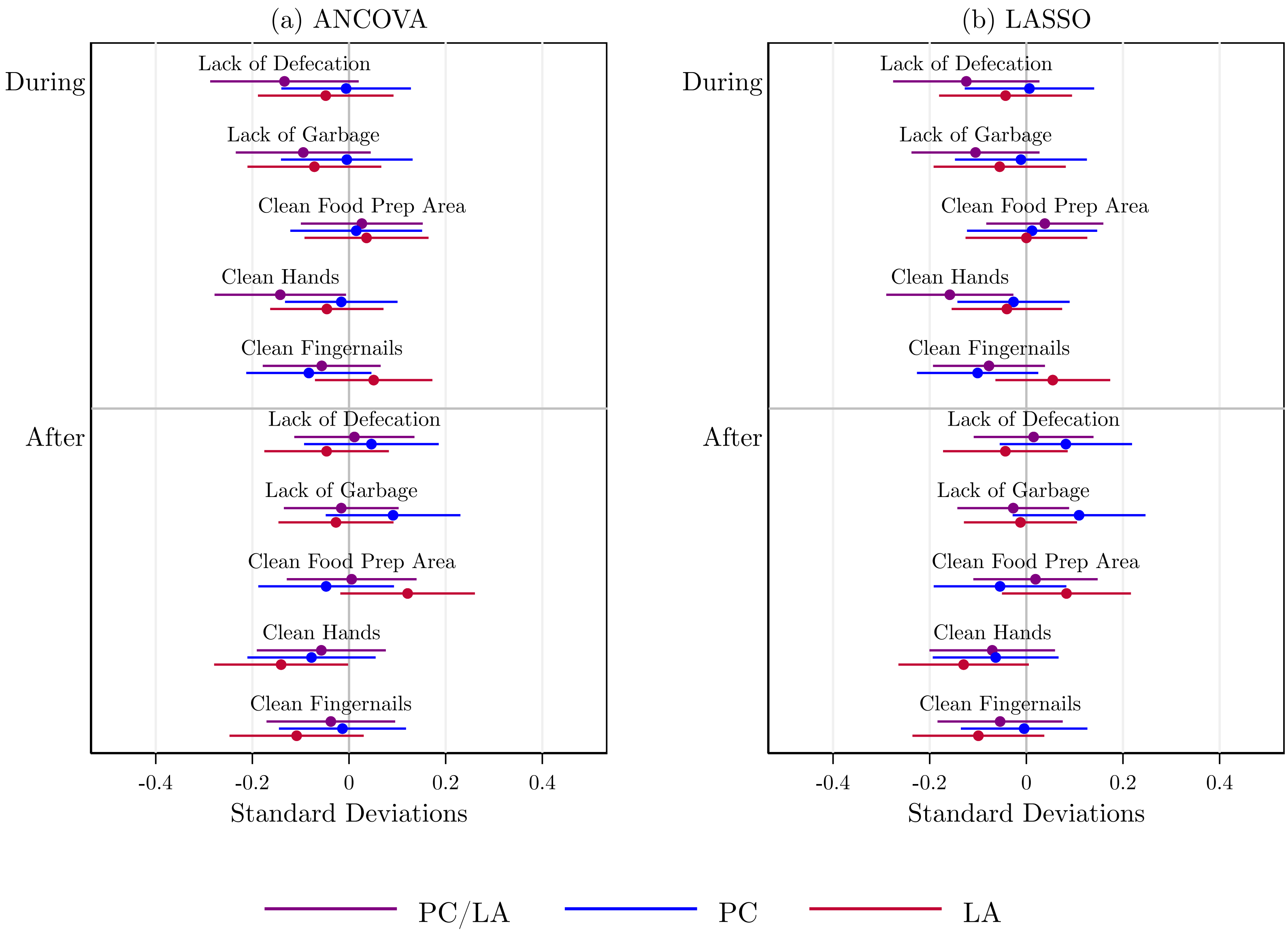

Figure A10: Impacts on the Components of the Sanitation/Hygiene Index

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the hygiene/sanitation index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. After this adjustment, all estimates are not statistically significant.

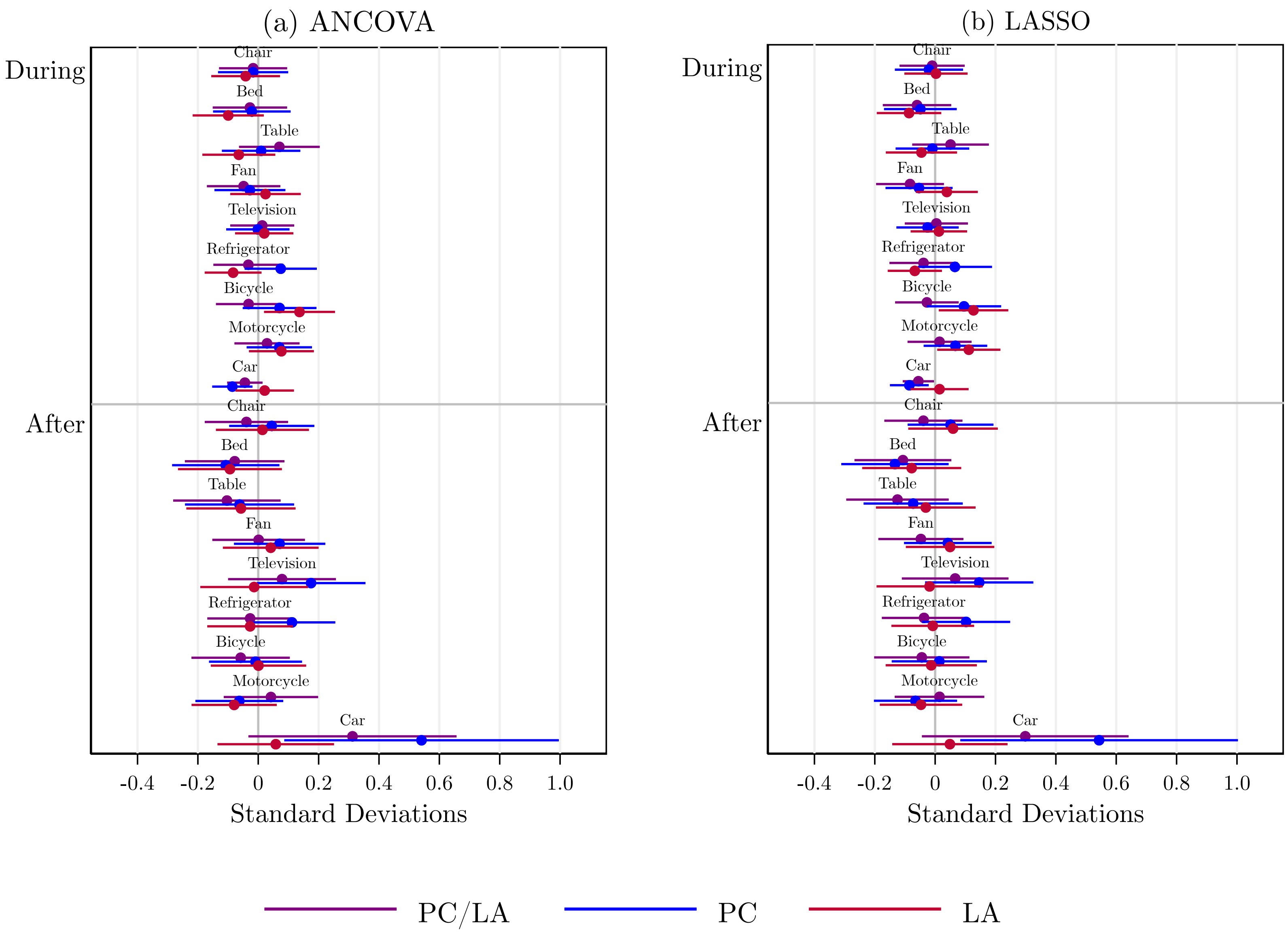

Figure A11: Impacts on Components of the Durable Goods Index

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the durable goods index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. After this adjustment, all estimates are statistically insignificant.

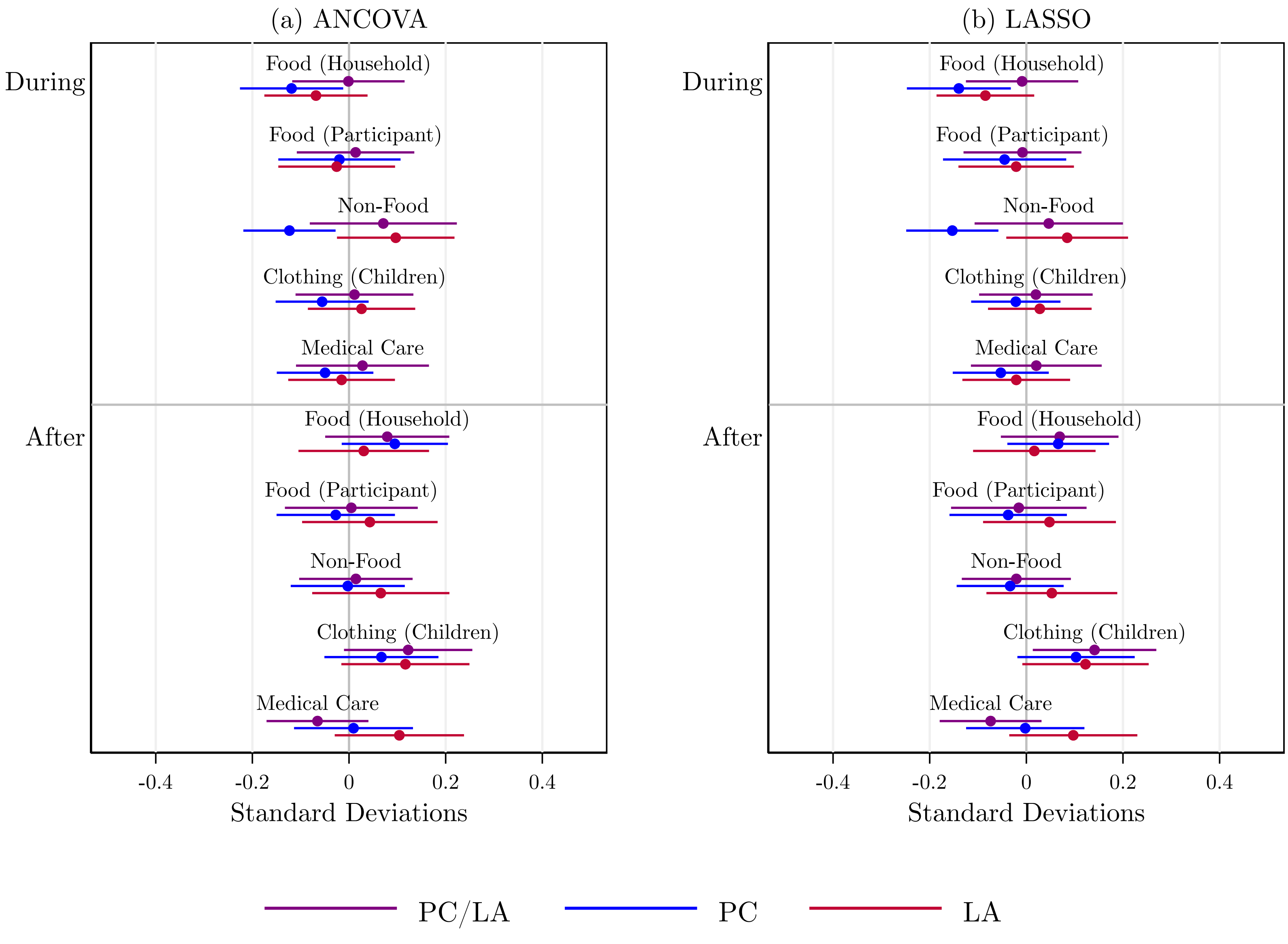

Figure A12: Impacts on Components of Consumption

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the durable goods index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. The following estimates are statistically significant after this adjustment: "food (household)" impact of PC in the "during" period under LASSO ($q = 0.07$); "non-food" impact of PC in the "during" period under LASSO ($q = 0.04$). All other estimates are not statistically significant after the adjustment.

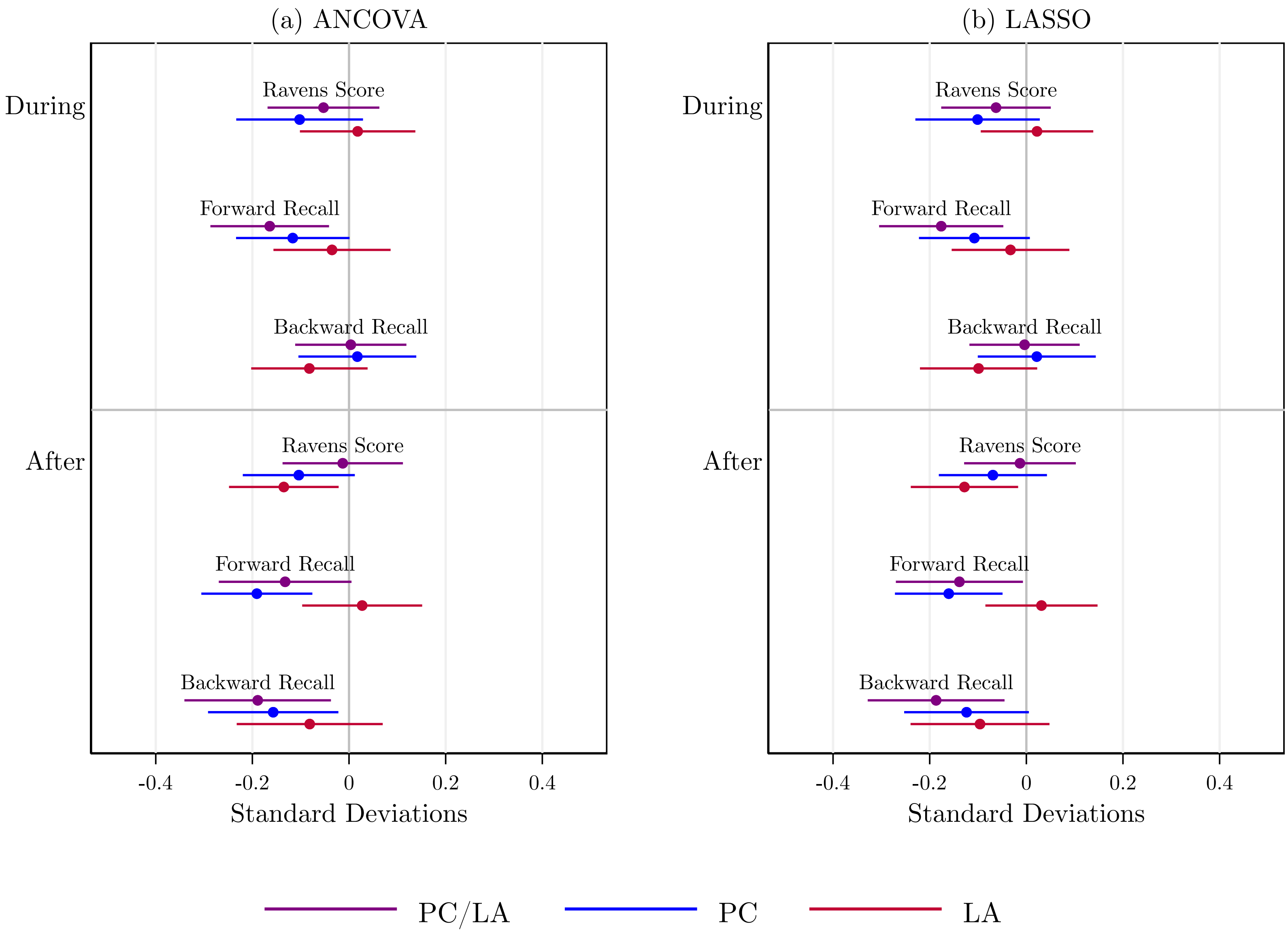

Figure A13: Impacts on Cognitive Performance

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the cognitive performance index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. The following estimates are statistically significant after this adjustment: "Ravens score" impact of PC in the "after" period under ANCOVA ($q = 0.09$); ' "forward recall" impact of PC/LA in the "during" period under ANCOVA ($q = 0.09$) and under LASSO ($q = 0.08$), impact of PC in the "after" period under ANCOVA ($q = 0.02$) and under LASSO ($q = 0.06$); "backward recall" impact of PC in the "after" period under ANCOVA ($q = 0.06$). All other estimates are statistically insignificant after adjustment.

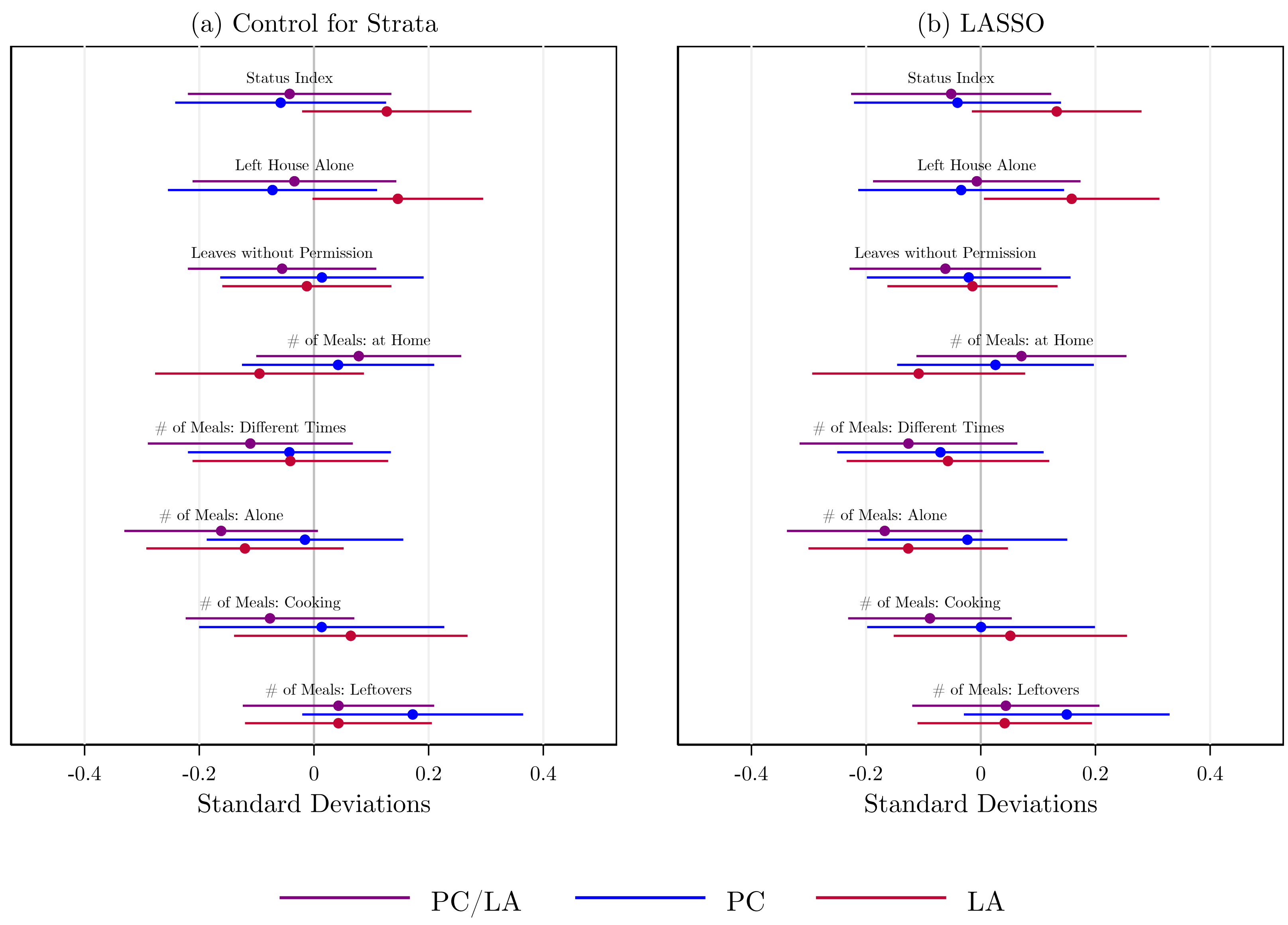

Figure A14: Impacts on Status Within the Household in Round 5

Note: Status variables are only available in Round 5. Panel (a) shows estimates that control for strata indicators. This approach corresponds most closely to our "ANCOVA" specification but does not control for the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. All estimates are statistically insignificant after adjustment.

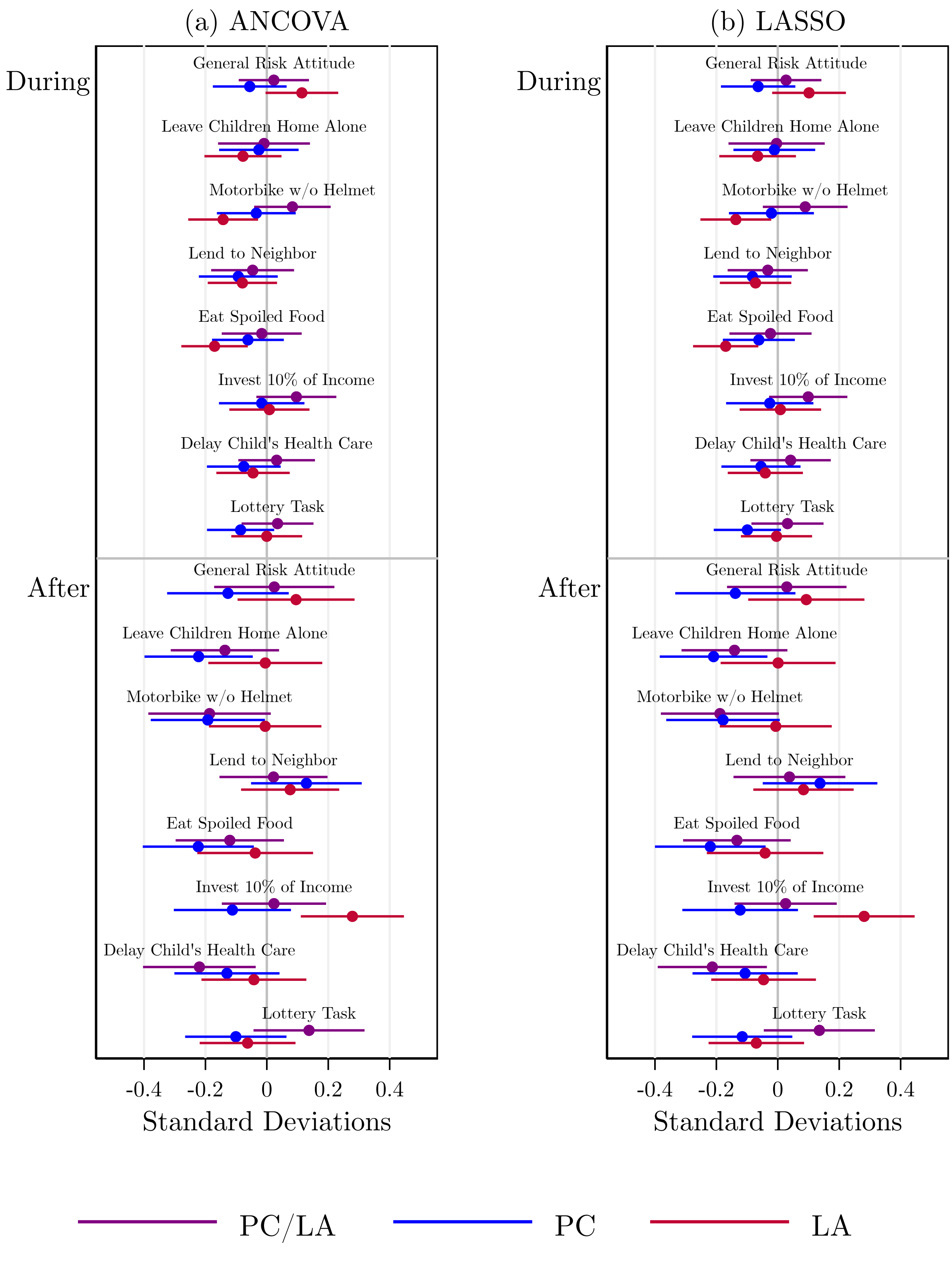

Figure A15: Impacts on Components of the Risk Intolerance Index

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the durable goods index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. The following estimates are statistically significant after this adjustment: "eat spoiled food" impact of LA in the "during" period under ANCOVA ($q = 0.09$) and LASSO ($q = 0.08$); "invest 10% of income" impact of LA in the "after" period under ANCOVA ($q = 0.06$) and LASSO ($q = 0.04$). All other estimates are statistically insignificant after adjustment.

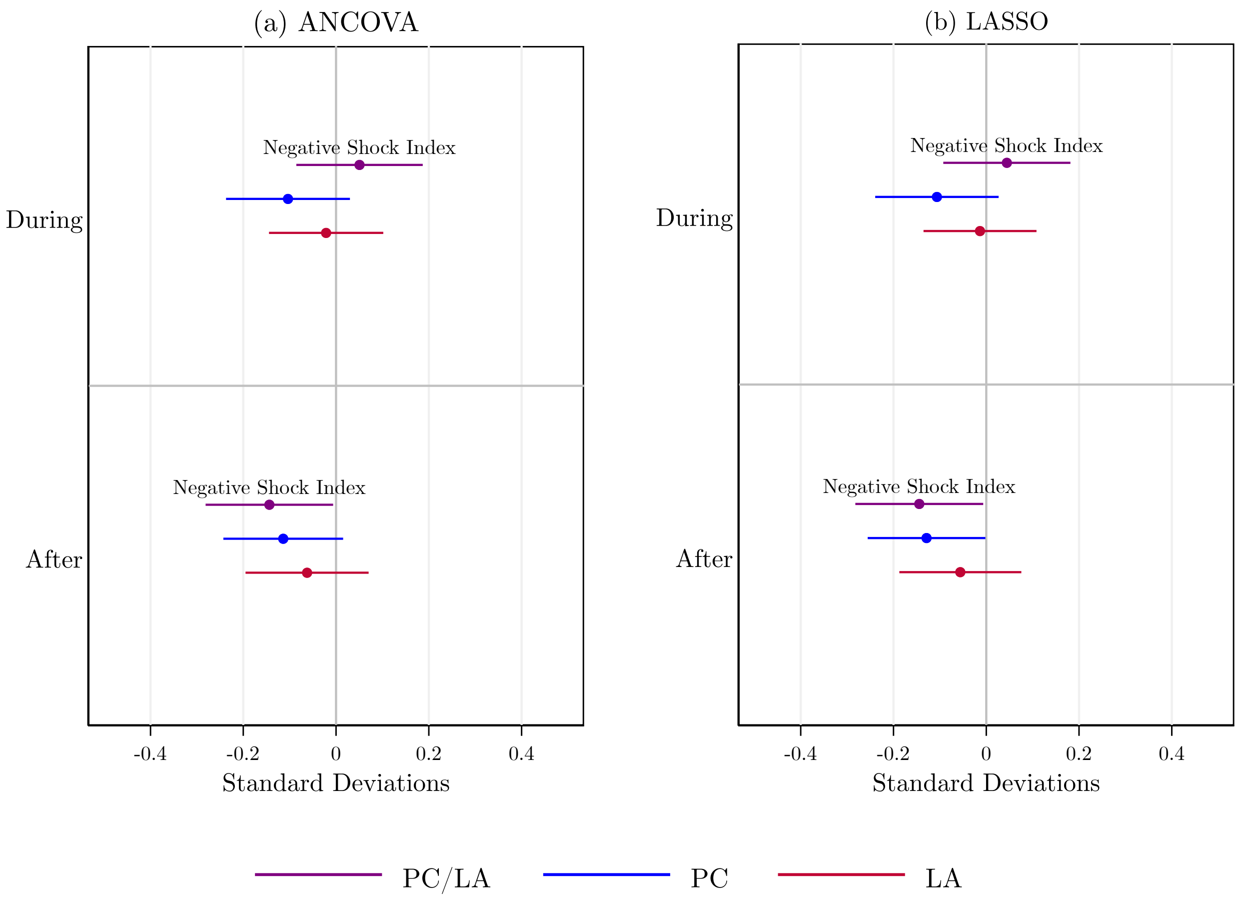

Figure A16: Impacts on Negative Shocks

Note: The figure shows standardized impacts and 90 percent confidence intervals the negative shock index. The index follows the Holmes and Rahe (1967) scale and includes indicators for whether the household has experienced the following shocks in the past four months: an illness lasting at least one month, a death, an unemployment spell, a natural disaster, incarceration, divorce, or another serious loss. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention.

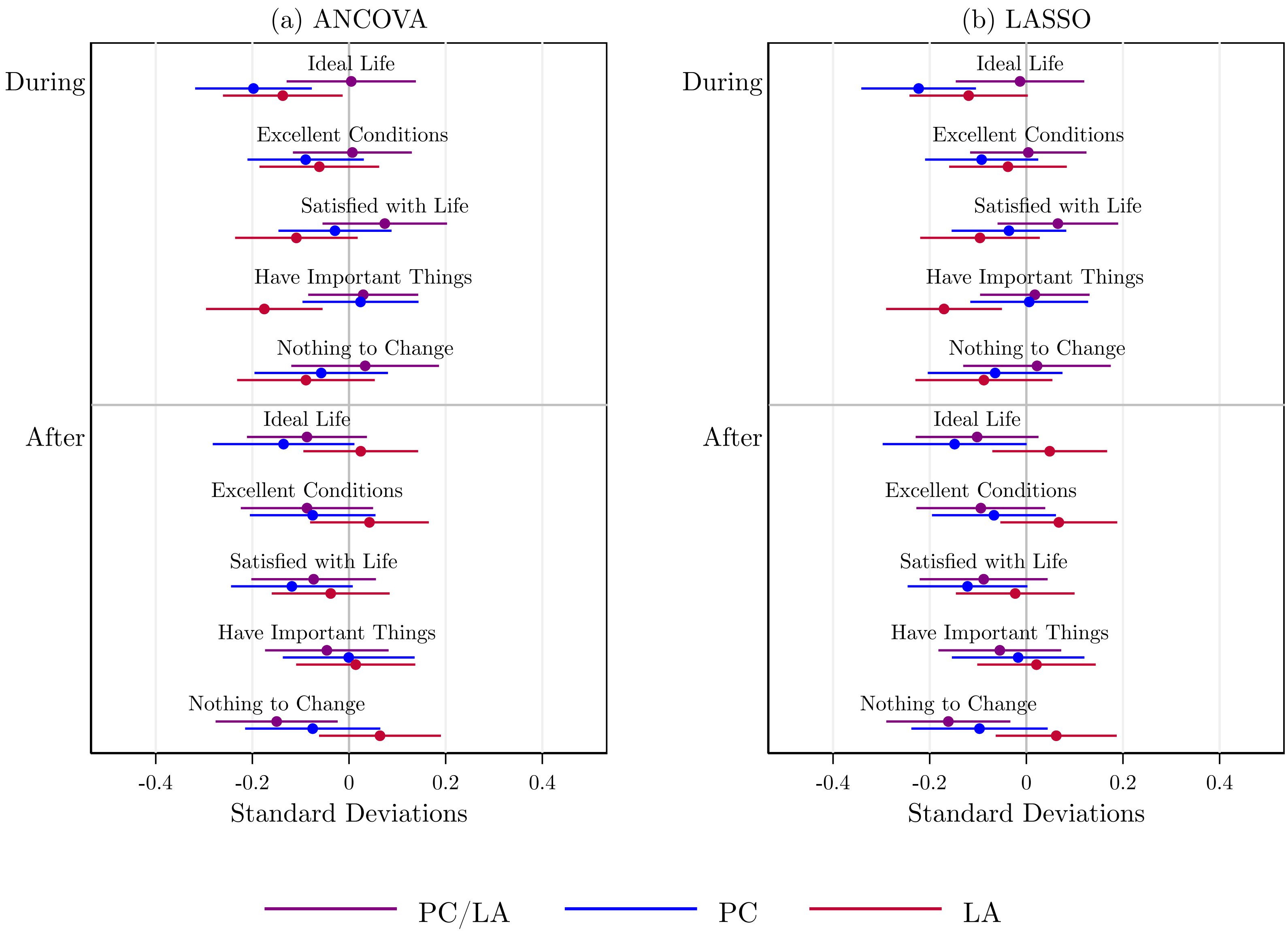

Figure A17: Impacts on Subjective Wellbeing

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the subjective wellbeing index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. The following estimates are statistically significant after this adjustment: "ideal life" impact of PC in the "during" period under ANCOVA ($q = 0.04$) and under LASSO ($q = 0.01$); "have important things" impact of LA in the "during" period under ANCOVA ($q = 0.09$). All other estimates are statistically insignificant after adjustment.

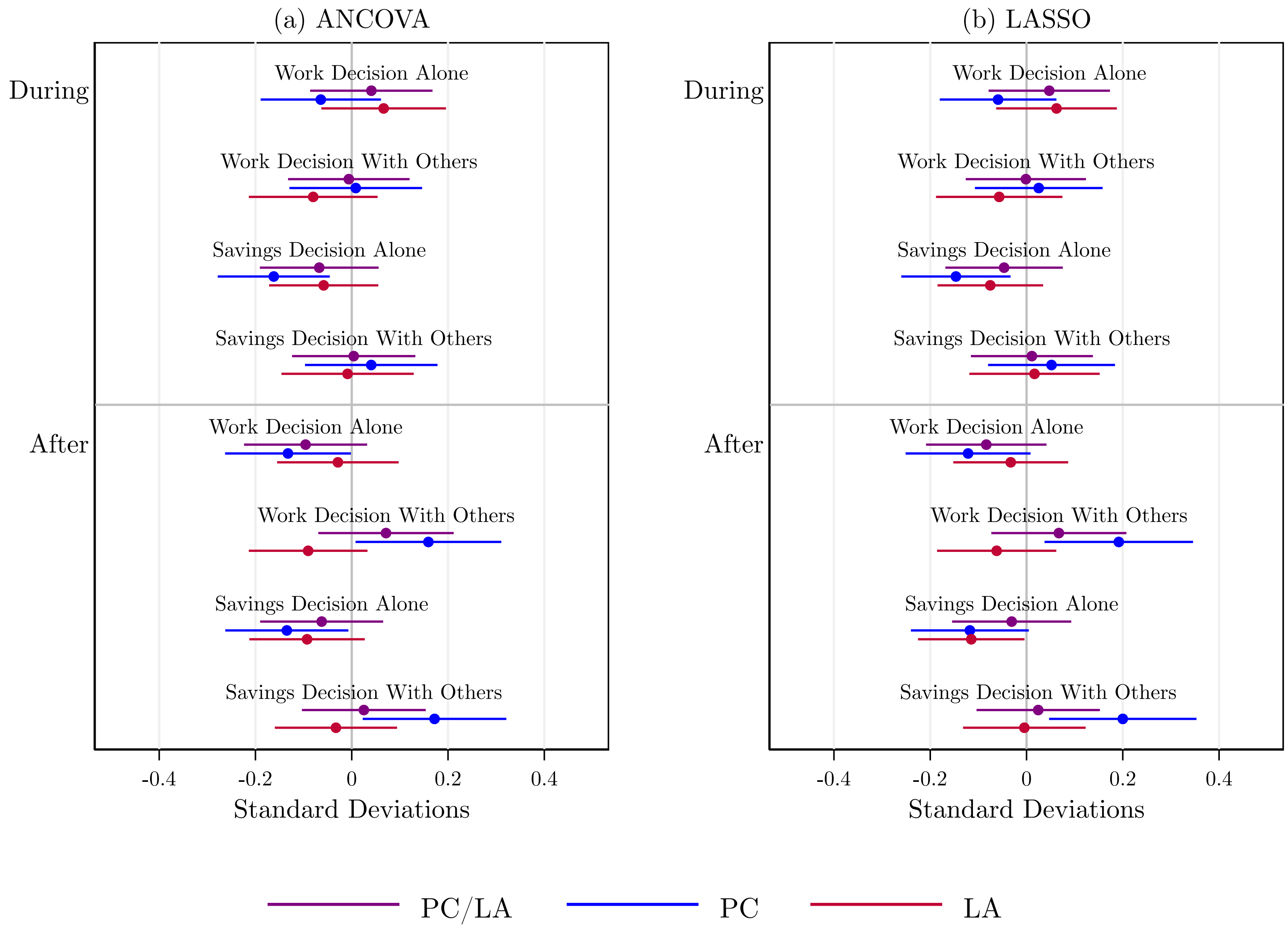

Figure A18: Impacts on Participation in Household Decisions

Note: The figure shows standardized impacts and 90 percent confidence intervals for the components of the subjective wellbeing index. All estimates follow Equation (1). Results in Panel (a) are based on the ANCOVA specification, which controls for time indicators, strata indicators, and the baseline dependent variable. Results in Panel (b) use the post-double-selection LASSO method to choose covariates (Belloni et al. 2014). Footnote 19 explains this approach in more detail. The top of each panel shows impacts during the PC intervention and the bottom of each panel shows impacts after the PC intervention. Confidence intervals are based on unadjusted p-values. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. The following estimates are statistically significant after this adjustment: "savings decision alone" impact of PC in the "during" period under ANCOVA ($q = 0.10$); all four components impact of PC in the "after" period under LASSO ($q = 0.09$ for all four outcomes). All other estimates are statistically insignificant after adjustment.

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