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

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This study evaluates the impact of depression treatment on economic behavior in Karnataka, India. We cross-randomize pharmacotherapy and livelihoods assistance among 1,000 depressed adults and evaluate impacts on depression severity, socioeconomic outcomes, and several potential pathways. When combined, the interventions reduce depression severity, with benefits that persist after treatment concludes. Pharmacotherapy alone has a weaker effect that is only marginally significant and dissipates sooner. Depression treatment does not significantly increase earnings, consumption, or human capital investment in children. (*JEL* I12, I15, I18, J13, J22, J31, O15)

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 top contributor to global disability (WHO 2017). 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.

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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). Stigma and the lack of awareness of mental illness also limit the demand for treatment.

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 pharmacotherapy in developing countries as well as evidence of the long-term effects of a single course of pharmacotherapy in general. It is also unclear 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-randomized trial that cross-randomized psychiatric care (PC) and livelihoods assistance (LA) among 1,000 adults (86 percent of whom were 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. By partnering with a local NGO that offers these programs to people with mental illness, we were able to provide both interventions using the existing local infrastructure. Use of local resources is an important factor that facilitates scale-up (Zamboni et al. 2019).

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-five percent of participants complied with PC, and 68 percent complied with LA. This level of participation suggests that it is possible to surmount barriers to mental health treatment such as stigma and a lack of awareness. 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 a single course of pharmacotherapy on mental health and other outcomes. At present, these effects are largely unknown.

We find that offering pharmacotherapy reduces depression severity when paired with livelihoods and that this mental health impact persists after treatment concludes. The effect of PC/LA is −0.26 SD (95 percent CI: −0.41 to −0.10) during the PC intervention and −0.24 SD (95 percent CI: −0.41 to −0.07) afterward. These effects correspond to a 15.0 percentage point (95 percent CI: 7.4 to 22.5) decrease in the frequency of moderate or severe depression during the PC intervention and a

7.8 percentage point (95 percent CI: −0.002 to 15.8) decrease in this frequency afterward. When pharmacotherapy is offered without livelihoods, the effect on depression symptoms is weaker and dissipates sooner. The effect of PC alone is −0.14 SD (95 percent CI: −0.30 to 0.03) while PC is ongoing, which is only significant at the 10 percent level, and −0.04 SD (95 percent CI: −0.19 to 0.12) after PC concludes. These effects correspond to a 7.1 percentage point (95 percent CI: −0.006 to 14.7) decrease in the frequency of moderate or severe depression during the PC intervention and 0.3 percentage point (95 percent CI: −6.9 to 7.5) decrease in this frequency afterward.[1,2] Bundling LA with PC is a cost-effective way to reduce depression symptoms because adding LA to PC only increases the intervention cost by 5 percent.

Pharmacotherapy does not increase work time or earnings. In fact, PC *reduces* work time by 5.4 hours per week (95 percent CI: 2.1 to 8.7) during the PC intervention, but this effect dissipates afterward. By contrast, PC/LA does not reduce work time during the PC intervention.[3] Household consumption follows a similar pattern: PC significantly reduces consumption during the intervention, but PC/LA does not. The differences between these effects of PC and PC/LA are statistically significant 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.

In contrast to Baranov et al. (2020), depression treatment does not have a statistically significant impact on child human capital investment overall. School holidays and the timing of decisions about enrollment may limit the scope for adjustments to human capital investment in the "during" period. However, overall effects are also statistically insignificant after the PC intervention: the effect of PC/LA is 0.12 SD (95 percent CI: −0.13 to 0.37), and the effect of PC is 0.18 SD (95 percent CI: −0.01 to 0.38). Despite the lack of an effect overall, we find some evidence of positive effects on human capital investment among older children. Among children who are older than 12 (the age of transition to secondary school), PC increases investment by 0.44 SD (95 percent CI: 0.12 to 0.75), and PC/LA increases investment by 0.40 SD (95 percent CI: −0.06 to 0.86), which is significant at the 10 percent level. The effects in the two arms are not statistically different from each other, although only one is statistically significant at conventional levels. Effect sizes among older children 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 2022). While this evidence is not strong, this comparison suggests that living

[1] We report average intent-to-treat effects and provide lower and upper bounds based on 95 percent confidence intervals in parentheses throughout the paper.

[2] The impact of LA on depression severity is −0.08 SD (95 percent CI: −0.25 to 0.09) during the intervention and 0.01 SD (95 percent CI: −0.15 to 0.16) afterward. The "during" period estimate corresponds to a 6.9 percentage point (95 percent CI: −0.01 to 14.8) decline in the probability of moderate or severe depression, which is significant at the 10 percent level.

[3] Despite the intention behind the program, LA alone does not have impacts on productive time. The lack of an impact suggests that the LA intervention alone is not sufficient to overcome the barriers to work among study participants.

with a depressed adult may create an important demand-side barrier to child human capital accumulation.[4]

Next, we consider several possible pathways through which depression treatment may affect behavior. We do not find evidence that depression treatment improves subjective well-being, cognition, or participation in household decisions. We find suggestive evidence that pharmacotherapy decreases risk tolerance, which is consistent with a "preferences" pathway and might contribute to an effect of depression on investment, as we discuss later.[5]

Our interpretation of these findings is that the combination of community-based pharmacotherapy and other light-touch interventions may help alleviate depression symptoms in low-income countries. This approach may be especially useful in settings where psychologists and counselors are scarce. An important next step is to understand why livelihoods assistance (which does not directly improve labor market outcomes) enhances the effectiveness of pharmacotherapy. The findings also indicate that pharmacotherapy per se does not lead to short-term poverty reduction. However, at the same time, there is suggestive evidence of a causal link between depression treatment and older children's human capital investment. Since fostering human capital accumulation is an important avenue to increase the future well-being of children and limit the intergenerational transmission of poverty, further research should continue to investigate this link.

This paper advances several areas of research. We contribute to research on 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 longer-term effects of a single course of pharmacotherapy on mental health and socioeconomic outcomes. Most medical studies examine either the contemporaneous effects on mental health or the side effects of long-term, uninterrupted treatment. Thirdly, we show that adding LA to PC enhances the effect 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 also contribute to the literature on child development, which correlates parental depression with impaired development (Cummings and Davies 1994) and lower human capital investment (Claessens, Engel, and Curran 2015; Dahlen 2016; Shen et al. 2016).

Finally, we contribute to the understanding of poverty traps and 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

[4] LA also increases child human capital investment for older children in the "after" period. 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.

[5] We create a risk intolerance index using items from the DOSPERT scale (Blais and Weber 2006), a generalized risk self-assessment (Dohmen et al. 2011), and an incentivized lottery game (Eckel and Grossman 2008). We also compute a negative shocks scale from socioeconomic shocks experienced in the previous four months (Holmes and Rahe 1967). After the PC intervention, PC/LA increases risk intolerance by 0.18 SD (95 percent CI: −0.05 to 0.41) and reduces the incidence of negative shocks by 0.14 SD (95 percent CI: −0.31 to 0.02), while PC increases risk intolerance by 0.24 SD (95 percent CI: 0.01 to 0.47) and reduces the incidence of negative shocks by 0.11 SD (95 percent CI: −0.27 to 0.04).

evidence that depression treatment improves labor market outcomes or increases consumption. This pattern is not consistent with a poverty trap due to the contemporaneous feedback between depression and low productivity. These results align with Baranov et al. (2020) and Bhat et al. (2022), who also focus on women in South Asia. At the same time, evidence suggests that it may be worth investigating whether and to what extent depression may prevent investment in older children's human capital, which may contribute to the intergenerational transmission of poverty.

I. 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.[6] To measure the prevalence and correlates of depression in this area, we concurrently surveyed a representative sample of adults in an adjacent nonstudy district. In this setting, 24 percent of adults aged 18 to 50 have some depression symptoms, and 9 percent have symptoms of at least moderate depression.[7] 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 online Appendix B.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 well-being 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 an accredited private hospital in Tumkur, Karnataka, near the study area. The facility has 750 beds, 80 percent of which are allocated for pro bono care of disadvantaged patients. The hospital sometimes receives patients from GASS. The initial visit included a diagnosis, an explanation of the significance of mental illness, and an individualized course of medical treatment. Patients returned for monthly follow-up visits. The most commonly prescribed antidepressants were selective serotonin reuptake inhibitors (SSRIs). These drugs are generally not under patent and are available inexpensively in India. They are widely used and have relatively few, well-tolerated side effects (Ferguson 2001; Cascade, Kalali, and Kennedy 2009).[8] In addition

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

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

[8] GASS organized all visits, transported participants to their appointments, and monitored patient welfare via home visits throughout the intervention.

to treating depression, the PC intervention may raise awareness and increase the salience of depression in the household, which could lead to additional effects. Online Appendix B.2 discusses ethical considerations.

SSRIs are often used as first-line pharmacotherapy for unipolar depression. They are usually taken daily, and a course of treatment lasts 4 to 12 months, although the optimal treatment duration is unclear (Kovich and DeJong 2015). Meta-analyses have found SSRIs to be effective for treatment of unipolar adult major depression disorder (Gartlehner et al. 2017; Cipriani et al. 2018) but have not identified consistent sources of heterogeneity by patient characteristics or depression severity.[9] Around 20 percent of patients who abruptly discontinue SSRIs experience antidepressant discontinuation syndrome. Symptoms such as dizziness, fatigue, nausea, and irritability may last for one to two 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). The long-term impacts of a single course of SSRIs are not well studied. The literature on the long-term effects of SSRIs is primarily qualitative and focuses on long-term side effects and the effects of discontinuation (e.g., Cartwright et al. 2016).

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).

II. Design, Sampling, and Recruitment

The study design and analysis follow the analysis plan that we prespecified and registered before collecting follow-up data (Angelucci and Bennett 2022b). Online Appendix Table B1 itemizes and explains the minor deviations from the analysis plan.[10] We used a cluster-randomized design to cross-randomize psychiatric care and livelihoods assistance by locality. Figure 1 provides a CONSORT chart for this study.

[9] 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 and the manifestations of depression often differ from inpatient psychiatric settings. A meta-analysis by DeMaat 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. It is unclear whether the effectiveness of SSRIs varies by baseline severity of symptoms (Maslej et al. 2021). For example, Fournier et al. (2010) suggest that SSRIs may be most effective for people with severe depression. However, Kirsch et al. (2008) argue that this is because people with severe depression respond less to the placebo.

[10] The main deviations include the addition of extra survey rounds and the inclusion of LASSO estimates as a robustness test. We also omit a few outcomes that were not collected reliably or that are analyzed in a separate paper, as detailed in online Appendix Table B1.

Before starting recruitment, we stratified the randomization by district and terciles of a locality socioeconomic index based on the 2011 census of India, for a total of nine strata.[11] We screened about 40 households per locality, with the target of selecting 1–2 participants per locality. The modal and median number of participants per locality is two. This design minimized spillovers and cross-arm contamination. Treating few people per locality limited information leakages, protecting patient confidentiality.

Our partner NGO could offer the interventions only to a limited number of people. 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 localities) in the control arm, 207 participants (from 99 localities) in the PC arm, 205 participants (from 102 localities) in the LA arm, and 195 participants (from 101 localities) in the PC/LA arm. With these sample sizes, the minimum detectable effect (MDE) for the comparison of any of the intervention arms with the control arm (e.g., PC/LA versus control) is 0.16 SD in either the "during" or "after" periods. This calculation is based on the assumptions of 80 percent power and 95 percent confidence. For a comparison of two interventions (e.g., PC/LA versus PC), the MDE is 0.19 SD. For a test of the complementarity between the interventions (i.e., whether the effect of PC/LA exceeds the sum of the effects of PC and LA), the MDE is 0.28 SD.[12] Online Appendix B.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 locality size. Once at the household, surveyors randomly chose an available adult to screen for eligibility. We screened people for depression symptoms with the PHQ-9 depression severity scale (Kroenke, Spitzer, and Williams 2001). This nine-item scale ranges from 0 to 27, and higher values indicate more severe symptoms. The PHQ-9 is widely validated to screen for depression and measure the response to treatment in India and throughout the world (e.g., Patel et al. 2008; Manea, Gilbody, and McMillan 2012; Indu et al. 2018). To obtain a sample of mildly or moderately depressed people, we recruited subjects with PHQ-9 scores of 9–20.[13] In total, surveyors screened 6,446 people in order to enroll a study sample of 1,000 participants across 506 localities. 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.

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

[12] The difference in sample size across intervention arms and time periods is small enough that it has negligible effect on the MDE.

[13] 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 6000 rupees per month, or whose childcare duties required them to remain at home throughout the day. We also excluded pregnant women due to the additional risks of pharmacotherapy during pregnancy.

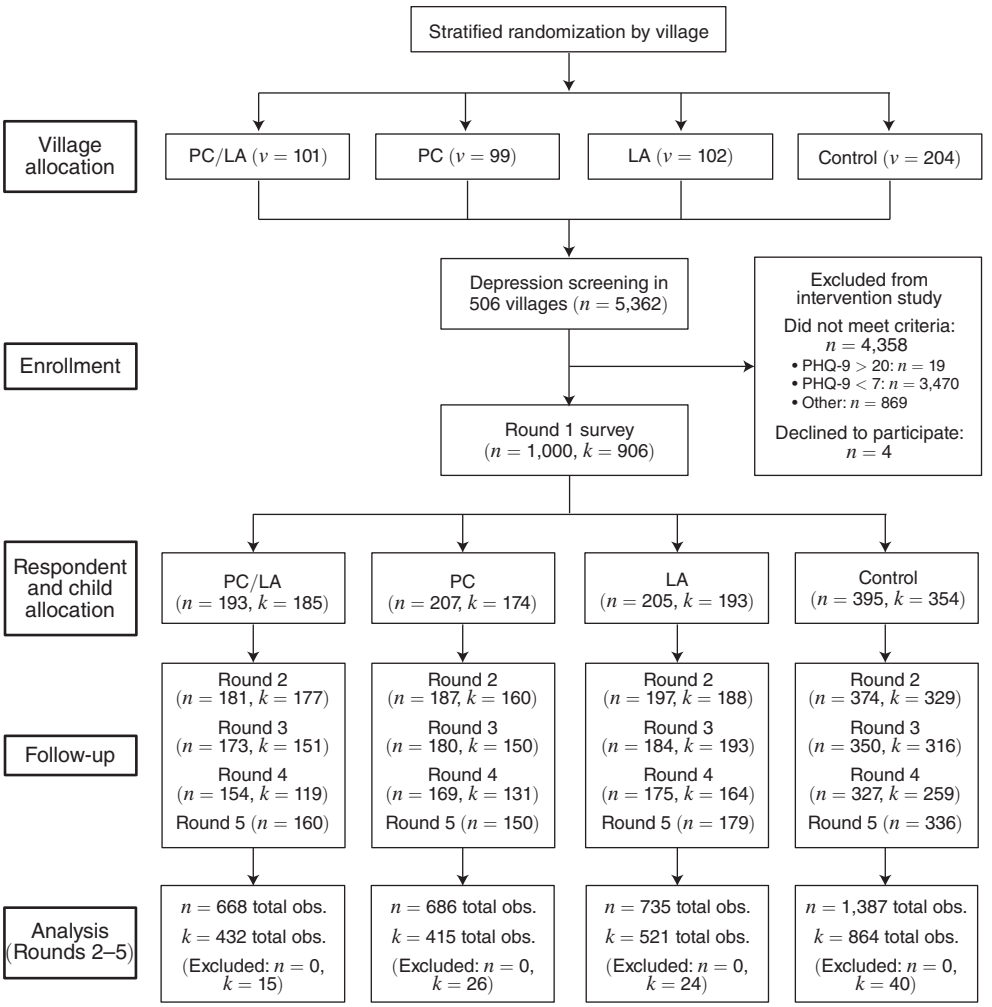

FIGURE 1. CONSORT FLOW DIAGRAM

Notes: The chart illustrates the trial design and the allocation of localities, respondents, and household children to intervention arms. v indicates the number of localities, n the number of respondents, and k the number of school-aged children. We randomized localities 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. In addition to the PHQ-9, participants could be excluded from the intervention study if they were pregnant, not interested in work, or had full-time childcare duties. Some participants failed to qualify for multiple reasons. Some children were excluded from the estimation sample because surveyors did not obtain information about their ages. Online Appendix Figure B2 illustrates the study timeline in more detail.

III. Data and Measurement

We surveyed respondents 5 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 rounds 4 and 5 as "after the PC intervention" in our analysis below. Online Appendix Figure B2 illustrates the study timeline.[14]

We study four categories of outcomes: (i) participants' depression severity, work hours, and earnings; (ii) child human capital investment; (iii) household consumption, wealth, and hygiene/sanitation; (iv) and potential pathways that link depression to the other outcomes. We winsorize monetary values at 5 percent and deflate to 2017 values using the Indian consumer price index.[15]

We measure depression severity using the PHQ-9 scale. Although the PHQ-9 is not a diagnostic tool, 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, Spitzer, and Williams 2001). We examine impacts on standardized PHQ-9 scores.

We measure work time—the time spent on productive activities—from a 24-hour time diary and then convert responses into weekly values. Productive activities include primary and secondary jobs, agricultural work, childcare, cooking, cleaning, doing laundry, and fetching water.[16] We measure weekly earnings from primary and secondary jobs. As in other informal economies, most people who work in our setting do not receive wages or salaries. Only 28 percent of people report receiving wages from their primary occupation, which suggests that many people are self-employed or work in the informal sector.

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 regressions, but we weight by the inverse number of children per household so that estimates are comparable to other results in the paper.[17]

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 nondurable nonfood commodities (converted into weekly values from 1- or 2-month recalls) divided by household size.[18] We measure durable goods ownership according to indicators for household ownership of nine goods.[19] 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 well-being, and participation in household decisions. We assess cognitive performance through

[14] Replication data are available in the AEA Data and Code Repository (Angelucci and Bennett 2024).

[15] Results are similar if we do not winsorize earnings and consumption.

[16] 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.

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

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

[19] 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.

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.[20] We use the five-item Satisfaction with Life Scale to measure subjective well-being (Kobau et al. 2010). As a measure of participation in household decisions, respondents indicate whether they make household financial and employment decisions alone, with other household members, or not at all. The negative shock 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.

Since each family of outcomes has multiple variables, we create family-specific indexes by computing the first principal component of the outcomes within each family.[21] 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 indexes to ease interpretation. As exceptions to this approach, total consumption is defined as the sum of food and nonfood consumption; for participation in household decisions, we count the number of decisions (across financial and employment decisions) that the respondent participates in.

IV. 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). Similar proportions of PC and PC/LA participants (46 and 43 percent) attended at least one psychiatric visit ($p = 0.51$ for this comparison) according to psychiatrist records. Participation in livelihoods assistance meetings was somewhat higher (68 versus 58 percent) in LA than in PC/LA ($p = 0.10$ for this comparison). Within PC/LA, 30 percent of participants took up both interventions. Online Appendix Figures B3 and B4 further illustrate intervention compliance.

Ninety-one 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 "almost every day," and 13 percent of patients continued to take SSRIs after the PC intervention ended. Medication adherence was 8 percentage points higher in the PC/LA arm ($p = 0.07$). This difference suggests that the LA treatment may have

[20] 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.

[21] The Anderson (2008) Summary Index is an alternative way to create indexes. Online Appendix Figure B18 shows impacts on all index outcomes calculated using the Anderson (2008) approach. Results are similar.

enabled participants to plan or follow through.[22] Among LA compliers, 81 percent attended at least one livelihoods workshop, and 47 percent received personalized livelihoods assistance.[23] Online Appendix B.4 considers the correlates of intervention compliance. PC and PC/LA compliers are more likely to be men than noncompliers, while LA compliers are more likely to have better mental health than noncompliers. However, these differences are small, and compliers and noncompliers 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.

V. Identification and Estimation

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

$$(1)\quad Y_{ijt} = \beta_1\big(PC_j \cdot D_t\big) + \beta_2\big(LA_j \cdot D_t\big) + \beta_3\big(PC/LA_j \cdot D_t\big) + \beta_4\big(PC_j \cdot A_t\big) + \beta_5\big(LA_j \cdot A_t\big) + \beta_6\big(PC/LA_j \cdot A_t\big) + \mathbf{X}'_{ij}\beta_7 + \varepsilon_{ijt}.$$

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") is an indicator for rounds 2 and 3 (while PC was ongoing or had just concluded), and *A* ("after") is an indicator for 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 that treatment assignment is independent of potential outcomes. Assigning treatment by locality minimizes instances of violations of the first assumption through spillovers such as social interactions, while treating one to two people per locality minimizes locality-specific equilibrium effects. Random assignment should ensure that the second assumption holds.

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 $\beta_6 - \beta_4 - \beta_5 = 0$). We also test whether the treatment effects differ by arm ($\beta_1 = \beta_2 = \beta_3$ and $\beta_4 = \beta_5 = \beta_6$) and whether other pairwise effects are identical (e.g., $\beta_1 = \beta_2$, and $\beta_3 = \beta_2$). We use OLS and cluster standard errors by locality.

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.[24] The LASSO approach uses the post-double-selection method of

[22] Fifty-five percent of patients were diagnosed with anxiety, which is a common depression comorbidity (Hirschfeld 2001), and 14 percent were diagnosed with other conditions (e.g., chronic pain, anemia).

[23] 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.

[24] 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 0.63. Therefore, we use ANCOVA to streamline the analysis. Difference-in-difference estimates closely resemble ANCOVA estimates and are available from the authors.

Belloni, Chernozhukov, and Hansen (2014) inference 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.[25]

Table 1 shows baseline summary statistics of key outcome variables and covariates by intervention arm. Column 1 shows the control mean of each variable. Columns 2–7 show the mean difference between each intervention arm and the control arm, along with p-values (based on locality-clustered standard errors) that indicate the statistical significance of these differences. Finally, column 8 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 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 bottom of Table 1 shows that, overall, attrition does not vary systematically by arm except in round 5, in which attrition is higher in the PC arm. Online Appendix B.5 shows that differential attrition does not confound the results we present below.[26]

VI. Impacts on Participants

A. *Depression Symptoms*

Table 2 shows treatment effects on depression symptoms. The impact of PC/LA is larger and more durable: PC/LA reduces the PHQ-9 score by 0.26 SD (95 percent CI: −0.41 to −0.10) during the PC intervention and by 0.24 SD (95 percent CI: −0.41 to −0.07) after, while PC alone reduces the PHQ-9 score by 0.14 SD (95 percent CI: −0.30 to 0.03) during the PC intervention, which is significant

[25] 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 nondurable consumption and expenditures (total, food, nonfood, 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 well-being index and components, and 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.

[26] As a separate inquiry, we provided free hand sanitizer and explained its uses to 80 percent of participants who were present in the study by round 2. Angelucci and Bennett (2022a) explain further. Online Appendix Figure B19 shows that adding an indicator for this intervention to equation (1) does not affect our estimates.

TABLE 1—BASELINE SUMMARY STATISTICS

	Control mean	PC/LA		PC		LA		Joint p-value
		Diff.	p-value	Diff.	p-value	Diff.	p-value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Respondent, child, and household characteristics								
Age	35.6	−0.32	0.65	−0.53	0.46	−0.69	0.32	0.76
Female	0.90	−0.07	0.04	−0.06	0.07	−0.05	0.09	0.07
Married	0.78	0.00	0.94	0.00	0.96	−0.03	0.38	0.82
Schooling (years)	4.95	0.32	0.39	−0.22	0.57	0.08	0.83	0.65
Scheduled caste/tribe	0.50	0.02	0.76	0.06	0.25	0.05	0.31	0.61
Literacy (1–3)	1.9	0.05	0.55	−0.05	0.54	−0.01	0.94	0.78
Household size	4.17	0.07	0.63	0.01	0.94	−0.19	0.18	0.38
Exposure to early-life shocks	92.5	−1.8	0.83	7.5	0.39	−7.0	0.43	0.57
Housing quality index	0	0.02	0.88	0.06	0.57	0.01	0.94	0.95
Panel B. Primary outcomes								
PHQ-9 depression scale (0–27)	14.4	−0.83	0.03	−0.5	0.21	−0.8	0.03	0.08
Weekly paid and unpaid work hours	57.0	−1.75	0.51	−2.0	0.35	−0.19	0.94	0.76
Weekly earnings (rupees)	308	103	0.14	57	0.37	7	0.9	0.44
Panel C. Household socioeconomic outcomes								
Hygiene and sanitation	0	−0.13	0.23	0.00	0.98	0.09	0.37	0.36
Durable goods	0	0.03	0.78	0.06	0.51	−0.08	0.40	0.62
Total per capita consumption (rupees)	463	−18	0.46	21	0.36	18	0.53	0.46
Panel D. Child outcomes								
Human capital investment index	0	−0.11	0.43	−0.05	0.71	0.11	0.29	0.40
Panel E. Potential mechanisms								
Risk intolerance	0	−0.26	0.02	−0.05	0.63	−0.21	0.05	0.04
Cognitive performance	0	0.05	0.62	−0.12	0.22	−0.06	0.47	0.43
Subjective well-being	0	−0.01	0.91	0.11	0.25	0.08	0.43	0.52
Participation in household decisions	1.24	0.12	0.16	0.05	0.57	0.17	0.04	0.16
Present in round 2	0.95	−0.01	0.66	−0.04	0.07	0.01	0.43	0.13
Present in round 3	0.89	0.01	0.71	−0.02	0.56	0.01	0.69	0.80
Present in round 4	0.83	−0.03	0.39	−0.01	0.74	0.03	0.47	0.57
Present in round 5	0.85	−0.02	0.51	−0.13	0.00	0.02	0.50	0.01

Notes: PC = psychiatric care, LA = livelihoods assistance, C = control. All statistics are computed at baseline. Column 1 shows the mean in the control arm. Columns 2, 4, and 6 show the difference between the PC/LA, PC, and LA arms and the control arm. Columns 3, 5, and 7 show the *p*-values for these differences based on regressions with locality-clustered standard errors. Column 8 reports the *p*-value for the joint significance of the parameters in columns 2, 4, and 6. 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. Observations = 743 for the housing quality index, and observations = 906 for child human capital. Observations ranges from 971 to 1,000 for all other outcomes.

at the 10 percent level, and by a statistically insignificant 0.04 SD (95 percent CI: −0.19 to 0.12) afterward.[27]

The impact of PC/LA is significantly larger than the impact of PC in the "after" period ($0.04 \leq p \leq 0.06$), and it is significantly larger than the impact of LA in

[27] Using entropy weights to correct for the baseline imbalance in PHQ-9 scores leads to estimates that are comparable and not statistically distinguishable from our main estimates. The most notable difference is that the ANCOVA estimate of the impact of PC in the "during" period shrinks from −0.14 SD to −0.13 SD and is no longer statistically significant (95 percent CI: −0.30 to 0.04). The comparable LASSO estimate is −0.13 SD (95 percent CI: −0.29 to 0.02), which is significant at the 10 percent level. These effect sizes are consistent with the literature, as we discuss in online Appendix B.6.

Table 2—Impact on Depression Severity

	PHQ-9 (SD)	
	(1)	(2)
Panel 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
Panel B. After the PC intervention		
PC/*LA*	−0.24	−0.24
	(0.086)	(0.087)
PC	−0.039	−0.067
	(0.077)	(0.075)
LA	0.0058	0.016
	(0.081)	(0.079)
H_0: $PC/LA = PC$	0.04	0.06
H_0: $PC/LA = PC + LA$	0.10	0.12
H_0: $PC = LA$	0.62	0.35
H_0: $PC/LA = LA$	0.01	0.01
H_0: $PC/LA = PC = LA$	0.03	0.03
Control mean of outcome	0	0
Baseline outcome coefficient	0.151	0.095
	(0.026)	(0.023)
Specification	ANCOVA	LASSO
Observations	3,476	3,476

Notes: 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, Chernozhukov, and Hansen 2014). Footnote 25 explains this approach in more detail. Locality-clustered standard errors appear in parentheses. "During" and "after" estimates are based on a common regression. The outcome is the standardized PHQ-9 depression severity score.

both periods ($0.01 \leq p \leq 0.07$). We also fail to reject that PC and LA have the same 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 a statistically insignificant effect on the PHQ-9 score: −0.08 SD (95 perfect CI: −0.25 to 0.09) during the PC intervention and 0.01 SD (95 percent CI: −0.15 to 0.16) afterward.

To quantify the differential impact of PC/LA relative to PC, we compute the total reduction in PHQ-9 $\times$ months over the study period for each arm.[28] 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 cost-effectiveness in terms of reducing depression symptoms. Online Appendix B.7 describes this exercise in more detail.

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. The Appendix provides estimates for indicators 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. In Appendix Table A1, PC/LA reduces the frequency of moderate or severe depression by 15.0 percentage points (95 percent CI: 7.4 to 22.5), PC reduces this frequency by 7.1 percentage points (95 percent CI: -0.006 to 14.7), and LA reduces this frequency by 6.9 percentage points (95 percent CI: -0.01 to 14.8) in the "during" period. In the "after" period, PC/LA reduces the frequency of moderate or severe depression by 7.8 percentage points (95 percent CI: -0.002 to 15.8), while PC and LA have smaller and statistically insignificant effects. Appendix Figure A1 shows means of these outcomes by intervention arm and round. Means for the "no depression" indicator are zero for all arms in round 1 because we only recruited people with PHQ-9 scores of at least 7. As a result, this outcome is balanced at baseline by construction. The figure shows the largest impacts on "no moderate/severe depression" and "no depression" for the PC/LA arm in all follow-up rounds.

Online Appendix Figure B5 estimates heterogeneity in the impacts on mental health by baseline characteristics, including gender, age, socioeconomic status, PHQ-9 score, physical health, cognition, and exposure to negative shocks during childhood. 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.

Online Appendix Figure B6 estimates impacts on the GAD-7 anxiety score and an index of activities of daily living (ADL). The PC/LA intervention significantly reduces anxiety, while the other interventions do not have statistically significant effects. The impact on activities of daily living varies by arm: PC/LA increases the ADL index, PC decreases it during the intervention, and LA does not have statistically significant effects.

B. *Work Time and Earnings*

Table 3 shows that PC/LA and PC have different treatment effects on work time and earnings while the PC intervention is ongoing. PC reduces weekly work time by 5.4 hours (95 percent CI: -8.7 to -2.1) and weekly earnings by

[28] We multiply the "during" period estimates in column 1 of Table 2 by 8 months and the "after" period estimates in column 1 by 18 months.

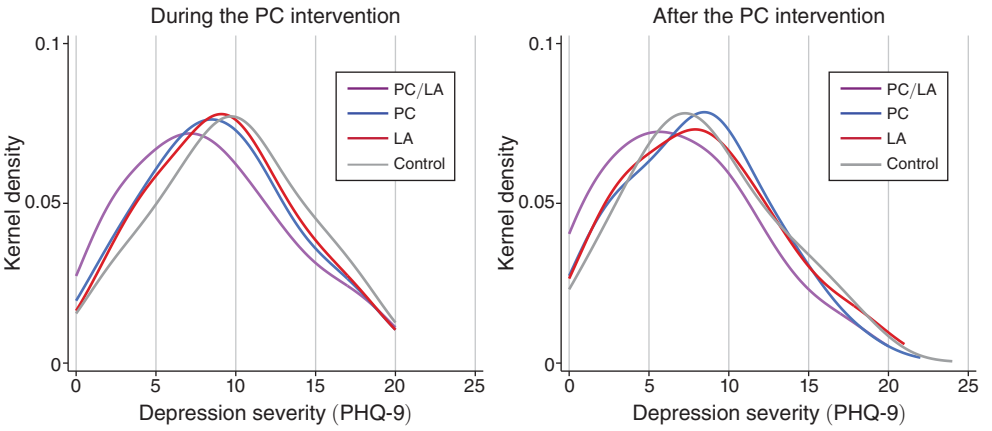

FIGURE 2. DENSITY OF PHQ-9 SCORES BY ARM

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).

65 rupees (95 percent CI: −172 to 41), a 10 percent decrease in both outcomes, although the effect on earnings is not statistically significant. Online Appendix Figure B7 shows that there is a concurrent increase in sleep and leisure time in the PC arm, as we discuss in online Appendix B.10. 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, Pai, and Suziedelyte 2017). By contrast, PC/LA increases weekly work time by 1.1 hours (95 percent CI: −2.2 to 4.3) and weekly earnings by 38 rupees (95 percent CI: −83 to 158), but neither effect is statistically significant. 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 ($p = 0.12$). None of the impacts of PC and PC/LA are statistically different from 0 or from each other at the 5 percent level in the "after" period.

In sum, our results suggest that pharmacotherapy does not increase the time spent on productive activities in our sample. Eighty-six 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. (2020) and Bhat et al. (2022) also find no long-term effects of depression treatment 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. (2022) find that various mental health interventions have positive effects on employment.

The LA intervention has no statistically or economically significant effects on work time or earnings. In the "during" period, the effect of LA on work time is −1.0 hours per week (95 percent CI: −4.3 to 2.3), and the effect on earnings is −33 rupees per week (95 percent CI: −154 to 89). In the "after" period, the effect of LA on work time is −1.5 hours per week (95 percent CI: −5.4 to 2.3), and the effect

Table 3—Impact on Weekly Work Time and Earnings

	Hours		Earnings	
	(1)	(2)	(3)	(4)
Panel 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
Panel B. After the PC intervention				
PC/LA	−3.31	−2.84	38.7	20.8
	(1.77)	(1.74)	(67.3)	(65.9)
PC	−1.18	−0.84	−52.8	−63.6
	(1.98)	(1.89)	(61.0)	(57.5)
LA	−1.52	−1.04	47.9	45.1
	(1.95)	(1.93)	(62.2)	(60.0)
H_0: $PC/LA = PC$	0.34	0.35	0.22	0.24
H_0: $PC/LA = PC + LA$	0.84	0.74	0.65	0.68
H_0: $PC = LA$	0.89	0.93	0.15	0.10
H_0: $PC/LA = LA$	0.42	0.41	0.90	0.74
H_0: $PC/LA = PC = LA$	0.58	0.58	0.29	0.23
Control mean of outcome	60.4	60.4	639.2	639.2
Baseline outcome coefficient	0.208	0.131	0.188	0.095
	(0.023)	(0.020)	(0.028)	(0.028)
Specification	ANCOVA	LASSO	ANCOVA	LASSO
Observations	3,476	3,476	3,476	3,476

Notes: 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, Chernozhukov, and Hansen 2014). Footnote 25 explains this approach in more detail. Locality-clustered standard errors appear in parentheses. "During" and "after" estimates are based on a common regression. The outcome in columns 1 and 2 is weekly productive time, which is the sum of time spent on primary and secondary jobs, agriculture, childcare, cooking, cleaning, laundry, and fetching water. The outcome in columns 3 and 4 is weekly earnings from primary and secondary jobs.

on earnings is 48 rupees per week (95 percent CI: −74 to 170). There appear to be multiple barriers to increasing work time and earnings for our sample. Our findings suggest that neither mental health care nor livelihoods assistance is sufficient to overcome these barriers.

VII. Impacts on Children and the Household

Impacts on child human capital investment appear in Table 4. Estimates are not statistically significant in the pooled data in columns 1 and 2. In the "during" period, PC/LA has an effect of −0.14 SD (95 percent CI: −0.32 to 0.04), and PC has an effect of 0.11 SD (95 percent CI: −0.04 to 0.25). In the "after" period, PC/LA has

Table 4—Impact on Child Human Capital Investment

	Child human capital investment index					
	Full sample		Child age $\leq$ 12		Child age $>$ 12	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. During the PC intervention						
PC/LA	−0.14	−0.12	−0.065	−0.065	−0.23	−0.22
	(0.090)	(0.090)	(0.059)	(0.060)	(0.17)	(0.17)
PC	0.11	0.13	0.00027	0.00065	0.17	0.20
	(0.073)	(0.077)	(0.056)	(0.059)	(0.12)	(0.13)
LA	0.036	0.042	−0.061	−0.061	0.12	0.12
	(0.065)	(0.067)	(0.059)	(0.059)	(0.10)	(0.12)
H_0: $PC/LA = PC$	0.01	0.01	0.35	0.35	0.03	0.03
H_0: $PC/LA = PC + LA$	0.02	0.01	0.96	0.96	0.01	0.02
H_0: $PC = LA$	0.34	0.24	0.38	0.36	0.67	0.56
H_0: $PC/LA = LA$	0.06	0.08	0.95	0.96	0.04	0.05
H_0: $PC/LA = PC = LA$	0.05	0.04	0.57	0.56	0.07	0.07
Control mean of outcome	0	0	0.22	0.22	−0.20	−0.20
Panel B. After the PC intervention						
PC/LA	0.12	0.12	−0.083	−0.073	0.40	0.30
	(0.13)	(0.13)	(0.13)	(0.13)	(0.24)	(0.27)
PC	0.18	0.21	−0.012	−0.0014	0.44	0.44
	(0.099)	(0.10)	(0.11)	(0.11)	(0.16)	(0.16)
LA	0.11	0.11	−0.025	−0.019	0.32	0.30
	(0.12)	(0.11)	(0.11)	(0.11)	(0.19)	(0.20)
H_0: $PC/LA = PC$	0.61	0.42	0.62	0.62	0.87	0.55
H_0: $PC/LA = PC + LA$	0.30	0.21	0.80	0.77	0.21	0.16
H_0: $PC = LA$	0.53	0.34	0.92	0.89	0.53	0.38
H_0: $PC/LA = LA$	0.97	0.96	0.69	0.71	0.76	0.98
H_0: $PC/LA = PC = LA$	0.78	0.56	0.88	0.88	0.82	0.62
Control mean of outcome	0	0	0.21	0.21	−0.27	−0.27
Baseline outcome coefficient	0.40	0.32	0.15	–	0.47	0.49
	(0.045)	(0.056)	(0.045)		(0.049)	(0.054)
Specification	ANCOVA	LASSO	ANCOVA	LASSO	ANCOVA	LASSO
Observations	2,232	2,232	1,244	1,244	988	988

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

an effect of 0.12 SD (95 percent CI: −0.13 to 0.37), and PC has an effect of 0.18 SD (95 percent CI: −0.01 to 0.38). Next, we examine heterogeneity by the median age of 12, which corresponds to the transition to secondary school. Estimates are small and statistically insignificant for younger children in columns 3 and 4. For older children, PC/LA has an impact of 0.40 SD (95 percent CI: −0.06 to 0.86), and PC has an impact of 0.44 SD (95 percent CI: 0.12 to 0.75) in the "after" period in columns 5 and 6. All older child estimates are statistically significant at the 10 percent level in the "after" period, with slightly larger estimates under LASSO.[29]

[29] The impact on child human capital investment may happen 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

The effects differ by child age for PC/LA ($p = 0.09$) and for PC ($p = 0.02$). This pattern may reflect a ceiling on the potential impact for younger children. For example, among 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 educational interventions on enrollment from Evans and Yuan (2022) 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 impacts from both studies, suggesting that these effects are economically relevant and that adult depression may cause substantial demand-side barriers to older children's human capital accumulation.

The effects of LA are also insignificant for the pooled sample and for younger children. However, there is an impact of 0.32 SD (95 percent CI: −0.05 to 0.70) for older children in the "after" period. Finding that the LA intervention, which had minimal mental health improvements, also increases human capital investment for older children suggests that the treatments could affect human capital investment 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.

Figure 3 shows treatment effect heterogeneity in the "after" period by several additional child and respondent characteristics. We show differential effects by the gender, relation to the study participant, and baseline human capital of children as well as by the baseline depression severity, gender, age, socioeconomic status, physical health, cognition, and exposure to childhood shocks of the associated study participants. PC/LA has a significantly larger effect for boys and for children with high baseline human capital. LA has a significantly larger effect for children living with study participants who are relatively old. Other differential effects are not statistically significant. In principle, an adult mental health improvement might increase child human capital investment by lessening the burden of home production that falls on school-aged children. Since girls play a larger role in home production than boys, the lack of a differential effect for girls suggests that this explanation is unlikely.

Figure 4 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.[30] Online Appendix B.12 shows impacts on the components of these indexes.

among nonenrolled students and among all students during periods when school is not in session. Enrollment, attendance, and homework may be unresponsive in round 2 because it occurred during the same academic year as round 1. Moreover, attendance and homework may be unresponsive in round 3 because school was not in session for many students at that time. Online Appendix B.11 shows impacts on the components of the child human capital investment index.

[30] PC reduces per capita household income by 44 rupees (95 percent CI: −3 to 90), which is significant at the 10 percent threshold, and reduces per capita household consumption by 59 rupees (95 percent CI: 13 to 104) in the "during" period. No other arms have statistically significant effects on this outcome either during or after the PC intervention.

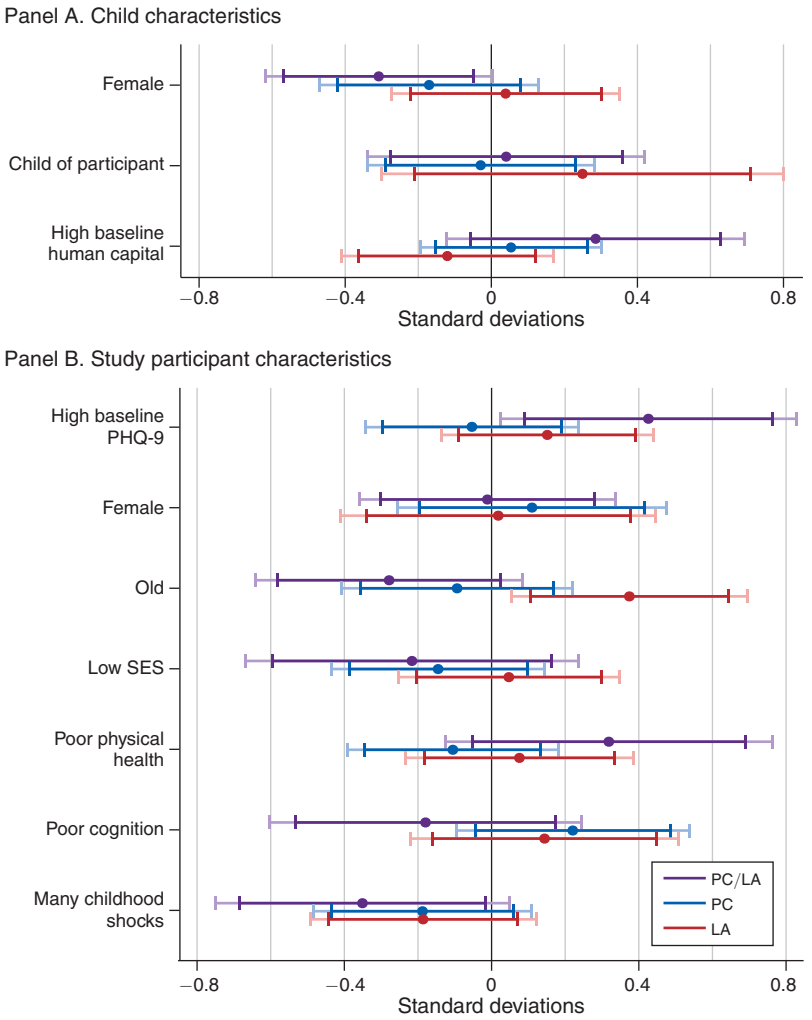

Figure 3. Differential Effects on Child Human Capital Investment by Child and Study Participant Characteristics in Round 4

Notes: The figure shows differential impacts on the child human capital index in round 4 for indicated subgroups. Light bars indicate 95 percent confidence intervals, and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. All estimates follow the ANCOVA specification of equation (1), which controls for time indicators, strata indicators, and the baseline dependent variable. Results using Belloni, Chernozhukov, and Hansen's (2014) post-double-selection LASSO method to choose covariates appear in online Appendix Figure B22. All estimates are weighted by the inverse number of school-aged children in the household. Panel A shows differential effects according to child characteristics, and panel B shows differential effects according to study participant characteristics. 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 follow the Holmes and Rahe (1967) index of childhood negative life events. Other variables are defined in the text. We divide at the median for baseline human capital investment (0.24 SD), PHQ-9 score (15), age (36), SES (−0.13 SD), physical health (−0.04 SD), cognition (−0.55 SD), and exposure to childhood shocks (65).

VIII. Potential Pathways

This section considers four pathways that may link depression and depression treatment to socioeconomic outcomes: risk intolerance, subjective well-being, cognitive

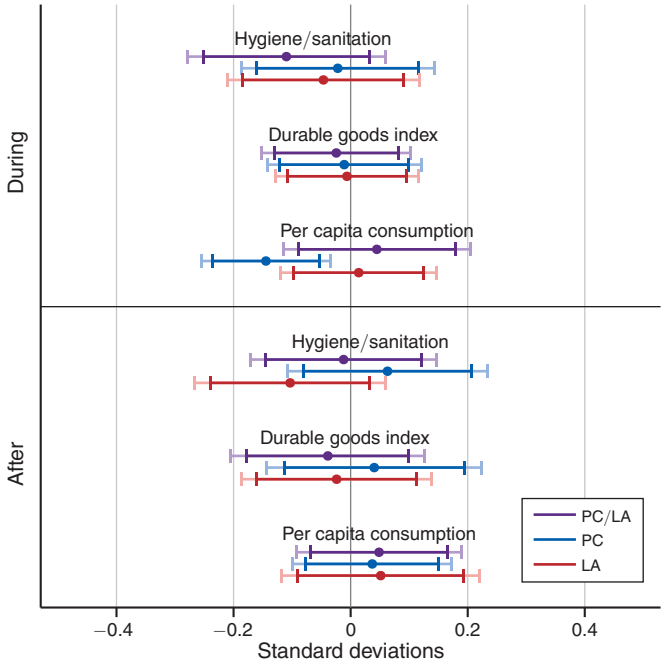

FIGURE 4. STANDARDIZED IMPACTS ON SOCIOECONOMIC OUTCOMES

Notes: The figure shows standardized impacts for socioeconomic outcomes, as explained in the text. Light bars indicate 95 percent confidence intervals, and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. All estimates follow the ANCOVA specification of equation (1), which controls for time indicators, strata indicators, and the baseline dependent variable. Results using Belloni, Chernozhukov, and Hansen's (2014) post-double-selection LASSO method to choose covariates appear in online Appendix Figure B20. The top of the figure shows impacts during the PC intervention, and the bottom of the figure shows impacts after the PC intervention.

performance, and participation in household decisions. Figure 5 shows treatment effects on these outcomes. While there is not strong evidence of improvements on any of these outcomes, a few interesting patterns emerge, as we describe below.

Although the results are only suggestive, pharmacotherapy may increase risk intolerance in the "after" period, with effects of 0.18 SD (95 percent CI: −0.05 to 0.41) for PC/LA and 0.24 SD (95 percent CI: 0.01 to 0.47) for PC.[31] An effect of depression on the marginal utility of consumption could jointly explain this result and the impact on child human capital investment above. The reasoning is as follows. Anhedonia, a common depression symptom, suppresses the ability to derive happiness from pleasant activities. By reducing the marginal utility of consumption, this symptom may narrow the utility gap between good and bad outcomes. Consequently, someone with depression may be less interested in achieving the consumption gains of human capital investment as well as avoiding the consumption losses associated with negative shocks. Since the willingness to avoid negative shocks is a key aspect of risk intolerance, anhedonia may also lead someone to take additional risks.[32] Consistent with this inter-

[31] The effect of LA in the "after" period is −0.03 SD (95 percent CI: −0.25 to 0.20), although it is bigger in the "during" period.

[32] This logic is commonly applied to the measurement of the value of statistical life (e.g., León and Miguel 2017), in which the willingness to pay to avoid mortality risk indicates the value of life over death.

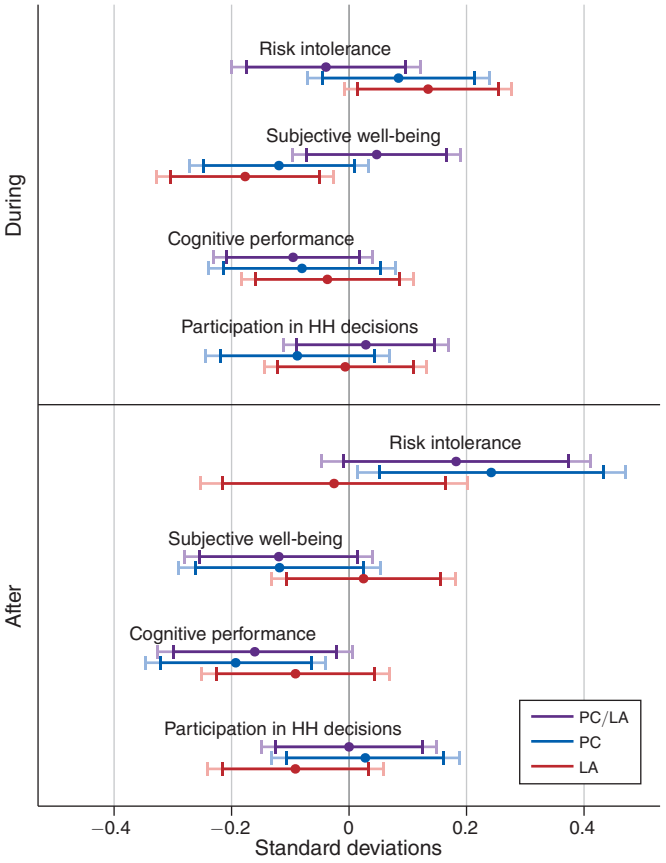

FIGURE 5. STANDARDIZED IMPACTS ON POSSIBLE PATHWAYS

Notes: The figure shows standardized impacts for possible pathways through which depression treatment may improve socioeconomic outcomes, as explained in the text. Light bars indicate 95 percent confidence intervals, and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. All estimates follow the ANCOVA specification of equation (1), which controls for time indicators, strata indicators, and the baseline dependent variable. Results using Belloni, Chernozhukov, and Hansen's (2014) post-double-selection LASSO method to choose covariates appear in online Appendix Figure B21. The top of the figure shows impacts during the PC intervention, and the bottom of the figure shows impacts after the PC intervention.

pretation, we find suggestive evidence that the pharmacotherapy interventions reduce the incidence of negative shocks in the "after" period: online Appendix Figure B15 shows that the effect of PC/LA on the incidence of negative shocks is −0.14 SD (95 percent CI: −0.31 to 0.02), which is significant at the 10 percent level, and the effect of PC is −0.11 SD (95 percent CI: −0.27 to 0.04).[33] Online Appendixes B.13 and B.14 provide further details on these outcomes.

Next, we consider estimates for subjective well-being. Effect sizes vary by arm. While most estimates are statistically insignificant at conventional levels, LA significantly decreases subjective well-being during the PC intervention (−0.18 SD; 95 percent CI: −0.02 to −0.33). LA participants may have been disappointed if they

[33] Estimates for individual shocks are not statistically significant after adjusting for multiple inference.

expected benefits of the intervention that did not occur. Such an effect would echo results by Adhvaryu, Nyshadham, and Xu (2023), who found that people whose material conditions improved by less than expected displayed lower subjective well-being.

Depression could also change behavior by affecting cognition. Figure 5 shows an impact of PC/LA on cognitive performance of −0.16 SD (95 percent CI: −0.33 to 0.01), which is significant at the 10 percent level, and an impact of PC on cognitive performance of −0.19 SD (95 percent CI: −0.35 to −0.04) in the "after" period. The lack of a positive effect rules out improved cognition as a pathway linking better mental health to socioeconomic improvements in our sample. Online Appendix B.15 discusses possible explanations for this finding and argues that low effort on the cognitive assessments and antidepressant discontinuation syndrome are both unlikely explanations for this effect.

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 online Appendix Figure B17 suggests a shift toward joint rather than individual decision-making under PC.

IX. Joint Significance and Treatment Complementarities

This section tests whether the interventions have effects that are jointly significant across the 11 main outcomes of our analysis.[34] We use the "omnibus" test proposed by Young (2019) to examine the joint significance of the interventions. 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 reestimate the effects on these 11 outcomes as a system of seemingly unrelated regressions (SUR) to test the additional hypotheses described in Section V jointly 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 also 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 do not find evidence of a complementarity in either the "during" period ($p = 0.76$) or the "after" period ($p = 0.78$). However, we reject the hypothesis of "no complementarity" if we pool time periods ($p = 0.02$).[35] 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 ($p = 0.18$).

[34] 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 well-being cognitive performance, and participation in household decisions.

[35] The SUR approach allows us to test the remaining Section V hypotheses jointly. We do not find strong evidence that the effects of PC and LA are different ($p = 0.10$ overall, $p = 0.29$ in the "during" period, $p = 0.24$ in the "after" period). For the hypothesis that the effects of PC/LA and PC are equal, the p-value is 0.00 overall, 0.00 in the "during" period, and 0.37 in the "after" period.

X. Discussion

There is an urgent need for mental health care in India and other developing countries. For example, 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 (e.g., Baranov et al. 2020; Haushofer, Mudida, and Shapiro 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, pharmacotherapy 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). There is also suggestive evidence that treatment increases human capital investment for older children. However, pharmacotherapy has some transitory negative effects (e.g., on productive time and consumption) and reduces cognitive performance. Pairing livelihoods assistance with pharmacotherapy increases the size and duration of the mental health benefit, preserves the positive effects on older children's human capital investment (although the effect becomes insignificant at the 95 percent level), and safeguards people against several of these negative effects. Adding livelihoods assistance is cost-effective since it increases the intervention benefits while raising 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 occurred 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 creating a "reason" for participating without admitting to mental illness.

Our findings suggest that there may be a negative effect of depression on investment. Anhedonia, a core feature of depression, could explain this pattern. Anhedonia lowers the marginal utility of consumption, which may lead people with depression to appear risk tolerant and unwilling to make investments. By alleviating this

symptom, pharmacotherapy may increase human capital investment as well as reduce risk tolerance and the incidence of negative shocks. We acknowledge that this evidence is tenuous and that this interpretation is speculative.[36]

Appendix

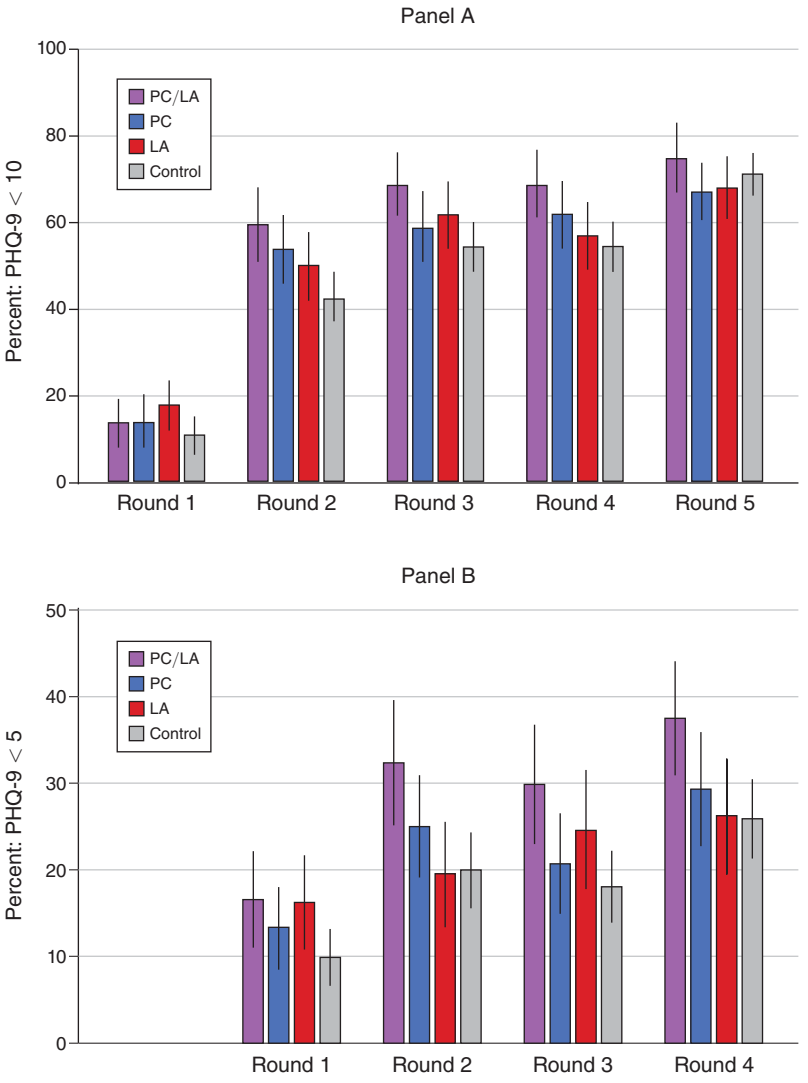

Figure A1. Depression Indicators by Round and Intervention Arm

Notes: 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 95 percent confidence intervals based on locality-clustered standard errors.

[36] This effect is consistent with findings by Finkelstein, Luttmer, and Notowidigdo (2013) and Schofield and Venkataramani (2021).

Table A1—Impact on Depression Indicators

	No moderate/ severe depression		No depression	
	(1)	(2)	(3)	(4)
Panel 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
Panel 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
Baseline outcome coefficient	0.106	–	–	–
	(0.029)			
Specification	ANCOVA	LASSO	ANCOVA	LASSO
Observations	3,476	3,476	3,476	3,476

Notes: 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, Chernozhukov, and Hansen 2014). Footnote 25 explains this approach in more detail. Locality-clustered standard errors appear in parentheses. "During" and "after" estimates are based on a common regression. The outcome in columns 1–2 is an indicator for PHQ-9 < 10, which is consistent with no moderate or severe depression. The outcome in columns 3–4 is an indicator for PHQ-9 < 5, which is consistent with no depression.

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

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August 9, 2023

B Online Appendix

B.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 more prevalent among 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.[1] 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 B1 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 B1 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 4.50 while those in the top quartile of the SES distribution have scores of 1.99 ($p < 0.001$ for this comparison). Table B2 shows how socioeconomic and demographic variables correlate with depression in the community. Age, female gender, low literacy and

[1] We randomly chose 120 localities and sampled a number of household per locality that was proportional to the locality'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.

education, and recent exposure to negative shocks are positively correlated with depression, which aligns with existing evidence (Gilman et al. 2002).

B.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 Committee 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. In practice, 19 people had a PHQ-9 score greater than 20 during screening. 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. 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.

B.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. We have 506 clusters (localities), with a median cluster size of 2. We first describe our "ex-ante" MDEs, and then discuss the "ex-post" MDEs.

Starting with the "ex-ante" MDEs, 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).[2] 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 0.212 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 0.005 SD. We can revise our MDEs using information from our sample to also estimate "ex-post" MDEs.[3] Using our data, we estimate: intra-class correlations 0.21 during and 0.19 after; baseline/follow-up serial correlations of 0.17 during and 0.12 after; and follow-up serial correlations of 0.38 during and 0.36 after. Using these revised correlations, in the "during" period, the study has power to detect effects of 0.217 SD (PC/LA vs. C, PC vs. C, LA vs. C), 0.251 SD (PC/LA vs. PC, PC/LA vs. LA, PC vs. LA), and 0.289 SD (PC + LA vs. PC/LA). In the "after" period, the study has power to detect effects of 0.216 SD (PC/LA vs. C, PC vs. C, LA vs. C), 0.25 SD (PC/LA vs. PC, PC/LA vs. LA, PC vs. LA), and 0.288 SD (PC + LA vs. PC/LA). These minimum effects sizes (treatment vs. control) are in line with Gartlehner et al.'s (2017) meta-analysis of the effects of pharmacotherapy, which we describe in Appendix B.6.

In the child sample, which we use to estimate impacts on child human capital investment, the "ex-ante" MDE for the comparison to the control arm is 0.17 SD in the "during" period and 0.24 SD in the "after" period. The MDE for the pairwise comparison of intervention arms is 0.20 SD in the "during" period and 0.264 SD in the "after" period. The MDE for the test of whether PC and LA are complements is 0.30 SD in the "during" period and 0.32 SD in the "after" period. Using our data for the "ex-post" MDEs, we estimate: intra-class correlations 0.22 during and 0.47 after; baseline/follow-up serial correlations of 0.40 during and 0.28 after; and a follow-up serial correlation of 0.44 during. Using these revised correlations, in the "during" period, the study has power to detect effects of 0.218 SD (PC/LA vs. C, PC vs. C, LA vs. C), 0.252 SD (PC/LA vs. PC, PC/LA vs. LA, PC vs. LA), and 0.252 SD (PC + LA vs. PC/LA). In the "after" period, the study has power to detect effects of 0.35 SD (PC/LA vs. C, PC vs. C, LA vs. C), 0.394 SD (PC/LA vs.

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

[3]Note that the ex-post MDE for a significance level of 0.05 and 80% power is $2.8 \times SE$, while for a significance level of 0.10 it is $2.48 \times SE$, where SE is the standard error of the treatment coefficient (Haushofer and Shapiro 2016).

PC, PC/LA vs. LA, PC vs. LA), and 0.392 SD (PC + LA vs. PC/LA). These effect sizes (treatment vs. control) are in line with Baranov et al.'s (2020) estimates of the effect of treatment for perinatal depression on parental monetary and time investment in children, which range from 0.20 to 0.35 SD.

B.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; we define 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 B3, 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 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.

B.5 Attrition

Survey participation is balanced across arms during Rounds 2-4, but falls differentially for the PC arm in Round 5. In Round 5, participation is 83% for PC/LA, 72% for PC, 87% for LA, and 85% for control. Differential attrition cannot confound estimates for child human capital investment or risk intolerance because these variables are not available in Round 5.

To understand who attrits, we select the correlates of attrition through LASSO (from the list in footnote 24 of the manuscript). The most notable variables in this list are marital status, education, and durable goods ownership. Attriters are 11 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 durable goods index scores ($p = 0.06$). 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.

B.6 Mental Health Impacts Compared to the Literature

This appendix elaborates on the comparison between our estimates and other studies in the literature. This comparison focuses 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 (95% CI: -0.30 to 0.03) and the effect of PC/LA on depression severity is -0.26 SD (95% CI: -0.41 to -0.10) 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.[4] This approach assumes that assignment to treatment does not affect the mental health of non-compliers. After this adjustment, Gartlehner et al.'s (2017) findings imply an intent-to-treat effect of -0.15 SD (95% CI: -0.13 to -0.17) for SSRIs and -0.09 SD (95% CI: -0.01 to -0.17) 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 that focus on developing countries and provide long-term impacts are even more scarce.[5]

B.7 Intervention Costs

Table B4 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). For

[4]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.

[5]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).

a back-of-the-envelope comparison, we compute the cost of reducing PHQ-9 scores by 0.1 SD per month under both PC and PC/LA over the duration of the study. 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 B4 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 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).

B.8 Heterogeneous Treatment Effects

In this appendix, we assess subgroup heterogeneity in the impact of the interventions on mental health and other outcomes. For each of several subgroups, we modify Equation (1) to interact intervention indicators with subgroup indicators in order to obtain subgroup-specific estimates. We examine heterogeneity by gender, age, depression severity, physical health, cognitive performance, and childhood experience of negative shocks, all of which are measured at baseline. 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.

Figure B5 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 both 95 percent and 90 percent confidence intervals. A negative and significant effect means that the first listed group has a larger reduction in depression symptoms. There are larger mental health benefits of PC for people with worse baseline physical health, and of PC/LA for people who experienced above median childhood shocks in the "after" period. Other differential impacts by subgroup are not statistically significant.

Figures B23 to B31 reproduce Figure B5 for the other study outcomes. We do not find

differential impacts that align with the differential effects on depression severity: there is not a differential effect of PC on these outcomes in the "after" period for people with worse baseline physical health, nor is there a differential effect of PC/LA on these outcomes for people with above-median exposure to childhood shocks in the "after" period.

B.9 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 B6 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 (95% CI: -0.33 to -0.03) during the PC intervention and by 0.23 SD (95% CI: -0.41 to -0.06) 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 0.12 SD (95% CI: -0.02 to 0.26) during the PC intervention and by 0.18 SD (95% CI: 0.02 to 0.35) afterward. Conversely, PC alone *reduces* the ADL index by 0.19 SD (95% CI: -0.35 to -0.02) 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.

B.10 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 productive time into these categories 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 B7 shows these estimates. In the "during" period, PC reduces time spent on primary and secondary jobs and agriculture by 0.12 SD (95% CI: -0.26 to 0.01), which represents a decline of 3.1 hours per week. It concurrently increases time spent on sleep by 0.11 SD (95% CI: -0.01 to 0.22), which represents an increase of 1.9 hours per week; it increases leisure by 0.14 SD (95% CI: 0.01 to 0.27), which represents an increase of 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 because "productive time" aggregates across both measures. In addition, LA may reduce sleep time in the "after" period, although the estimate is only statistically significant in the LASSO specification.

B.11 Impacts on the Human Capital Index Components

Figure B8 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.

B.12 Impacts on Components of Consumption, Wealth, and Sanitation/Hygiene

Figures B9 and B10 show estimates for the components of the hygiene/sanitation and durable goods indices, while Figure B11 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.[6] In Figure B9 most estimates are not statistically significant, which is consistent with the lack of an effect of the interventions on the overall index in Figure 4. Figure B10 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 B5 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.

B.13 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

[6]PC reduces per capita household income by Rs. 44 (95% CI: -3 to 90) and reduces per capita household consumption by Rs. 59 (95% CI: 13 to 104) in the "during" period. No other arms have significant effects on this outcome either during or after the PC intervention.

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 B15 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 5. 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 B15. Estimates are available upon request.

One possible concern is that depression could affect the recall of negative events. To investigate, we asked respondents and their family members to recall eight negative shocks in Round 5. Study participants and their family members agree about the occurrence of particular shocks 88 percent of the time. Weighting these responses according to the Holmes and Rahe (1967) scale, we find that study participants recall 8 percent more shocks than their family members ($p = 0.004$). Intervention assignment is uncorrelated with the probability of agreement within the household ($p = 0.98$) and with the gap between the scores of study participants and family members ($p = 0.30$). Baseline depression severity is also uncorrelated with the probability of agreement ($p = 0.60$) and the gap between the scores ($p = 0.15$). These patterns suggest that selective recall by study participants is unlikely to spuriously generate the treatment effects on the negative shock index in Figure B15.

B.14 Impact on the Dispersion in Risk Attitudes

Table B6 shows the standard deviation in the risk intolerance index by treatment arm and round. The index is standardized for the control arm in Round 1 to allow for comparisons across arms and over time. The PC/LA and PC interventions significantly reduce the variance in risk intolerance in Round 4. We initially proposed to measure effects on the variance in risk preferences because Angelucci and Córdova (2018) found that lab-induced stress did not affect average risk preferences but reduced the likelihood of having extreme risk preferences. This pattern is not evident in our current study, since the treatments reduce both average risk tolerance and the variance in risk tolerance.

B.15 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 B12 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.

B.16 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 B13. 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.

Table B1: 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) stepdown procedure control for the false discovery rate (FDR) across index components.	Use Benjamini et al. (2006) sharpened q-values to control for the FDR.	Benjamini et al. (2006) approach is more straightforward to implement.
Construct the child human capital investment index using enrollment, attendance, and homework components.	Also include (the lack of) child labor as a component.	This item was collected in conjunction with the other child human capital investment items. Omitting it from the pre-specified index was an oversight. Avoiding child labor is an important aspect of human capital investment.
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.
Analyze DOSPERT items using the methodology of Blais and Weber (2006).	Directly combine DOSPERT risky behavior variables with other pre-specified risk tolerance measures.	The Blais and Weber (2006) approach requires indicators of the perceived benefit of each risky behavior, which we do not measure.
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 the responses are inconsistent with a downward sloping demand for leisure.
Estimate the impact of treatment on the adoption of liquid hand sanitizer.	Omit from the analysis.	We are pursuing this study in another paper.
The PAP is ambiguous about whether child human capital investment is a primary study outcome or a household spillover outcome.	Treat child human capital investment as a primary outcome.	"Child investment" appears in the title of the PAP and child investment is listed as a primary outcome in the Social Science Registry entry.
Estimate the health impact for children under 5.	Omit these estimates.	These estimates lack power because only 85 study participants live with children who provide measurements.
No pre-specified way to deal with outlying monetary values.	Winsorize monetary values at 5 percent.	Winsorizing reduces measurement error without qualitatively changing the results
No proposed analysis of the impact on negative economic 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 B2: Healthy and Depressed Adults in the Community Compared to the Intervention Sample

	Community Sample		Intervention	P-Value	
	Healthy	Depressed	Sample	(1) vs. (2)	(2) vs. (3)
	(1)	(2)	(3)	(4)	(5)
PHQ-9 depression scale	1.29	11.29	13.99	0.00	0.00
Age	34.5	37.0	35.3	0.00	0.00
Female	0.48	0.61	0.86	0.00	0.00
Scheduled caste/tribe	0.24	0.26	0.64	0.40	0.00
Schooling (years)	7.7	4.7	5.0	0.00	0.42
Literacy (1-3)	2.3	1.8	1.9	0.00	0.27
Any household savings	0.52	0.47	0.30	0.33	0.00
Bedrooms (number)	1.5	1.5	1.5	0.55	0.67
Negative life event scale	39	54	95	0.00	0.00
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.

Table B3: 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	0.224	0.151	-0.127	0.75	0.14
	(0.173)	(0.134)	(0.167)		
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 are clustered by locality and p-values are based on univariate regressions of the characteristics on a compliance indicator.

Table B4: 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 B5: 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	-32	-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	-60	-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	0.61	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	-2240	-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 24 of the manuscript explains this approach in more detail. Locality-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.

Table B6: Variance in Risk Intolerance by Intervention Arm and Round

	Control	PC/LA		PC		LA	
	St. Dev.	St. Dev.	P-value	St. Dev.	P-Value	St. Dev.	P-Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Round 1	1.00	1.04	0.52	1.07	0.27	1.01	0.92
Round 2	1.13	1.21	0.31	1.13	0.93	1.00	0.04
Round 3	1.02	0.98	0.56	1.00	0.80	0.84	0.004
Round 4	1.32	1.18	0.09	1.17	0.06	1.30	0.79

Note: The figure shows the standard deviation in the risk intolerance index by intervention arm and round. The index is standardized for the control arm in Round 1. Columns 3, 5, and 7 show p-values for the comparison of each treatment arm (Columns 2, 4, and 6) with the control arm (Column 1).

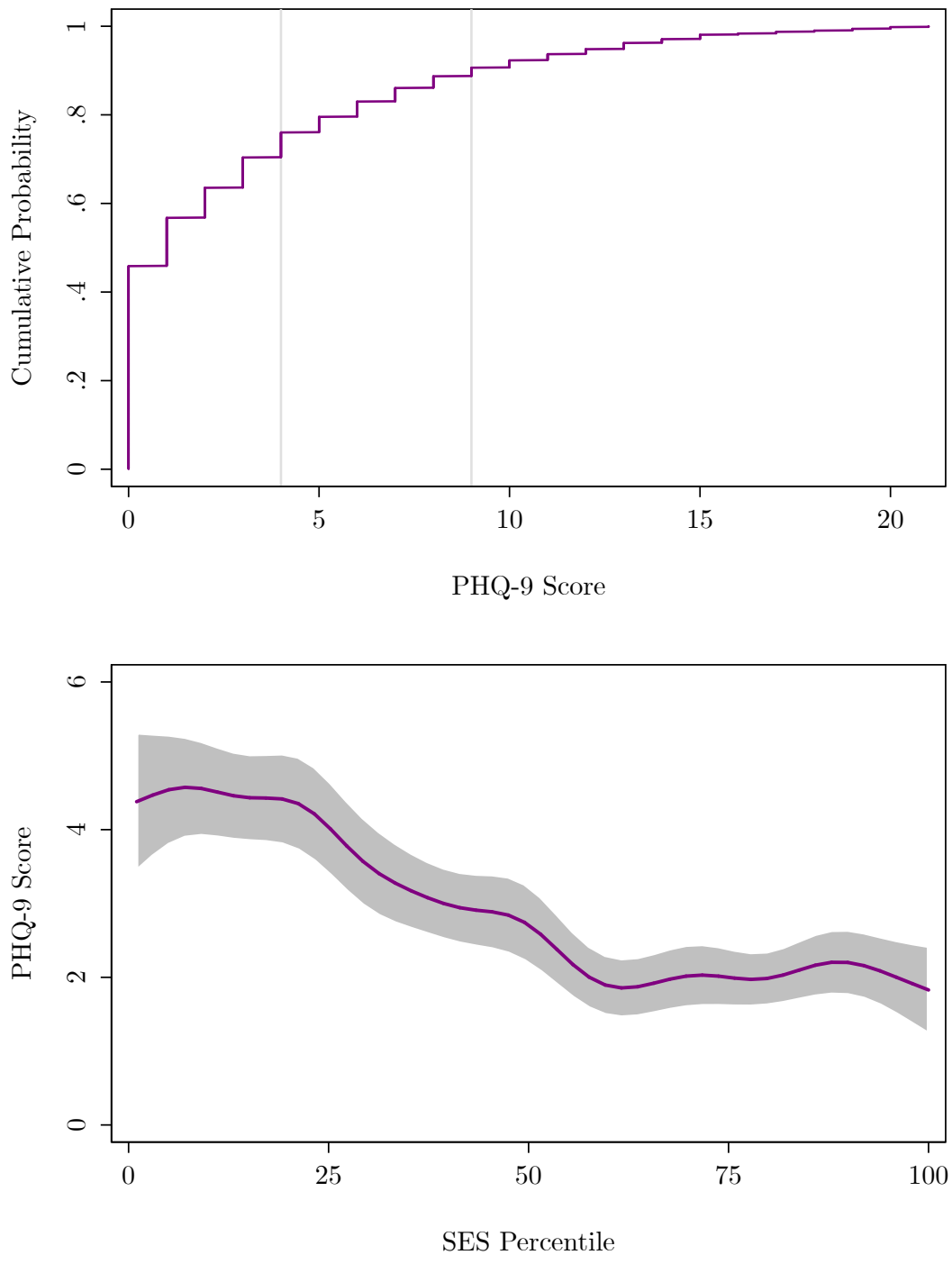

Figure B1: Community Depression Prevalence (Panel A) and Association with SES (Panel B)

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.

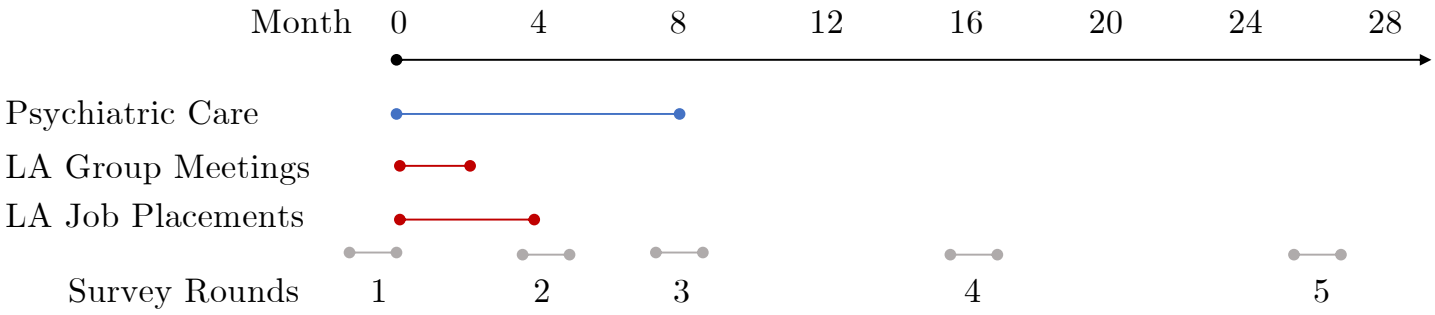

Figure B2: Study Timeline

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.

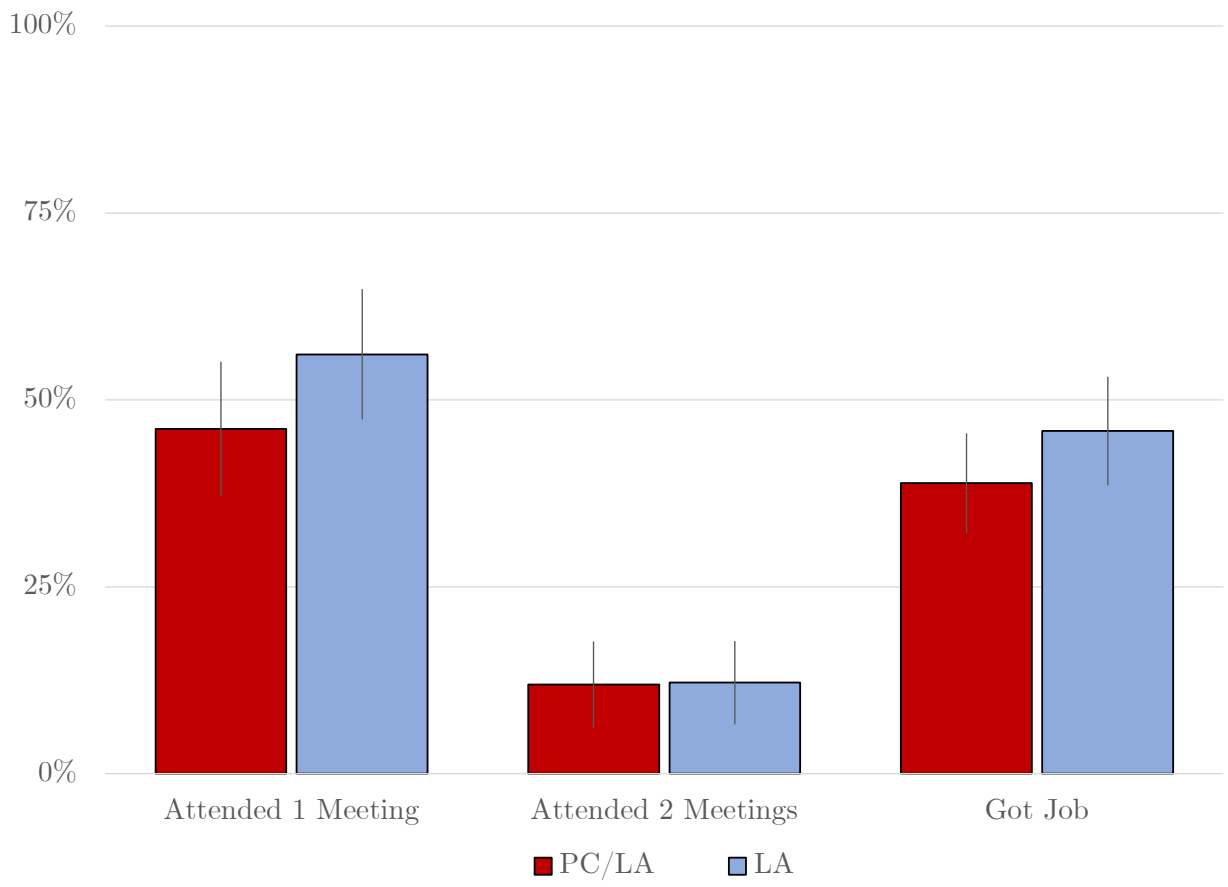

Figure B3: Participation in the LA Intervention

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 placement or other livelihoods activity. Error bars show 95 percent confidence intervals based on locality-clustered standard errors.

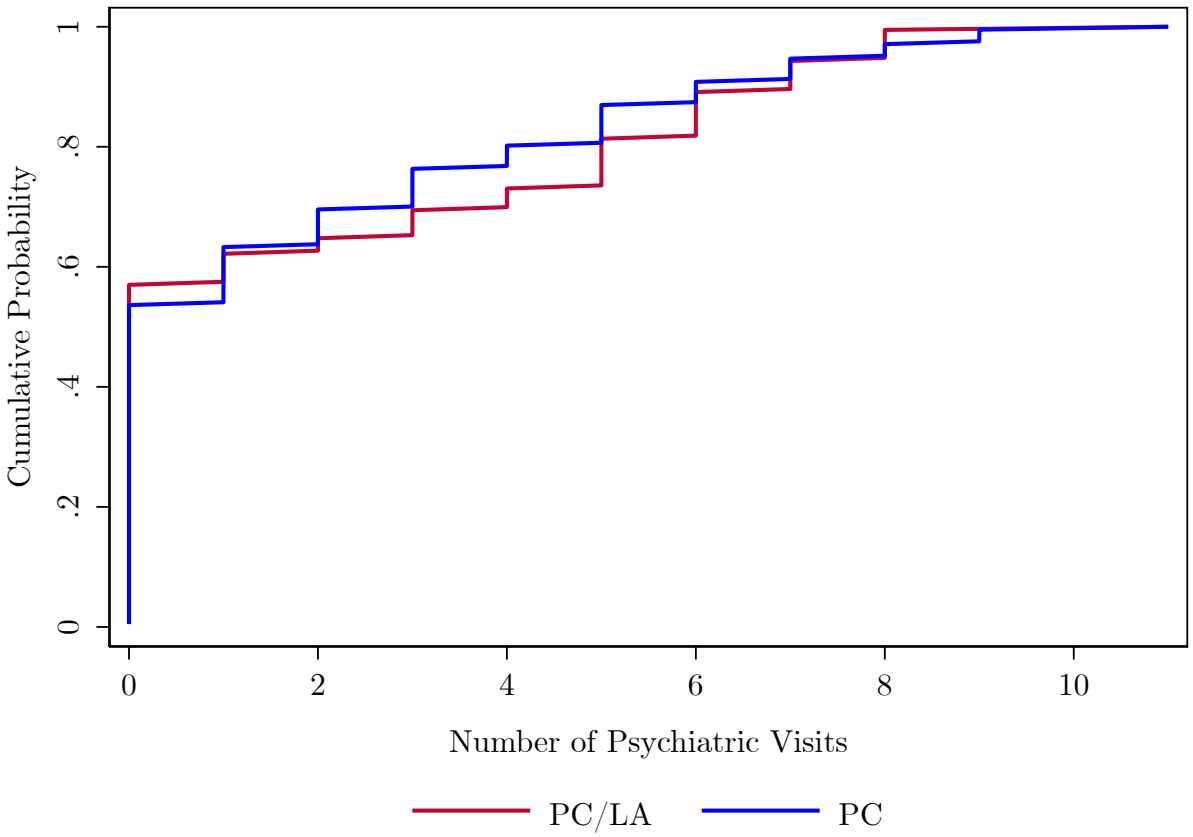

Figure B4: Participation in the PC Intervention

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

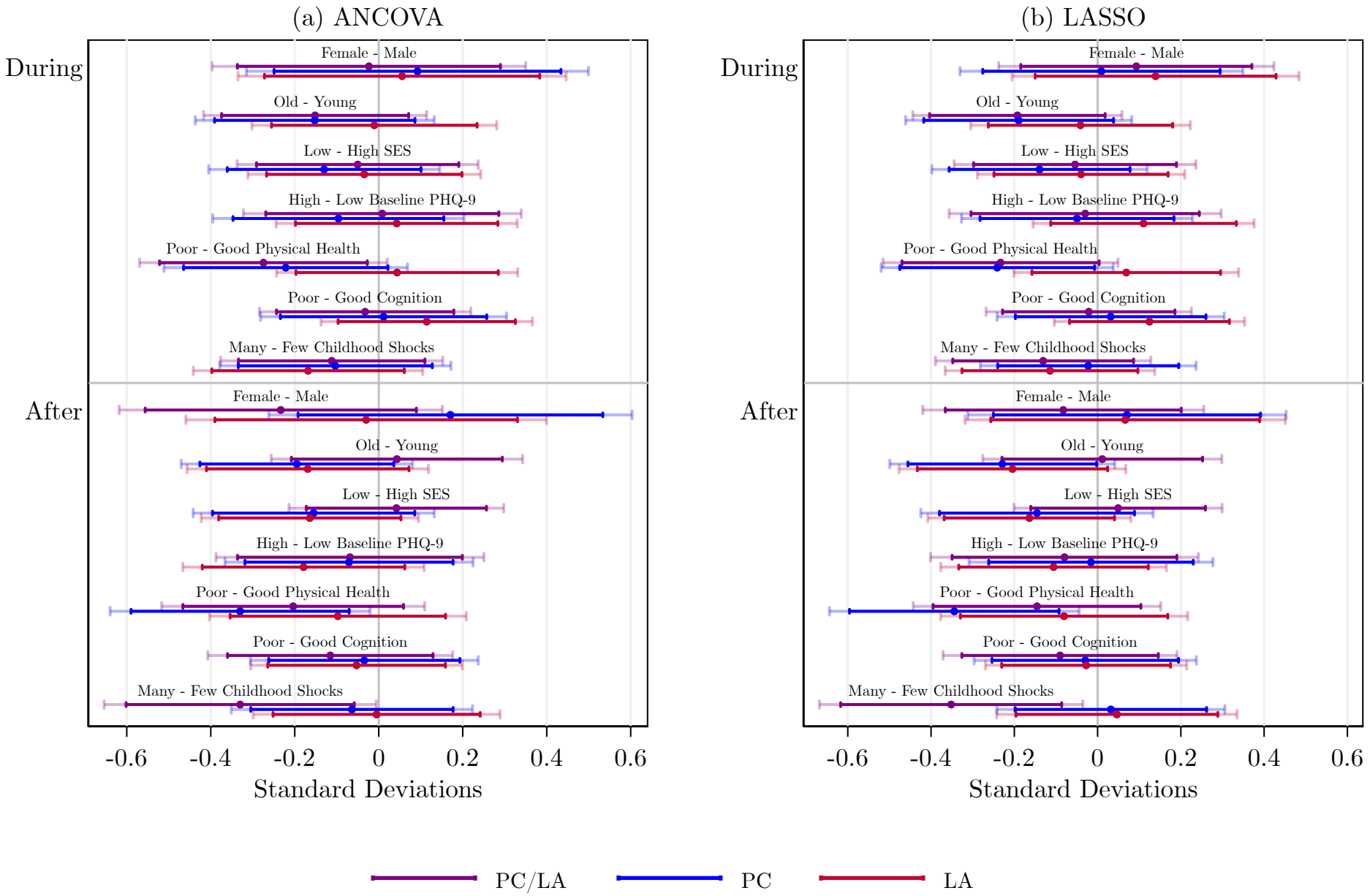

Figure B5: Heterogeneous Impacts on Depression Severity (PHQ-9)

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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

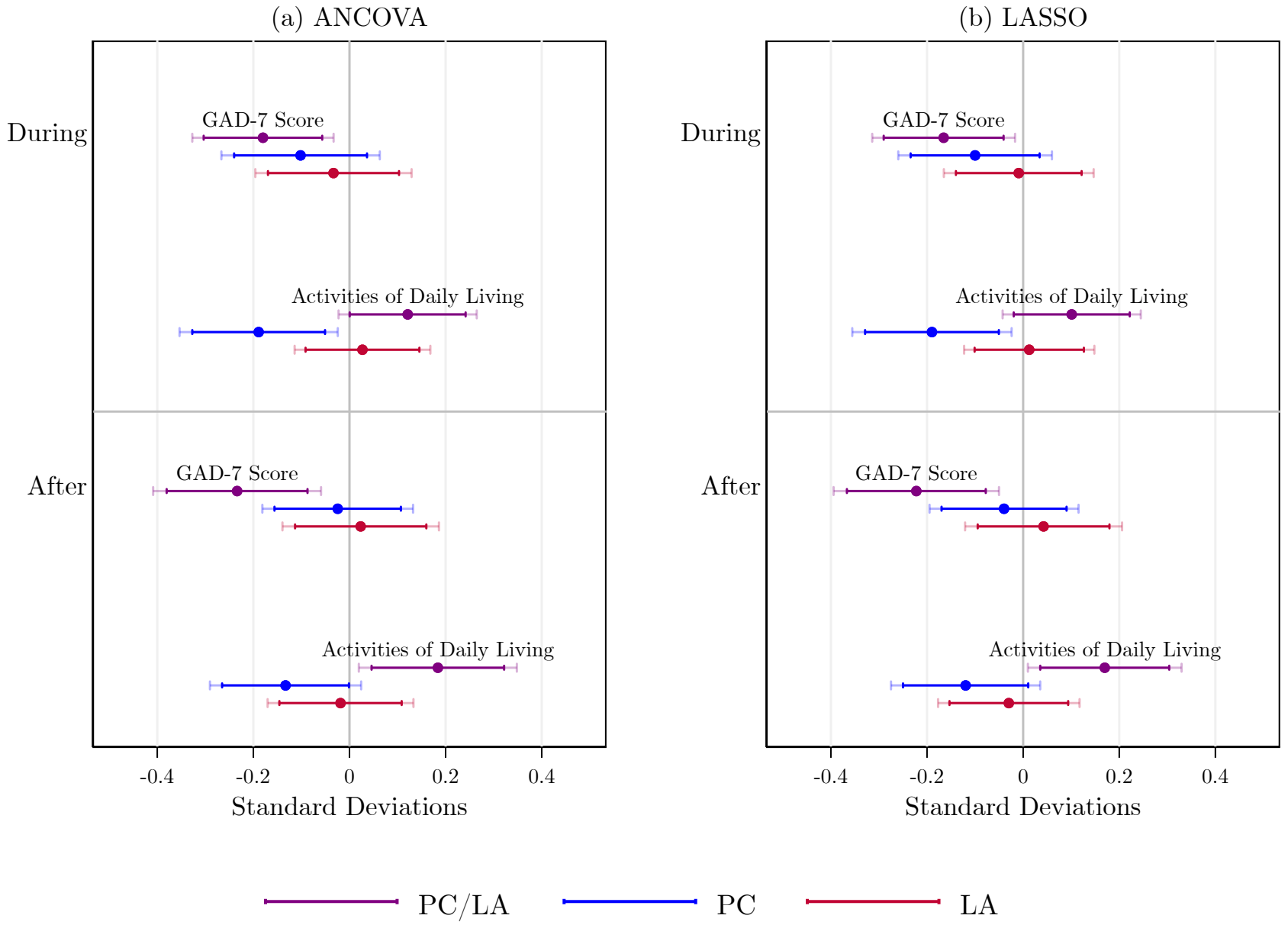

Figure B6: Impacts on Additional Health Outcomes

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

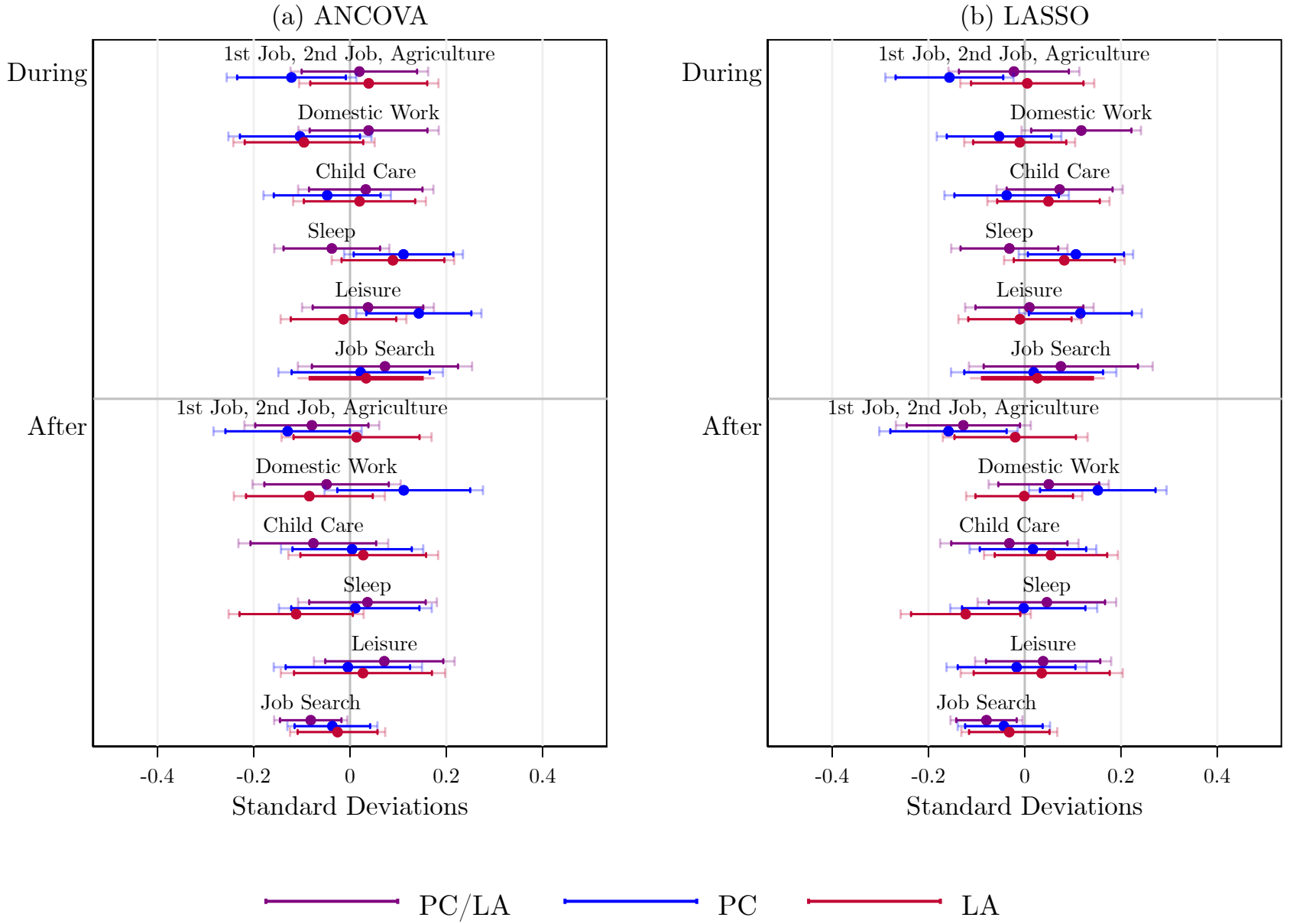

Figure B7: Impacts on Time Use

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. All estimates are statistically insignificant after adjustment.

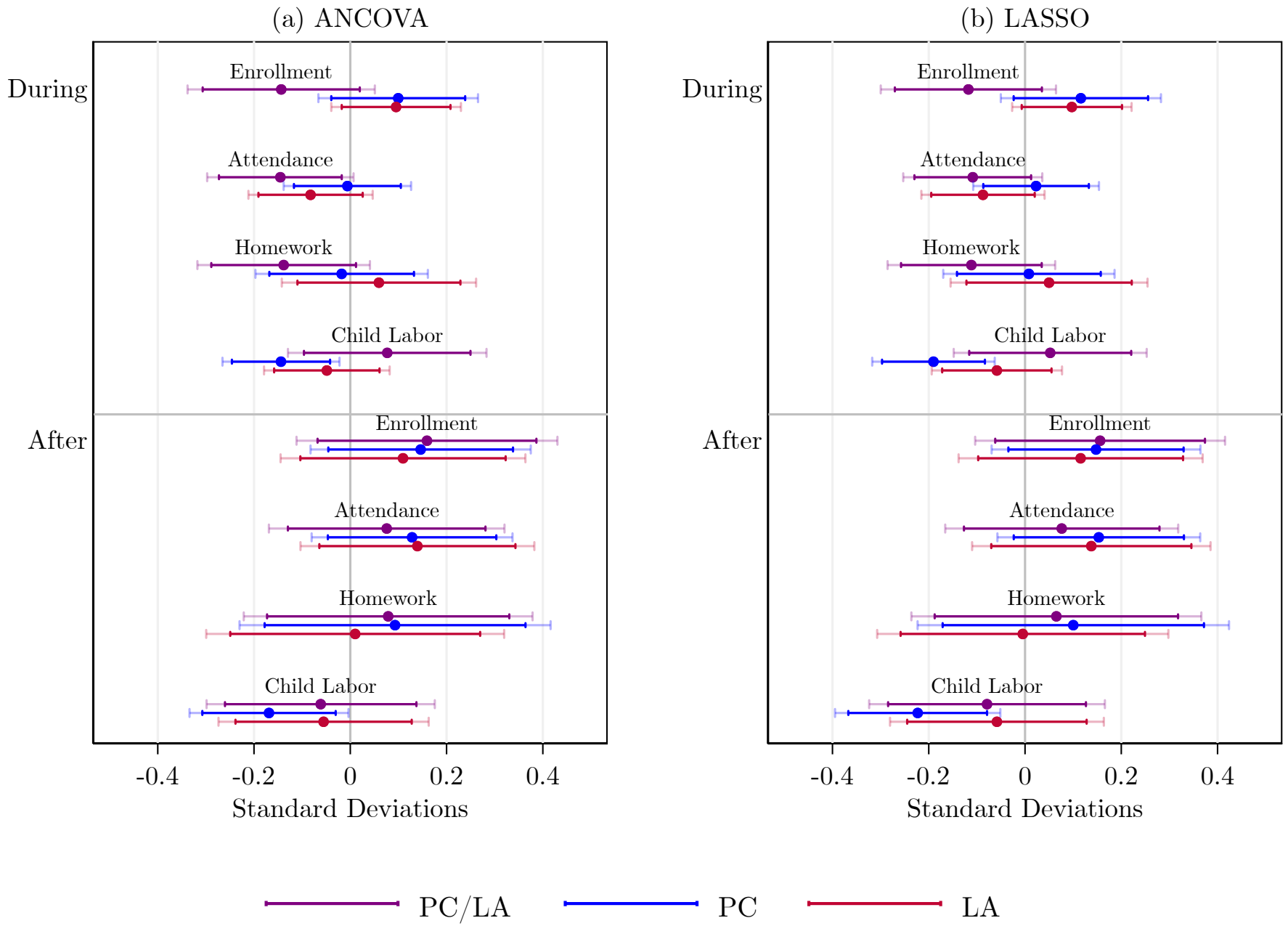

Figure B8: Impacts on Components of the Education Index

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

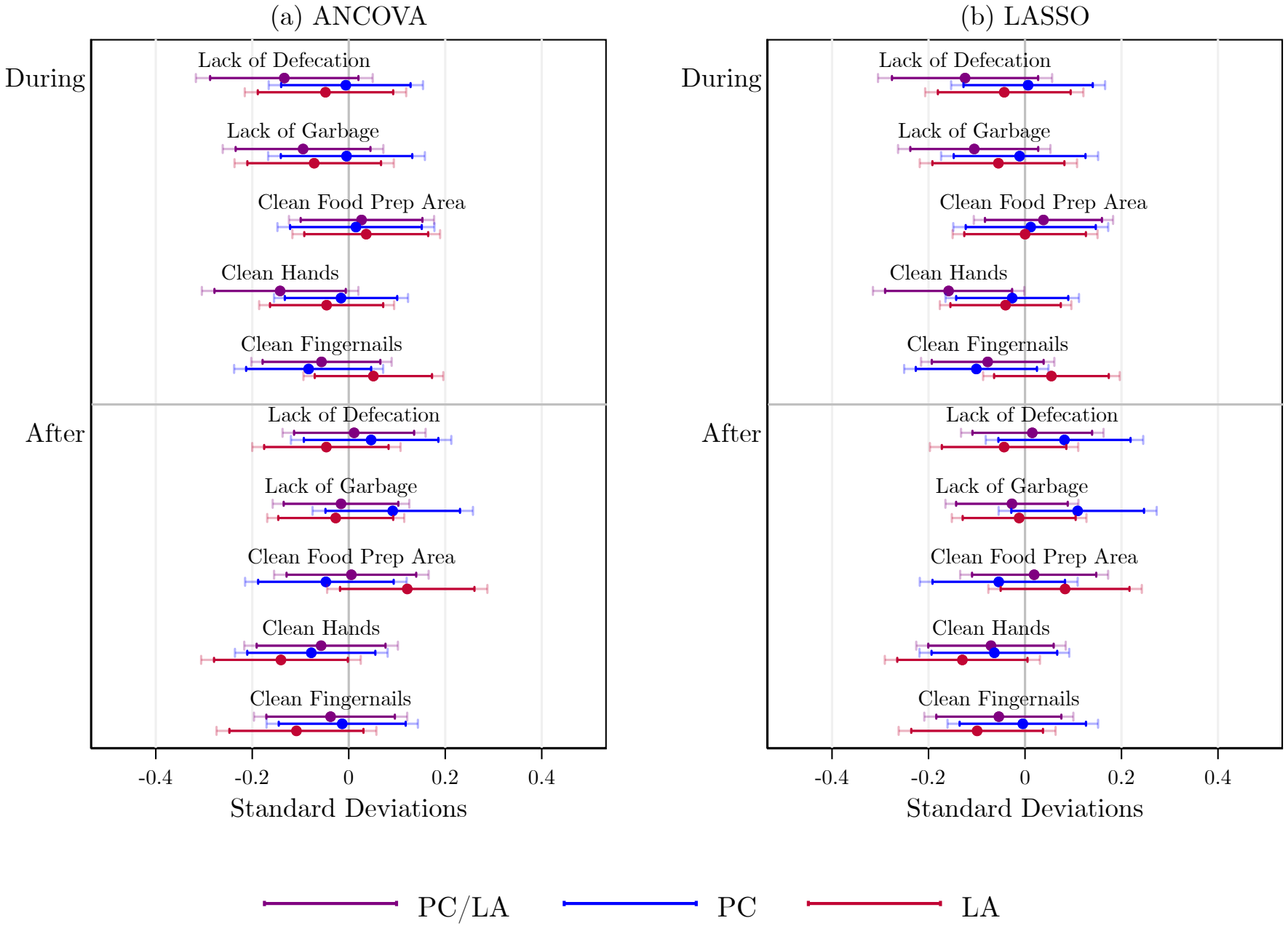

Figure B9: Impacts on the Components of the Sanitation/Hygiene Index

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

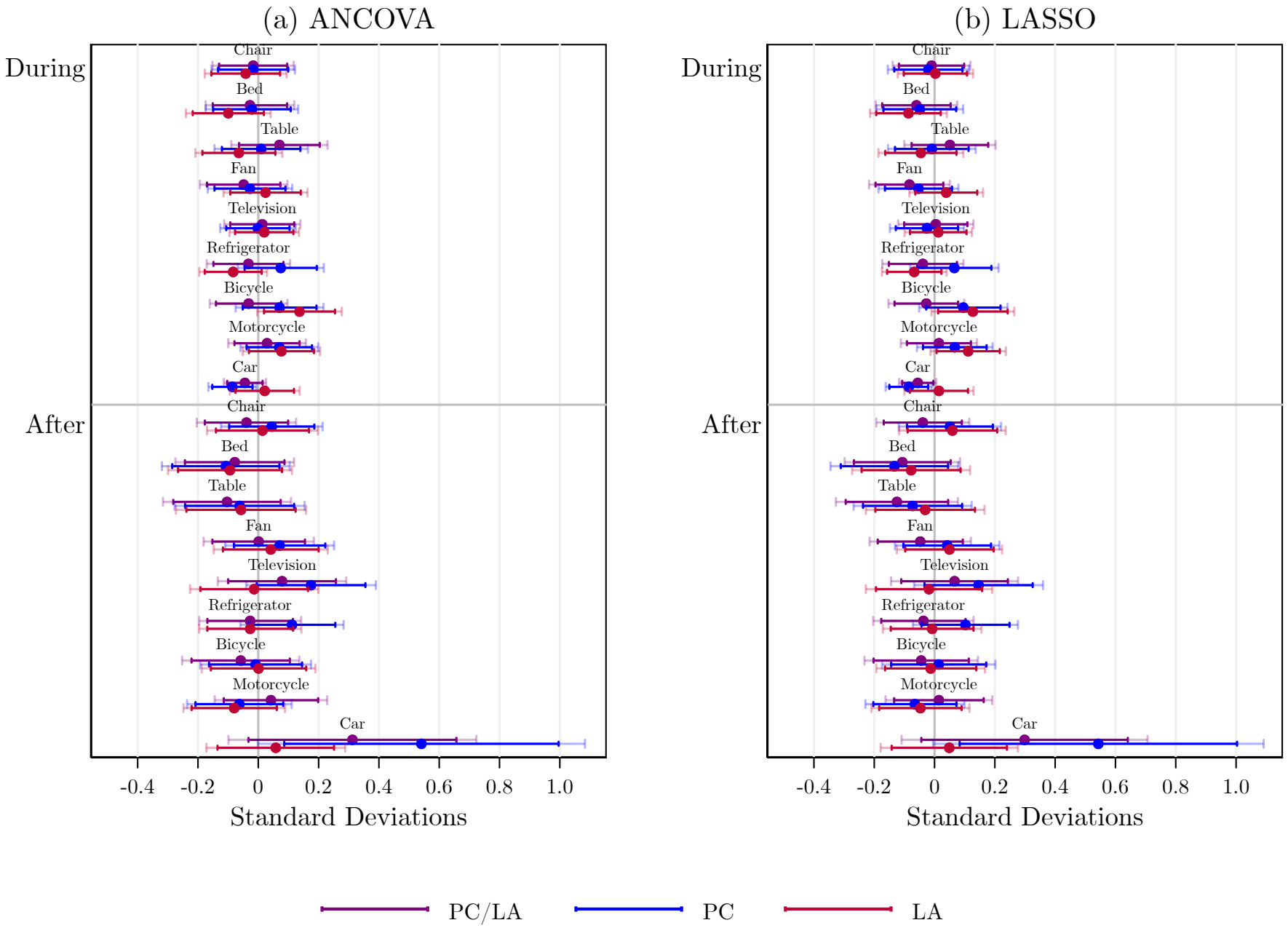

Figure B10: Impacts on Components of the Durable Goods Index

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. After this adjustment, all estimates are statistically insignificant.

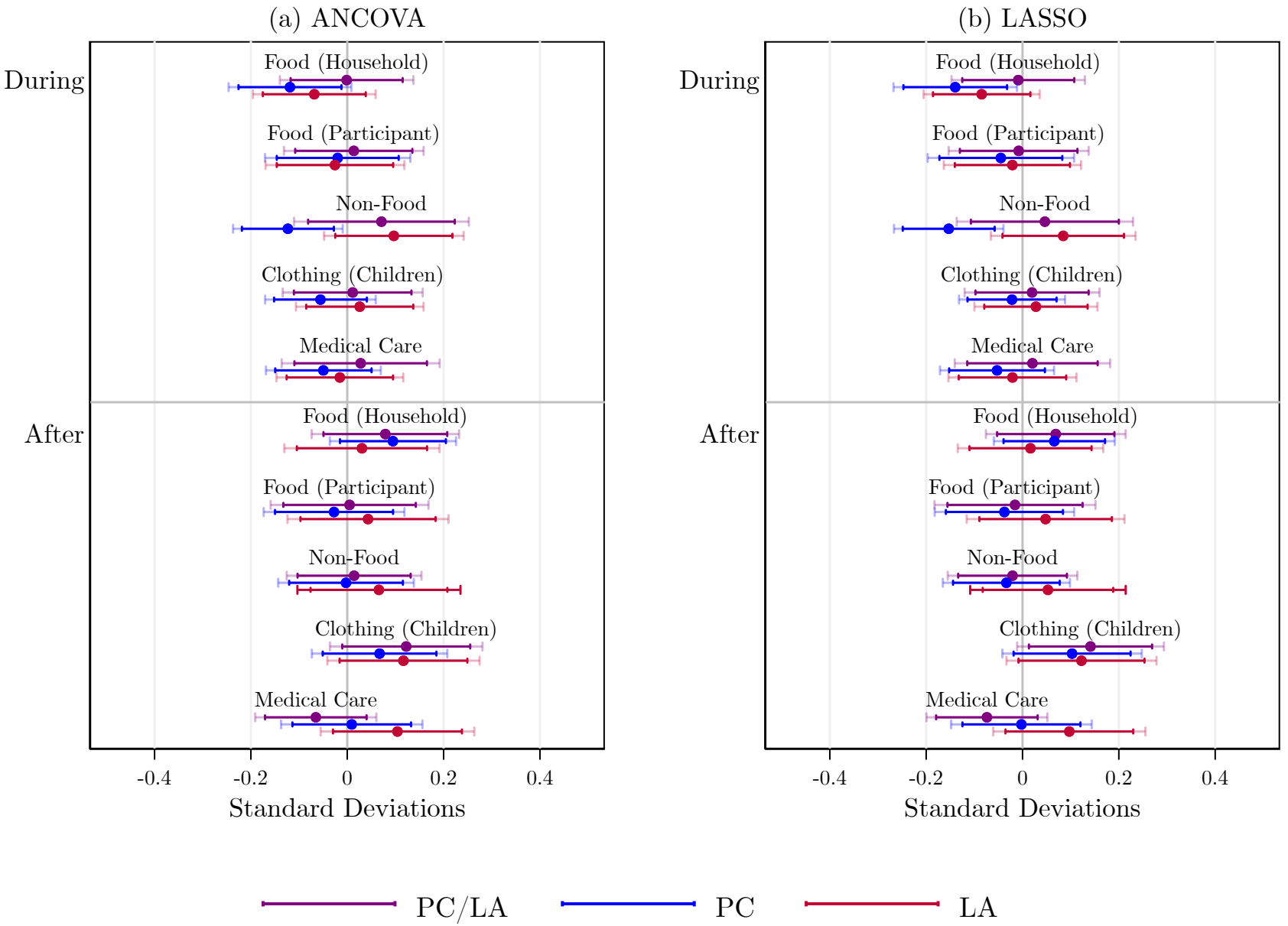

Figure B11: Impacts on Components of Consumption

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

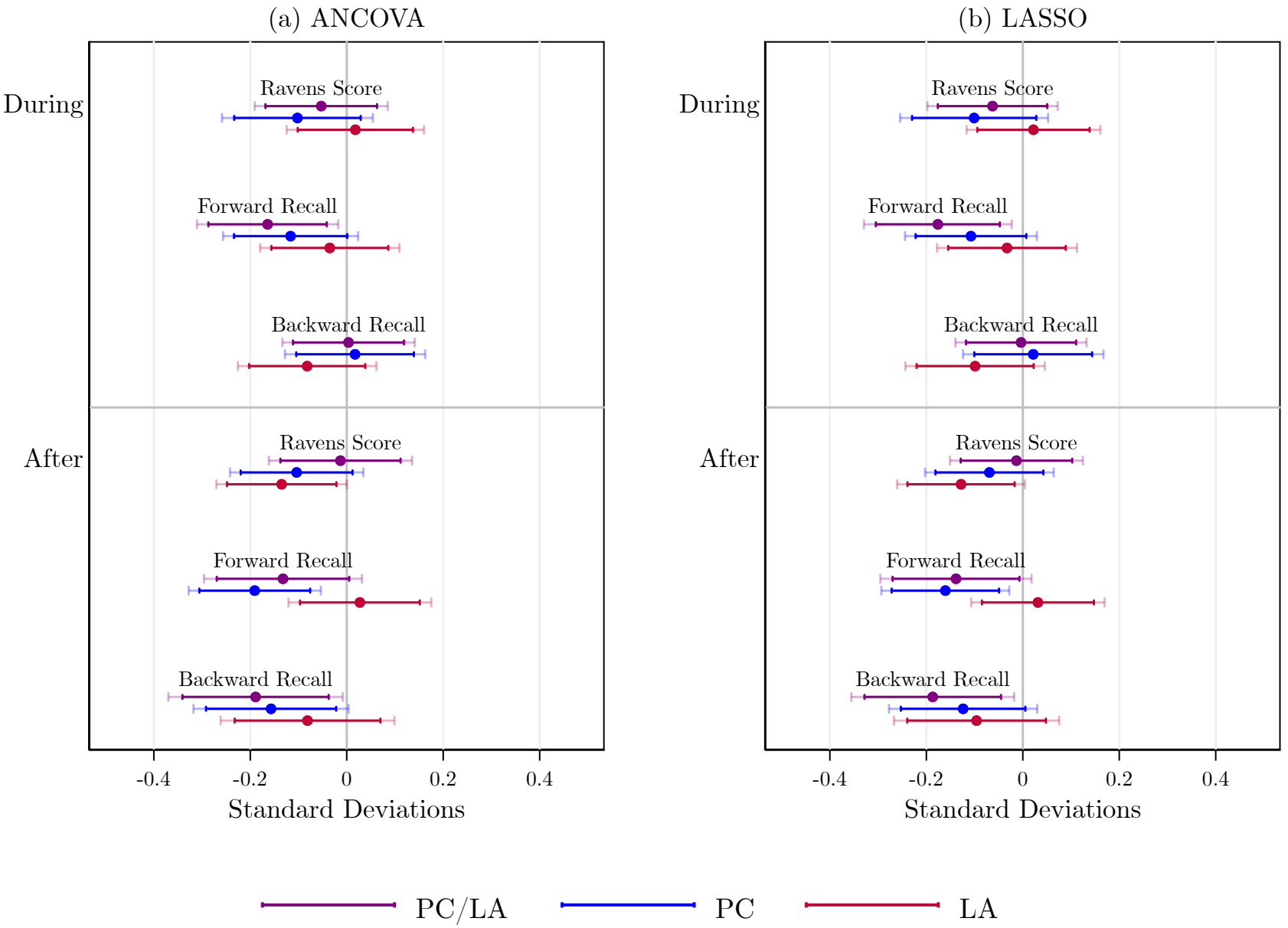

Figure B12: Impacts on Cognitive Performance

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

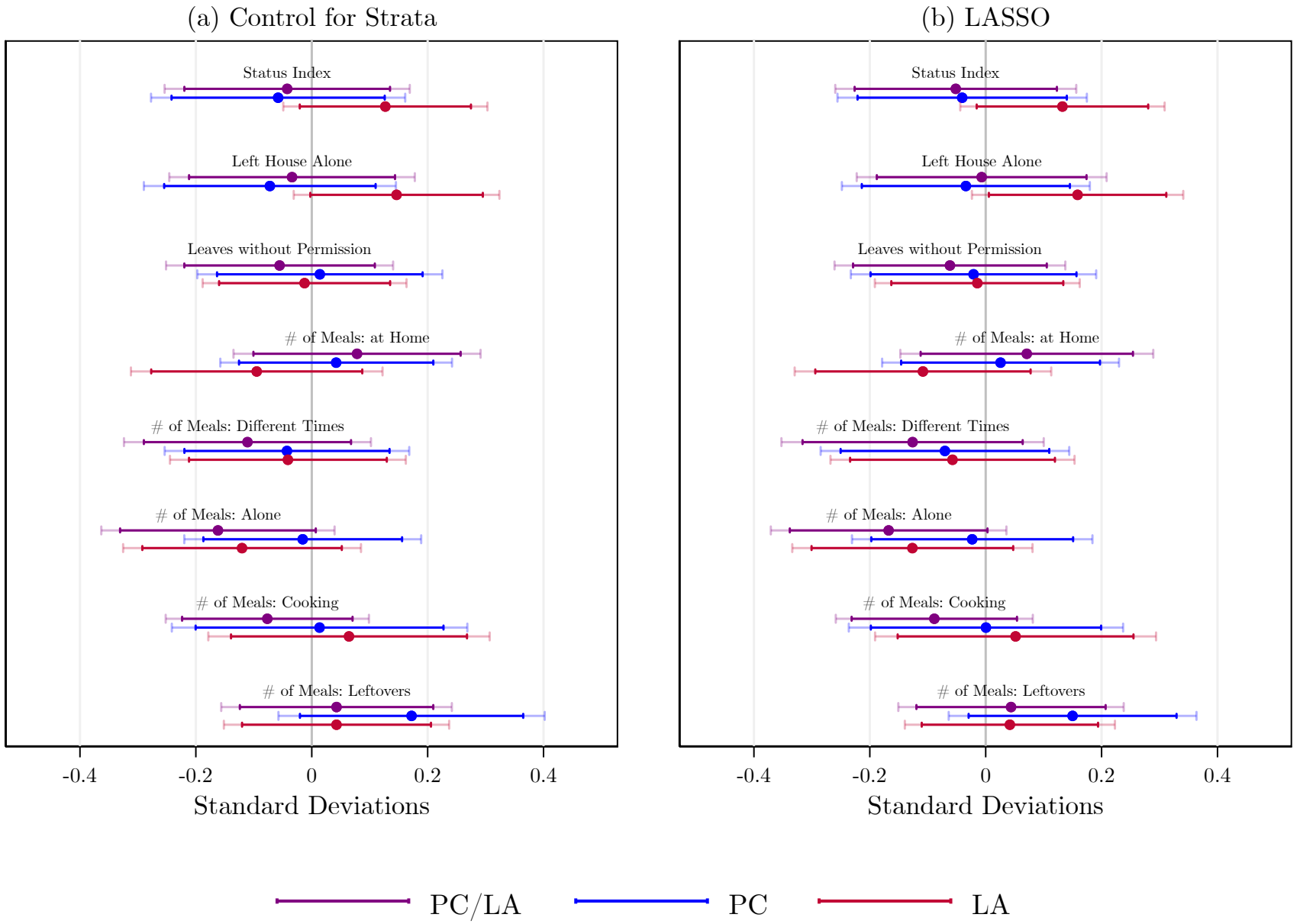

Figure B13: Impacts on Status Within the Household in Round 5

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 24 of the manuscript explains this approach in more detail. Confidence intervals are based on unadjusted p-values. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. We also adjust for multiple inference across outcomes using Benjamini et al. (2006) sharpened q-values. All estimates are statistically insignificant after adjustment.

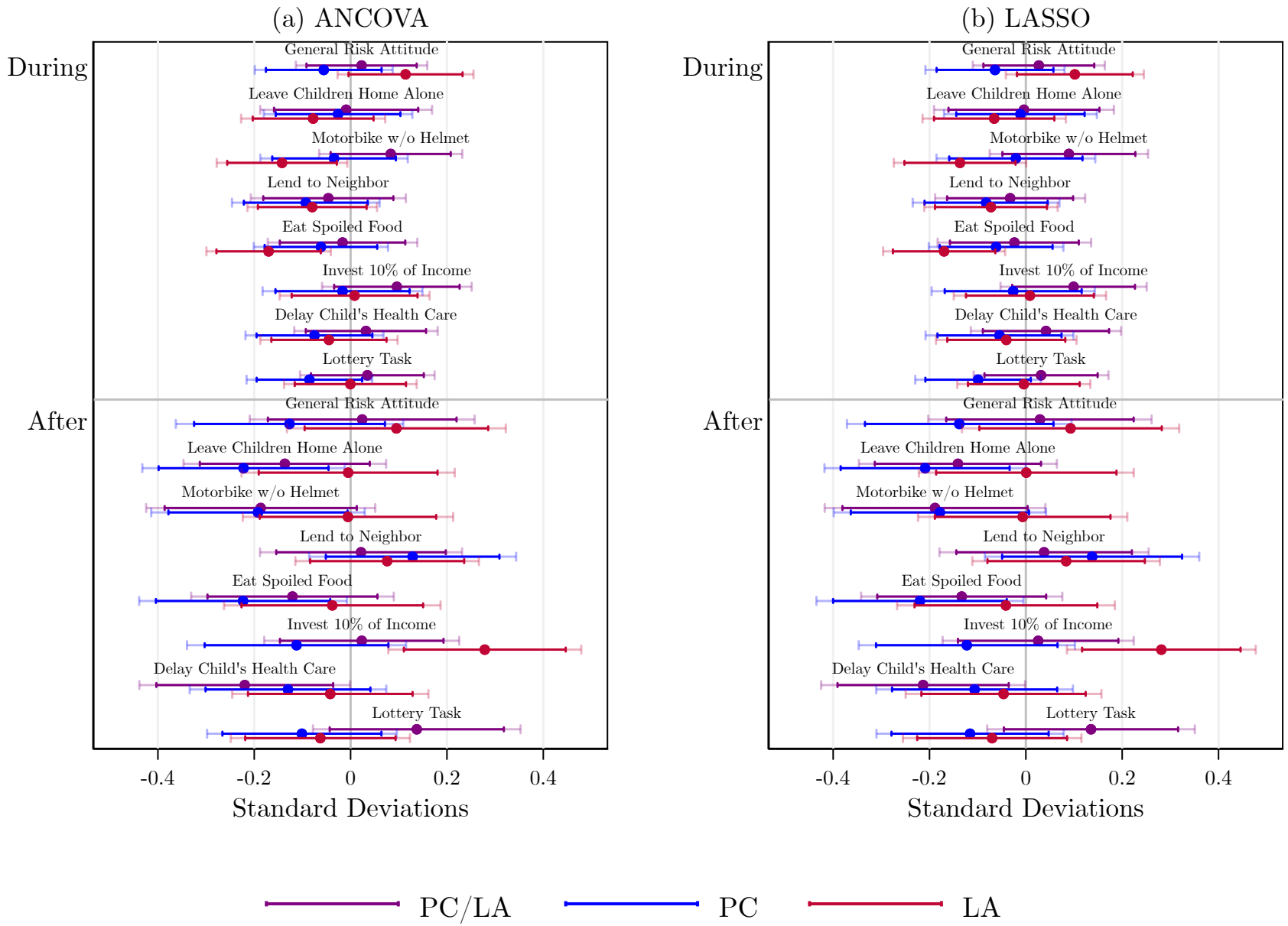

Figure B14: Impacts on Components of the Risk Intolerance Index

Note: The figure shows standardized impacts for the components of the risk intolerance 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

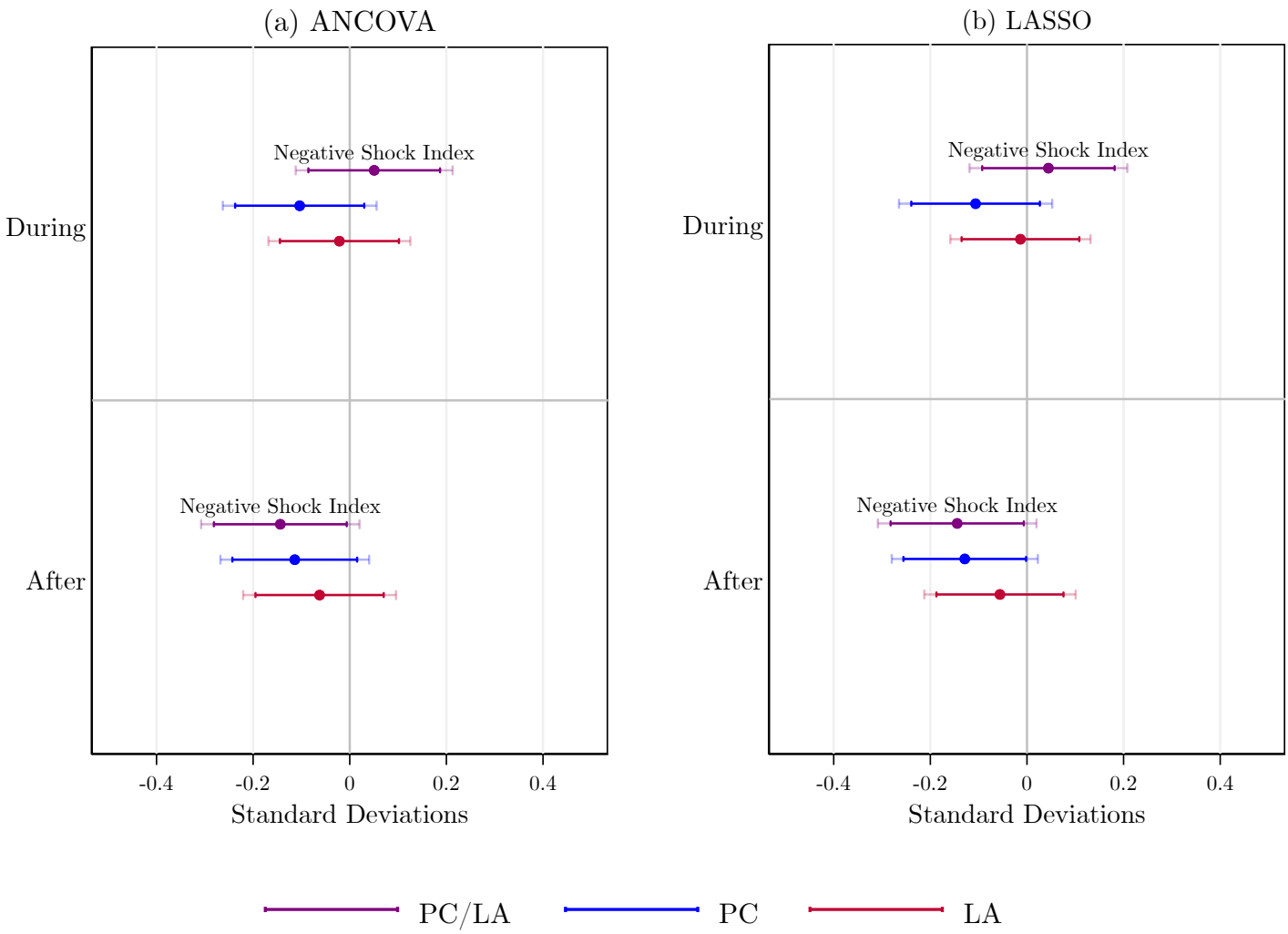

Figure B15: Impacts on Negative Shocks

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

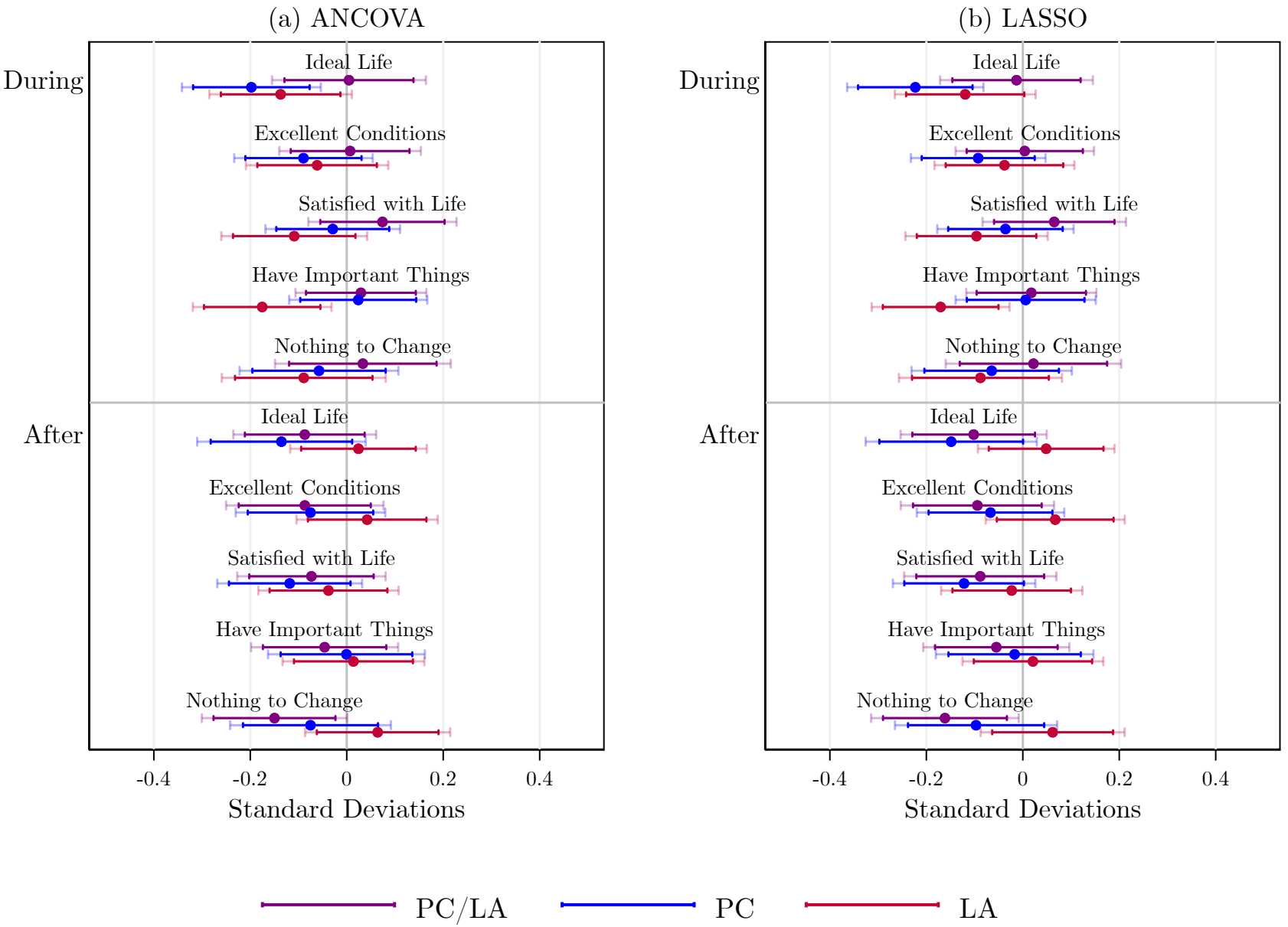

Figure B16: Impacts on Subjective Wellbeing

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

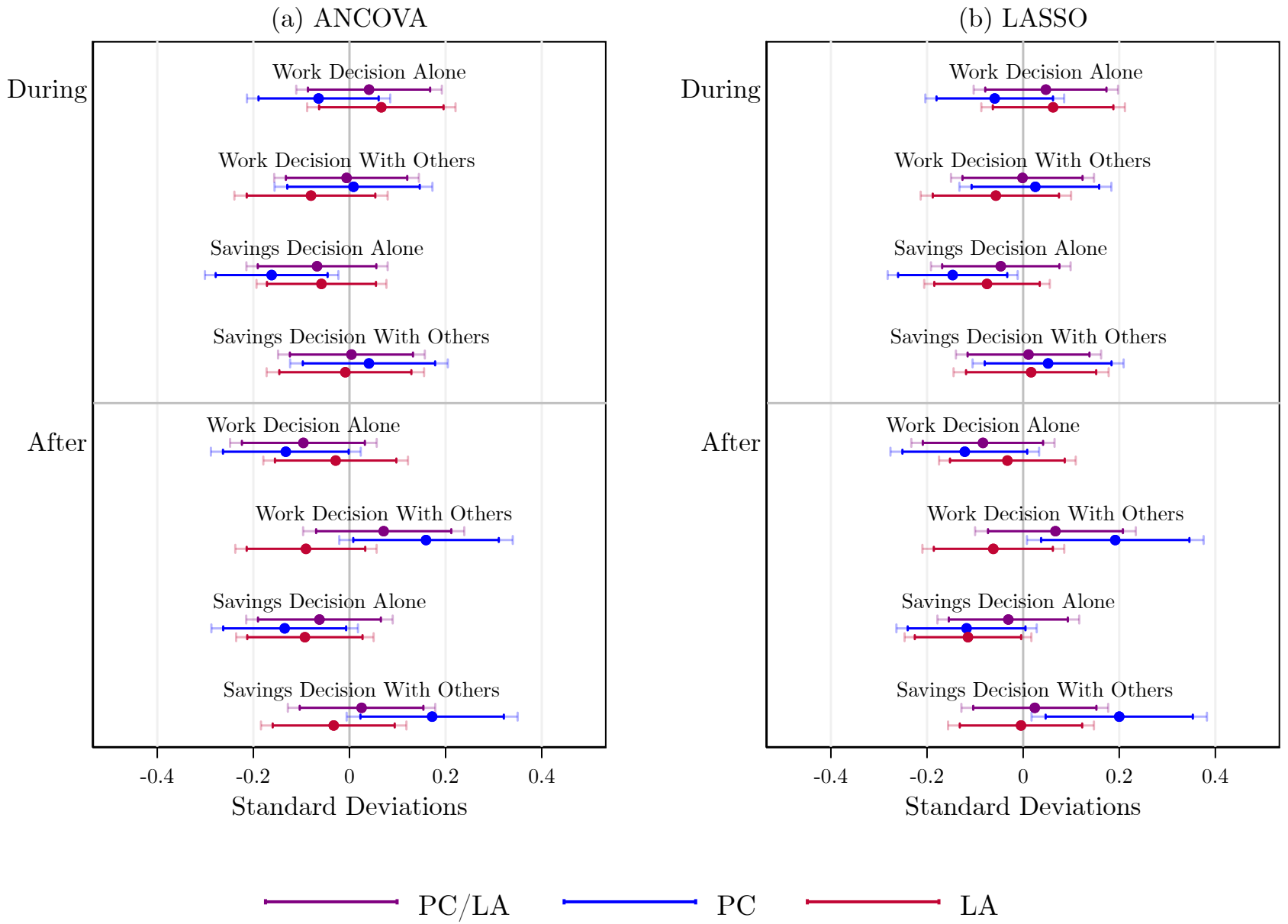

Figure B17: Impacts on Participation in Household Decisions

Note: The figure shows standardized impacts 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. 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.

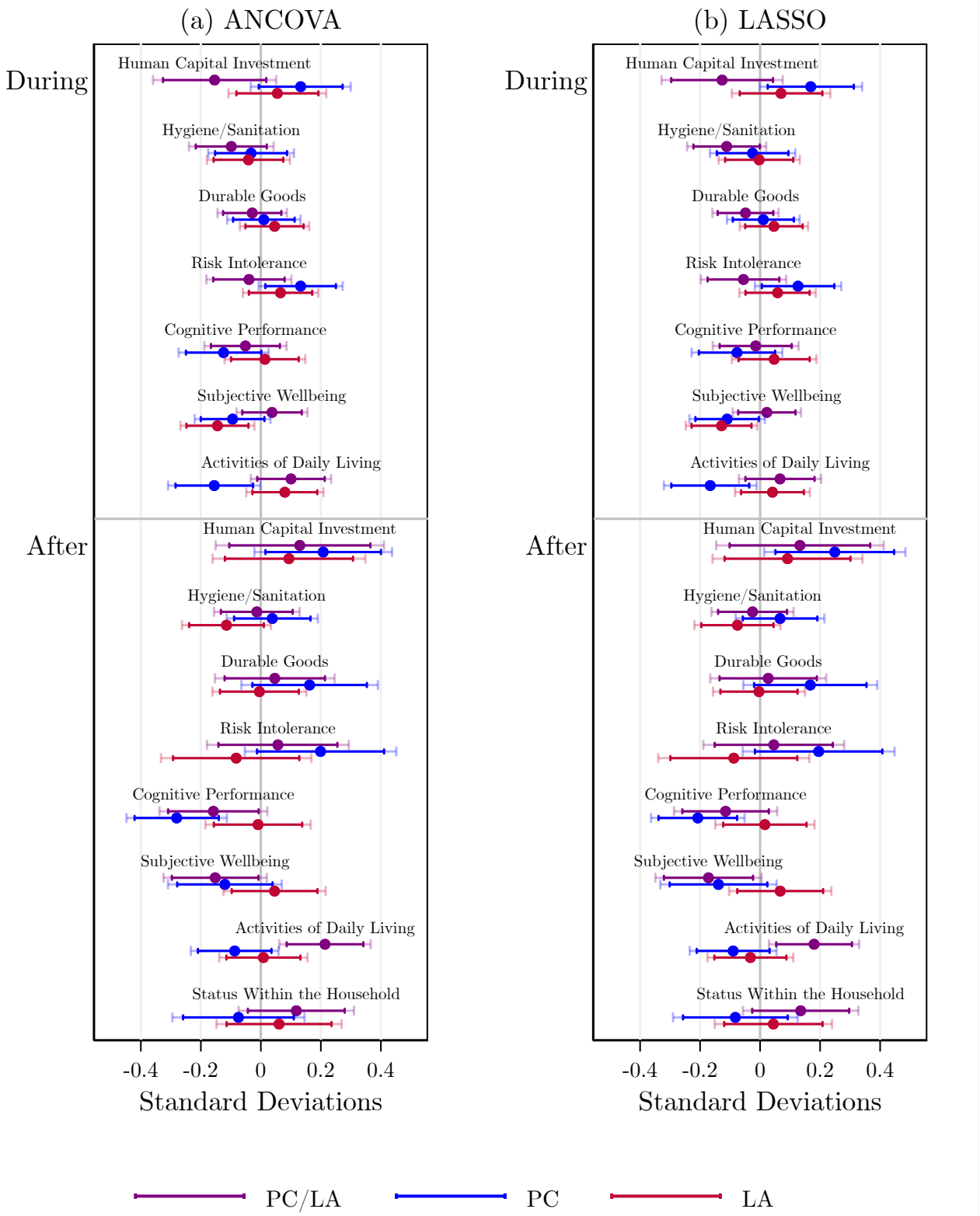

Figure B18: Impacts on Indices Calculated Using the Anderson (2008) Summary Index

Note: The figure shows standardized impacts for all indices, computed following Anderson (2008). 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

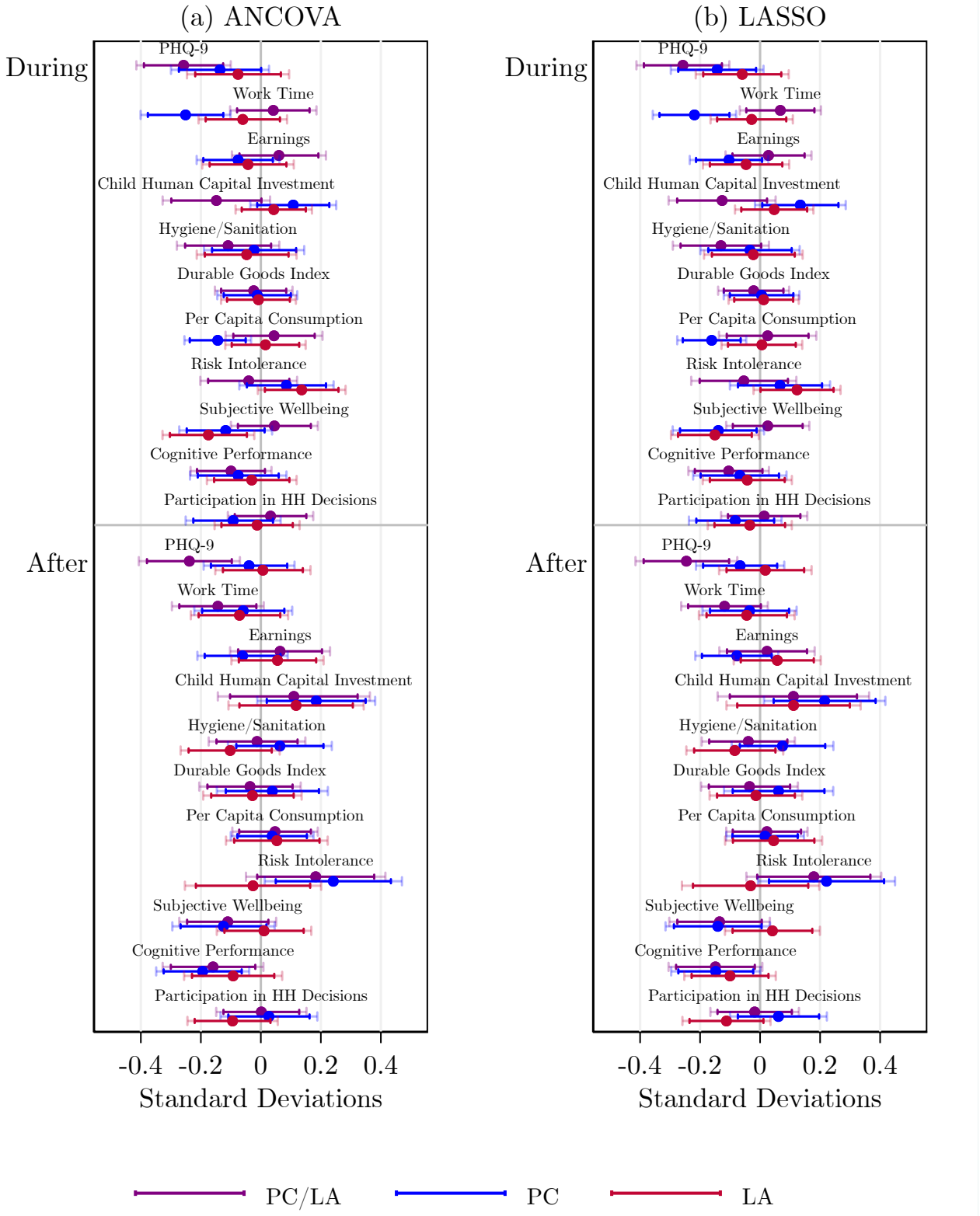

Figure B19: Impacts After Controlling for Free Distribution of Hand Sanitizer

Note: The figure shows standardized impacts for all outcomes. All estimates follow Equation (1) and also include an indicator participation in the intervention to distribute 600 ml of free hand sanitizer in Round 2, which is interacted with "during" and "after" indicators. 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 24 of the manuscript 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

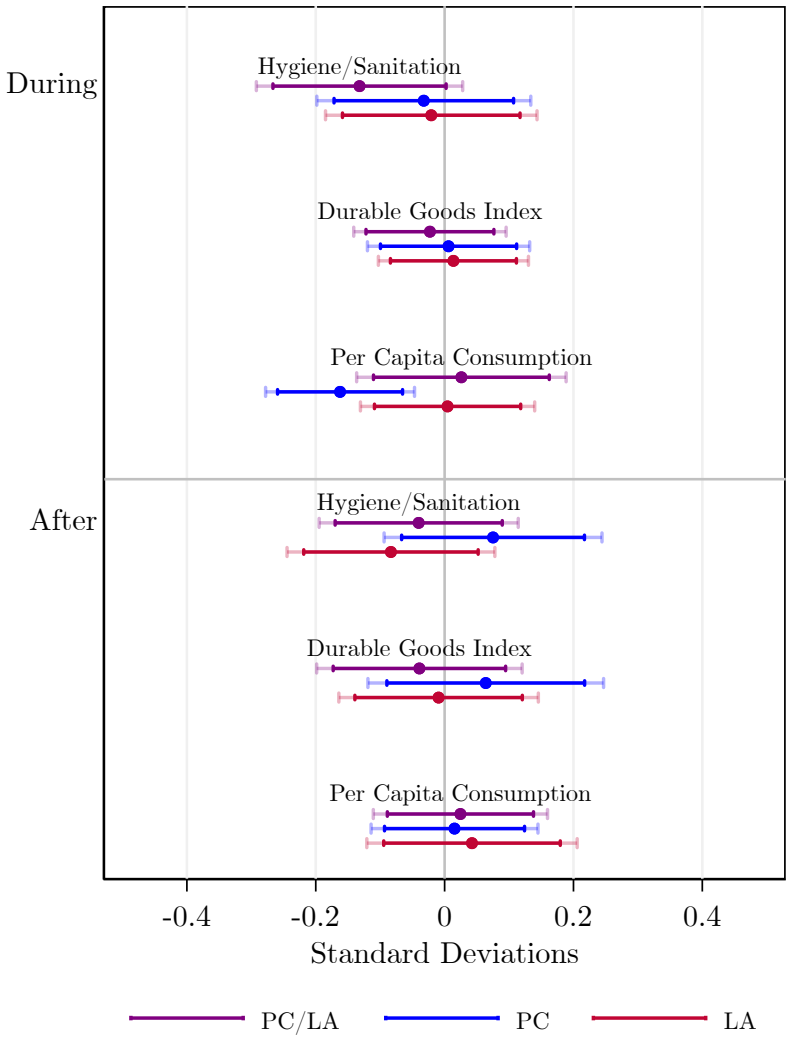

Figure B20: LASSO Estimates of Standardized Impacts on Socioeconomic Outcomes

Note: The figure shows standardized impacts for socioeconomic outcomes, as explained in the text. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. All estimates follow the Belloni et al.'s (2014) post-double-selection specification of Equation (1). Results using the ANCOVA specification appear in Figure 4. The top of the figure shows impacts during the PC intervention and the bottom of the figure shows impacts after the PC intervention.

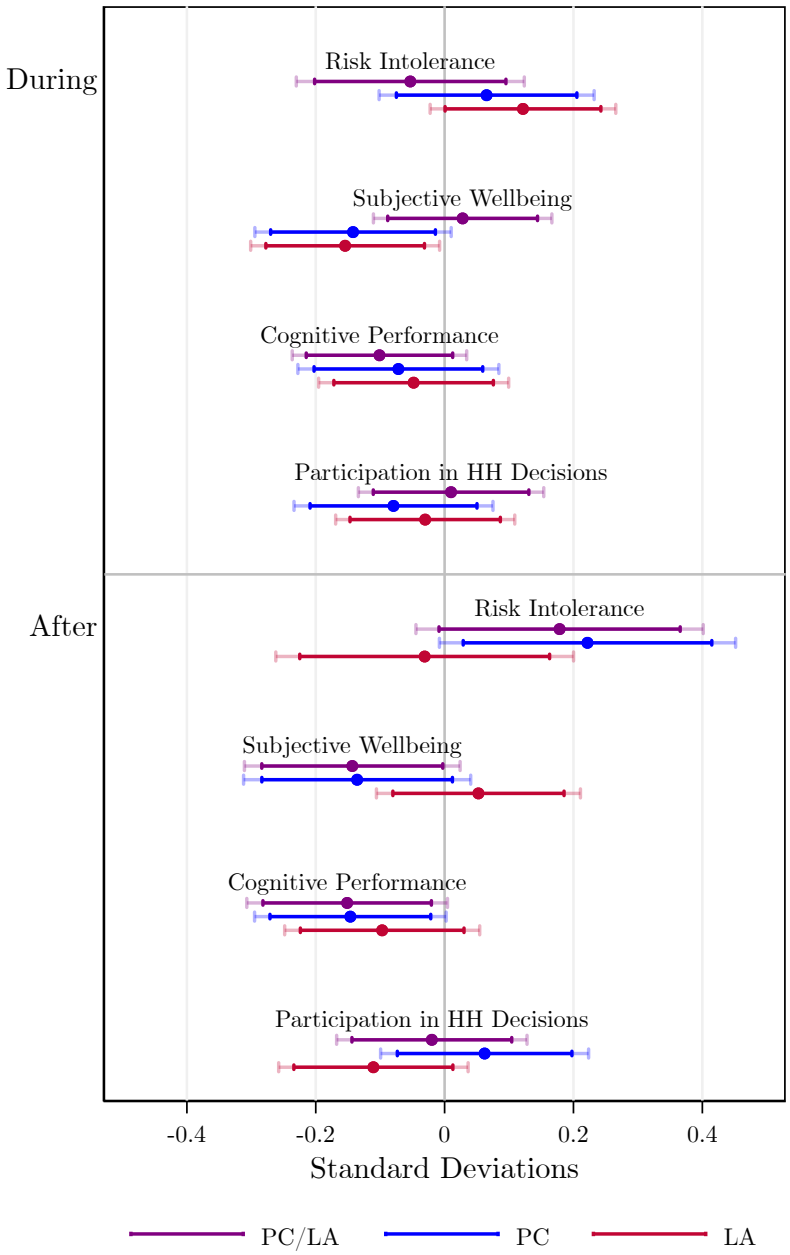

Figure B21: LASSO Estimates of Standardized Impacts on Possible Pathways

Note: The figure shows standardized impacts for possible pathways through which depression treatment may improve socioeconomic outcomes, as explained in the text. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. All estimates follow the Belloni et al.'s (2014) post-double-selection specification of Equation (1). Results using the ANCOVA specification appear in Figure B20. The top of the figure shows impacts during the PC intervention and the bottom of the figure shows impacts after the PC intervention.

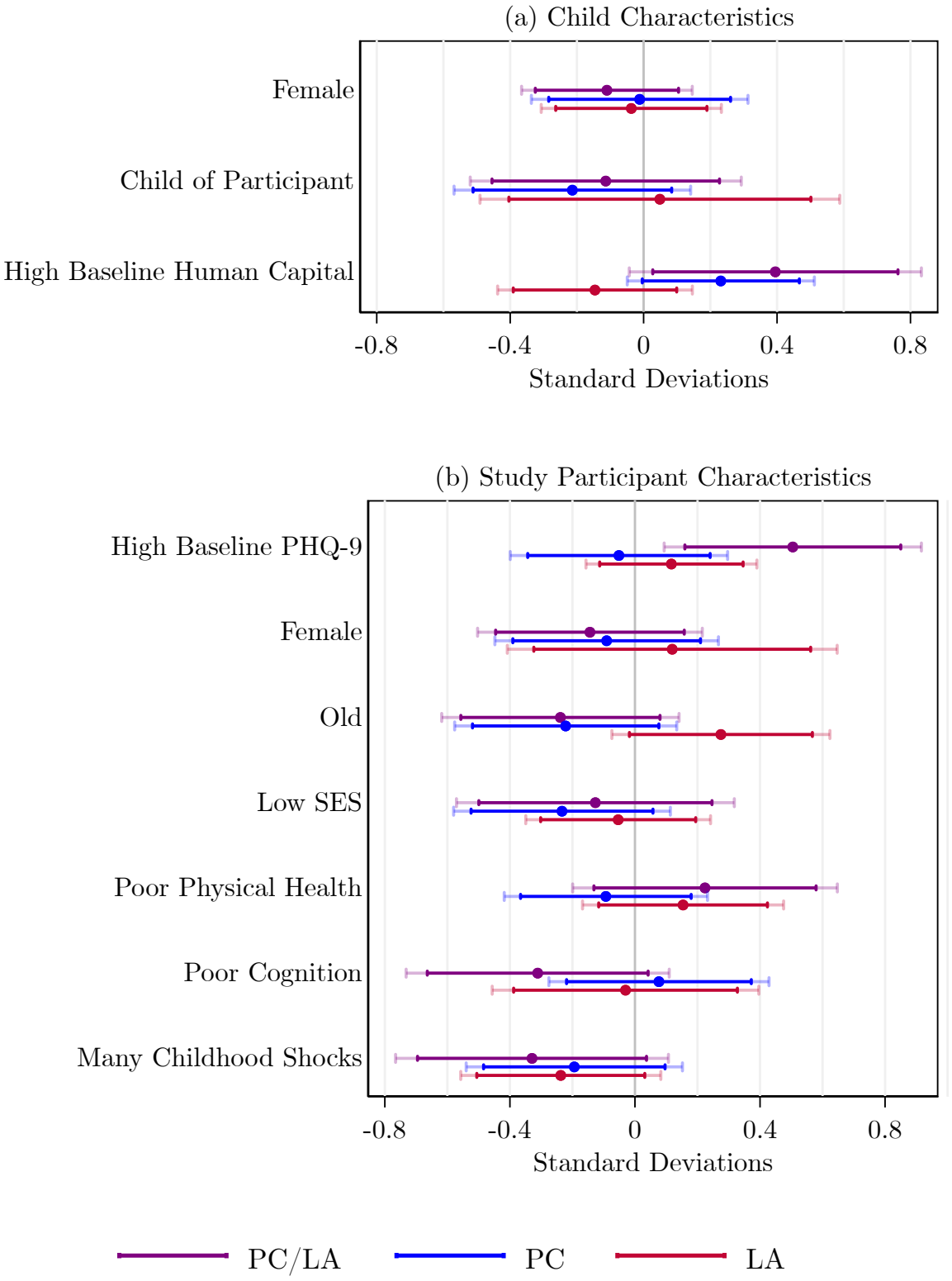

Figure B22: LASSO Estimates of Differential Effects on Child Human Capital Investment by Child and Study Participant Characteristics in Round 4

Note: The figure shows differential impacts on the child human capital index in Round 4 for indicated subgroups. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors. All estimates follow the Belloni et al. (2014) post-double-selection LASSO specification of Equation (1). ANCOVA estimates appear in Figure 3. All estimates are weighted by the inverse number of school-aged children in the household. Panel (a) shows differential effects according to child characteristics and Panel (b) shows differential effects according to study participant characteristics. 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. Other variables are defined in the text. We divide at the median for baseline human capital investment (0.24 SD), PHQ-9 score (15), age (36), SES (-0.13 SD), physical health (-0.04 SD), cognition (-0.55 SD), and exposure to childhood shocks (65).

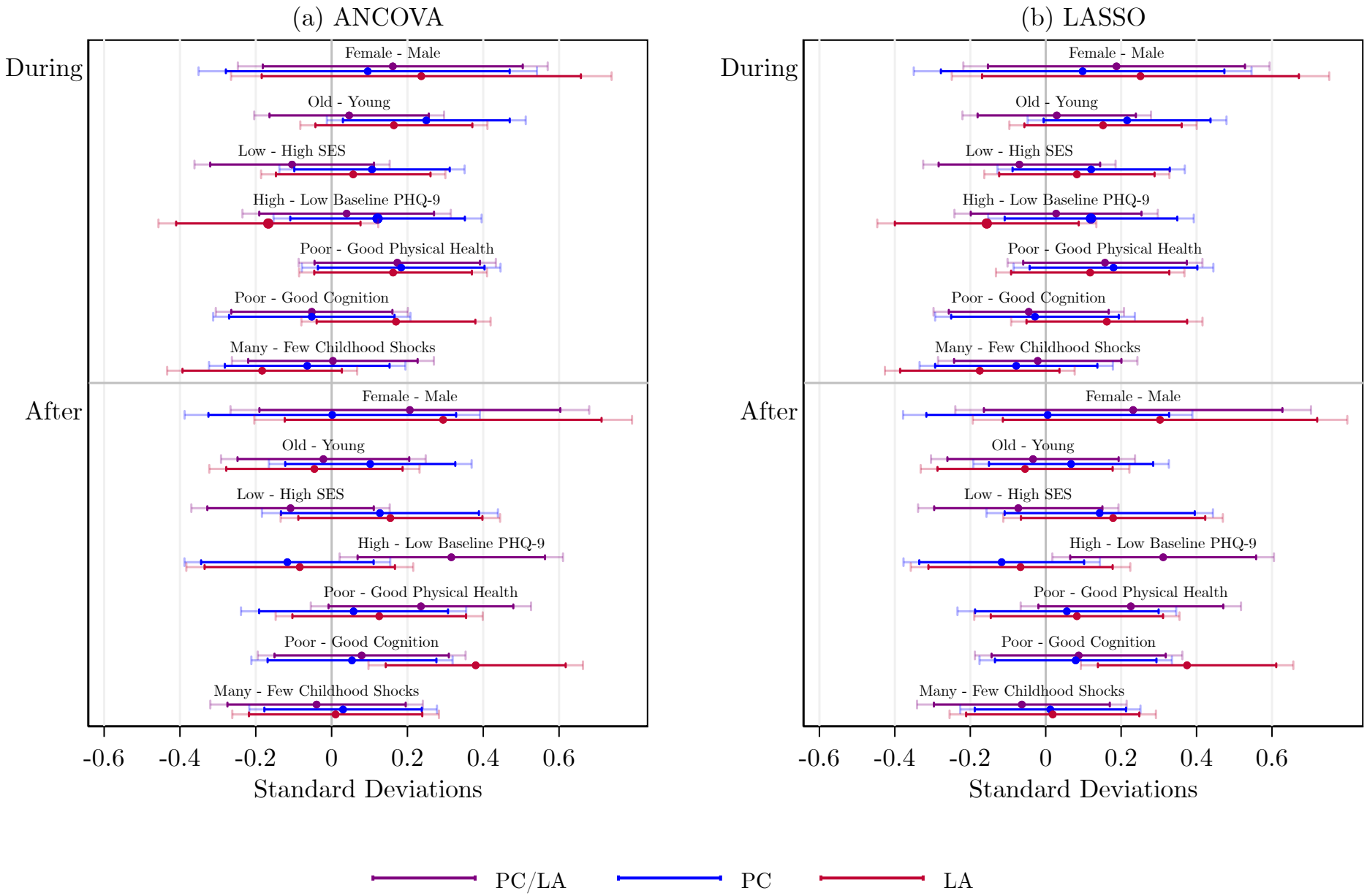

Figure B23: Heterogeneous Impacts on Work Time

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 positive and significant effect means that the first listed group has a larger increase in work time. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

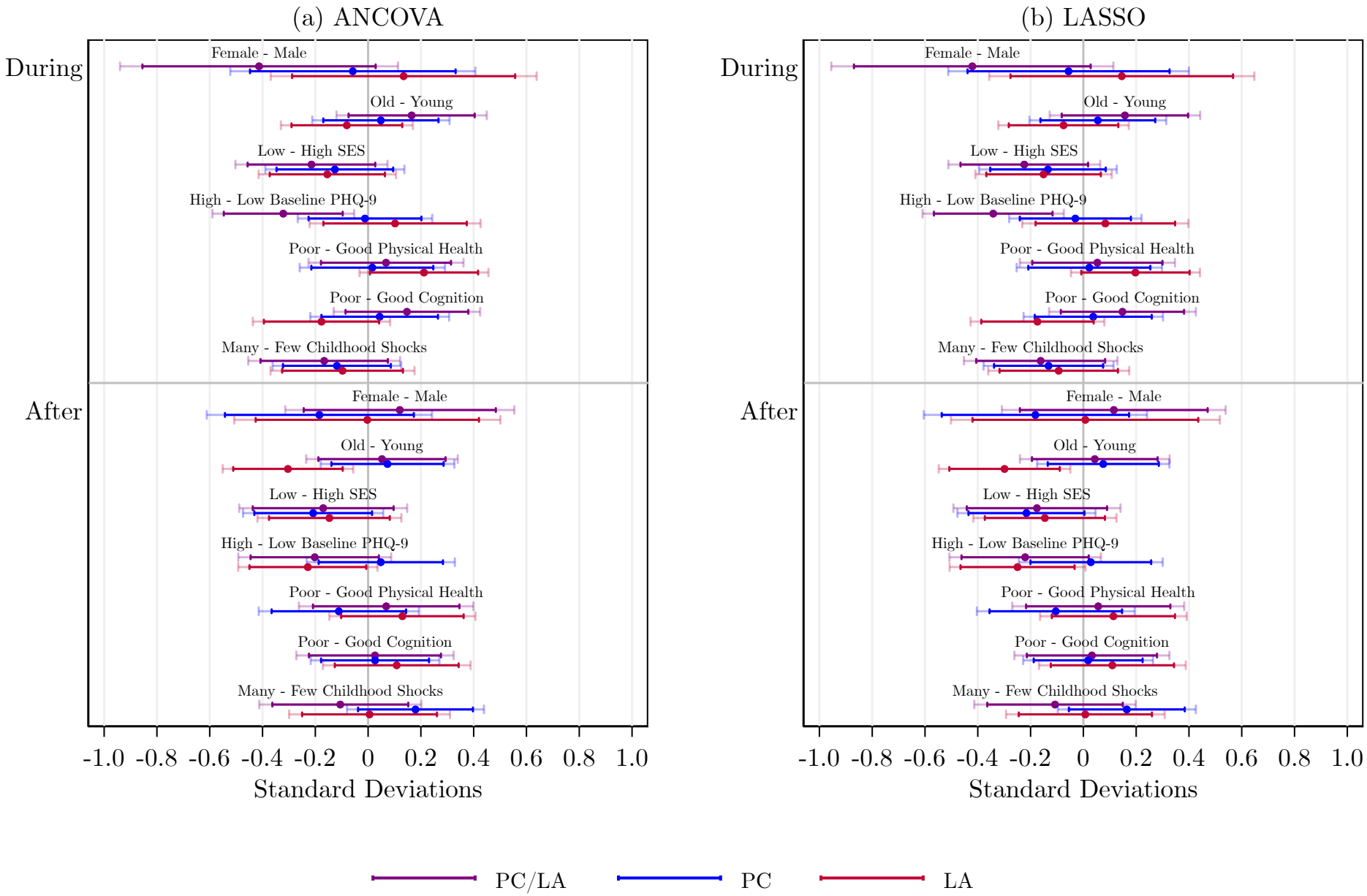

Figure B24: Heterogeneous Impacts on Earnings

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 positive and significant effect means that the first listed group has a larger increase in earnings. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

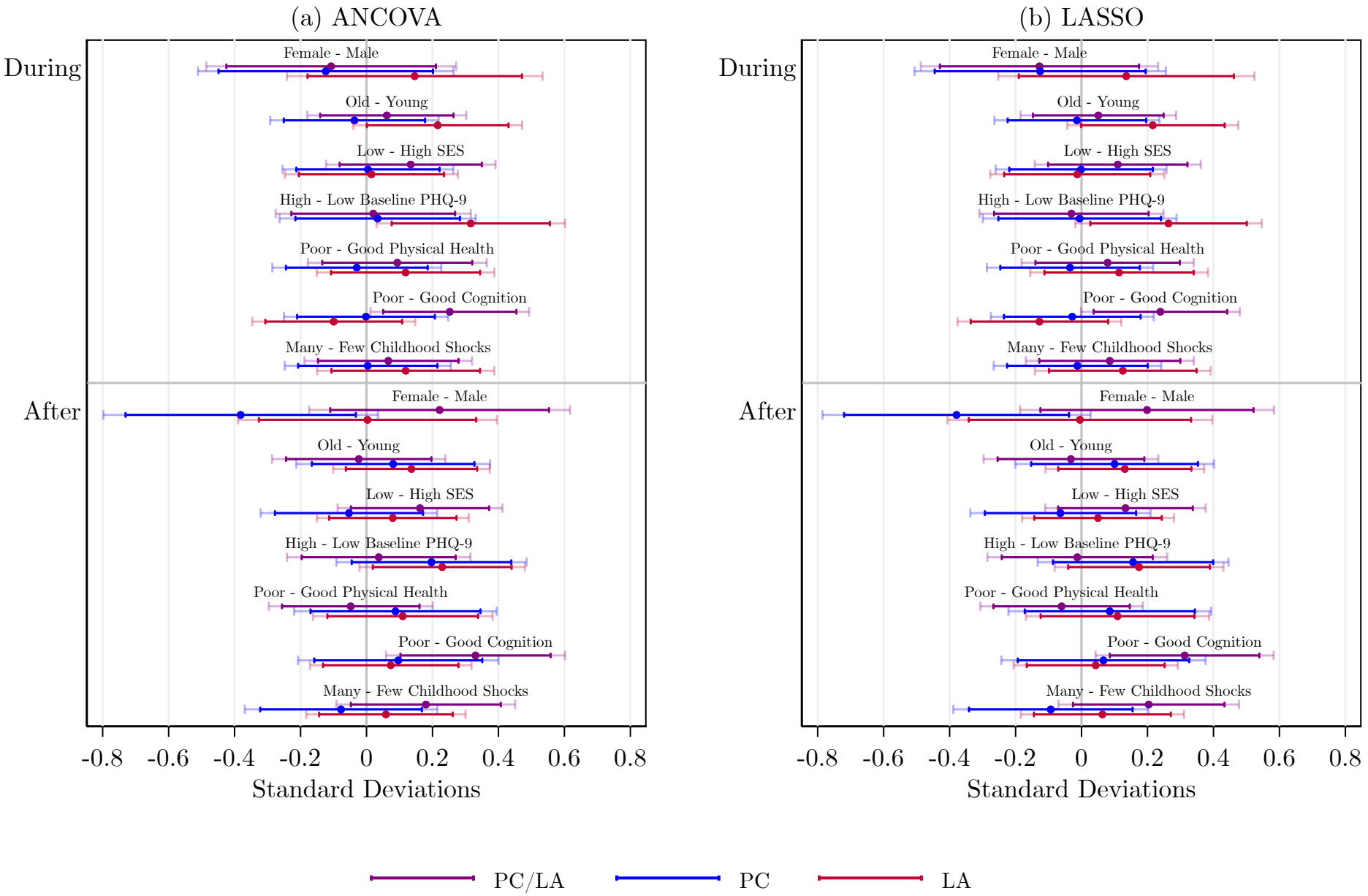

Figure B25: Heterogeneous Impacts on Hygiene/Sanitation

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 positive and significant effect means that the first listed group has a larger improvement in the hygiene/sanitation index. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

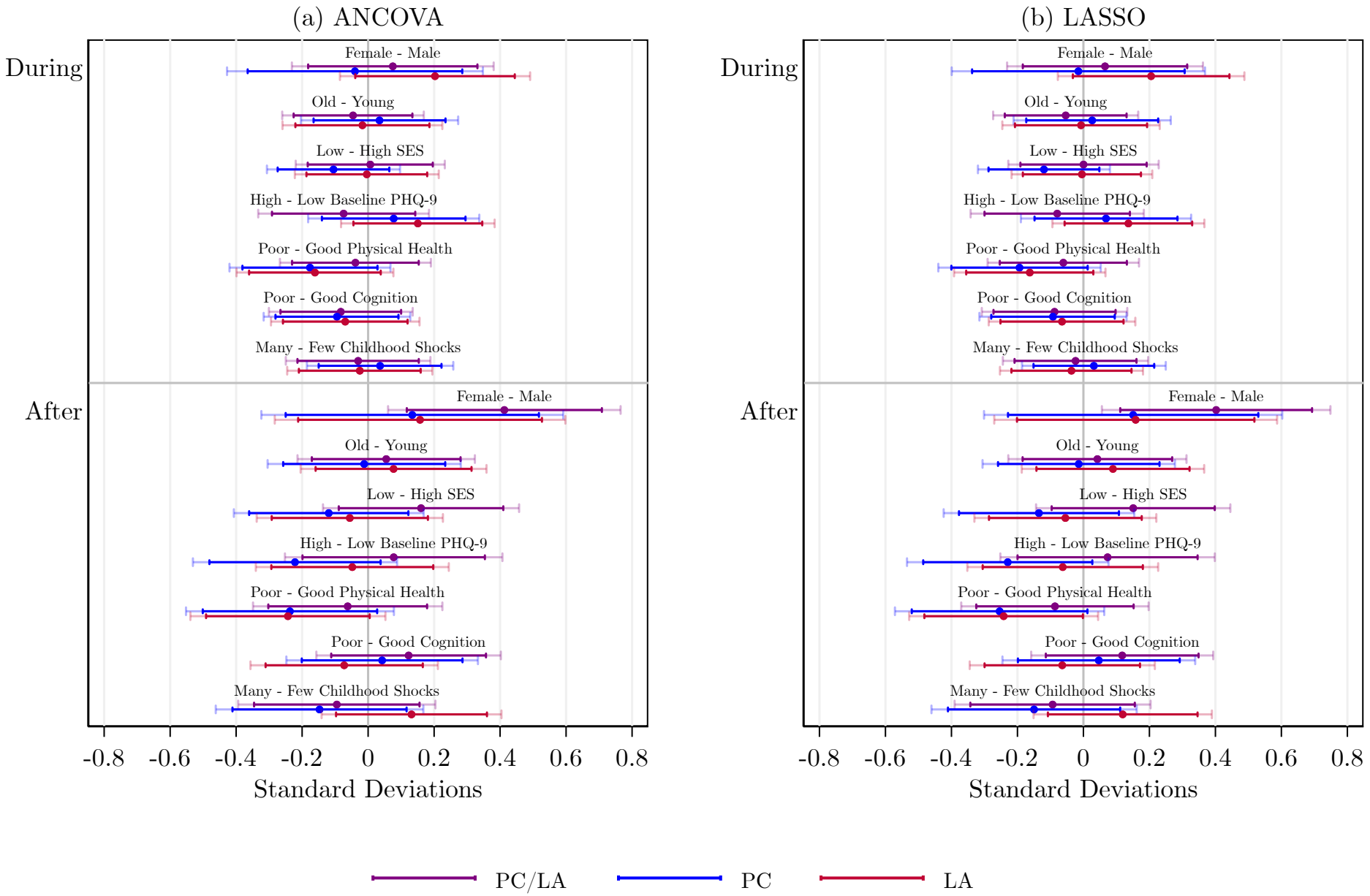

Figure B26: Heterogeneous Impacts on the Durable Goods Index

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 positive and significant effect means that the first listed group has a larger increase in durable goods ownership. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

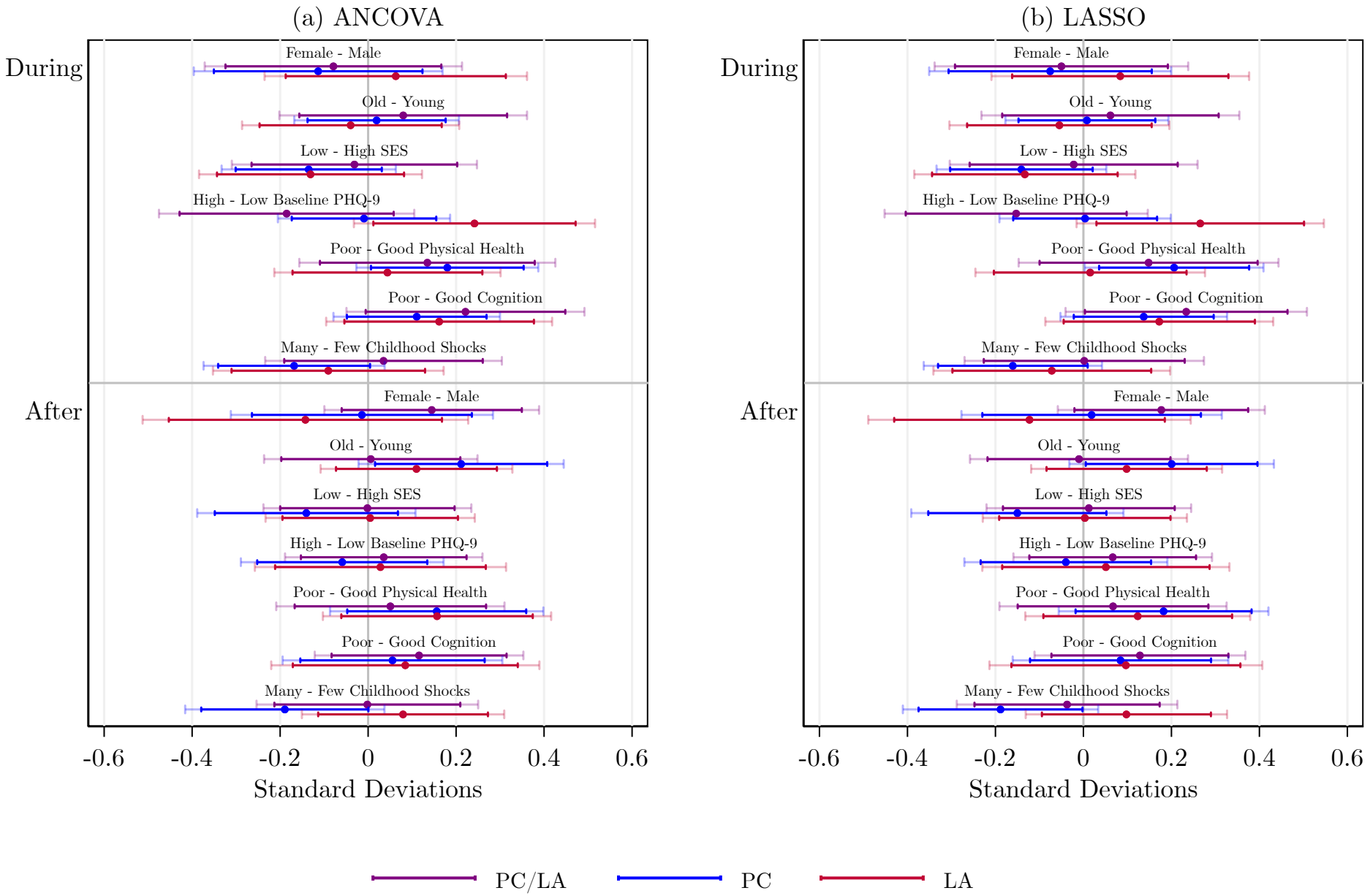

Figure B27: Heterogeneous Impacts on Per Capita Consumption

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 positive and significant effect means that the first listed group has a larger increase in per capita consumption. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

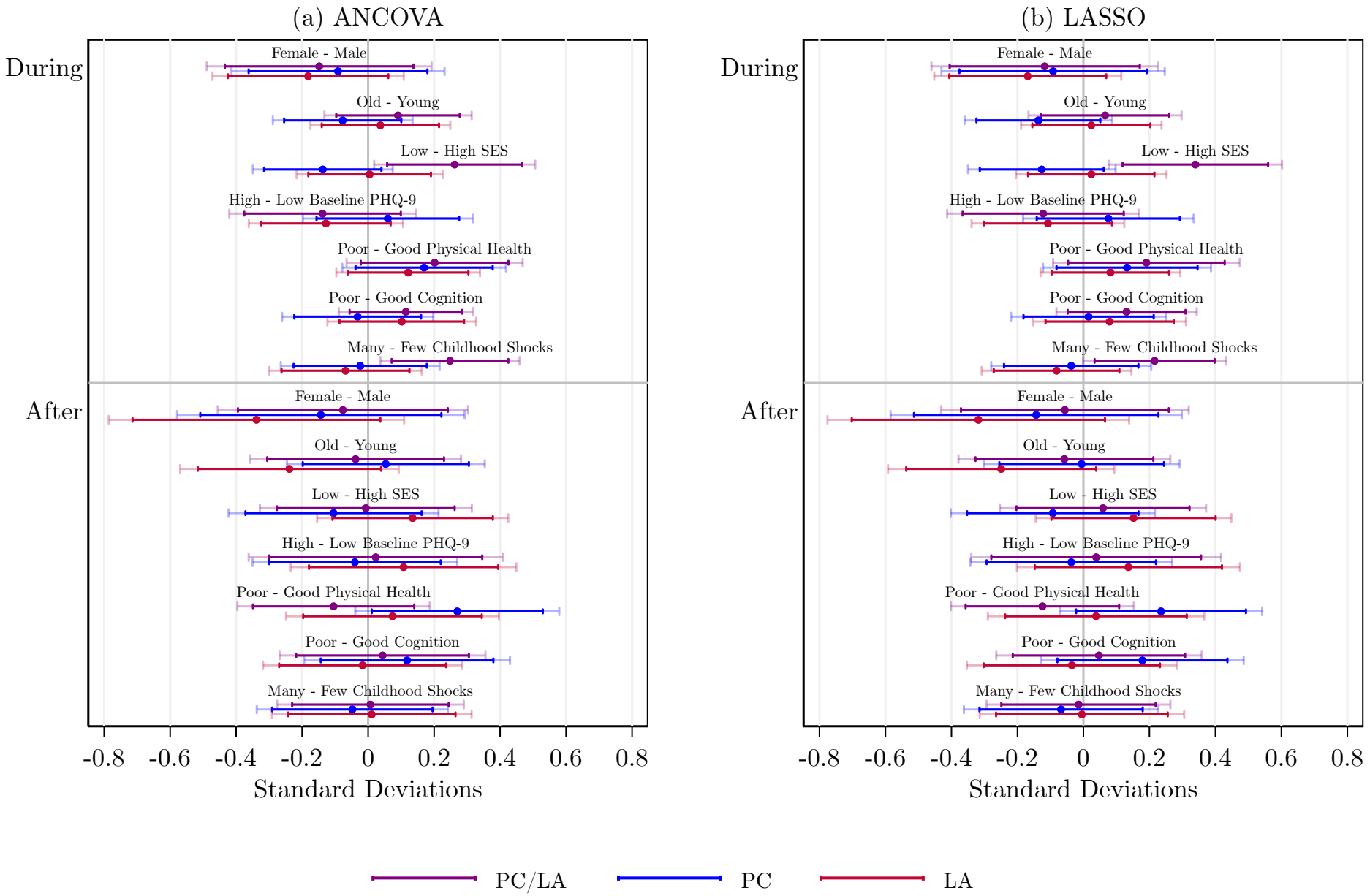

Figure B28: Heterogeneous Impacts on Risk Intolerance

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 positive and significant effect means that the first listed group has a larger increase in risk intolerance. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

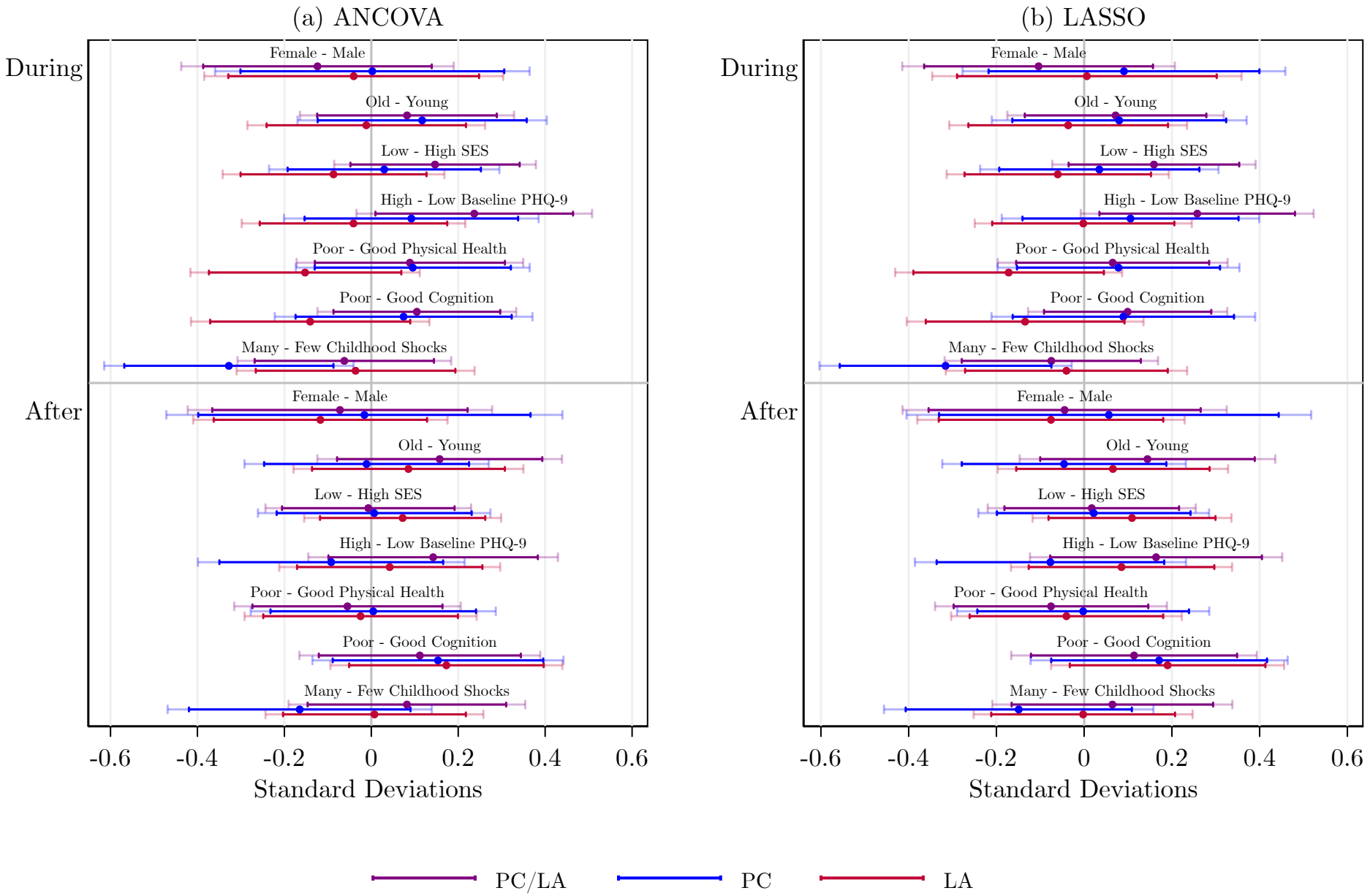

Figure B29: Heterogeneous Impacts on Subjective Wellbeing

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 positive and significant effect means that the first listed group has a larger increase in subjective wellbeing. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

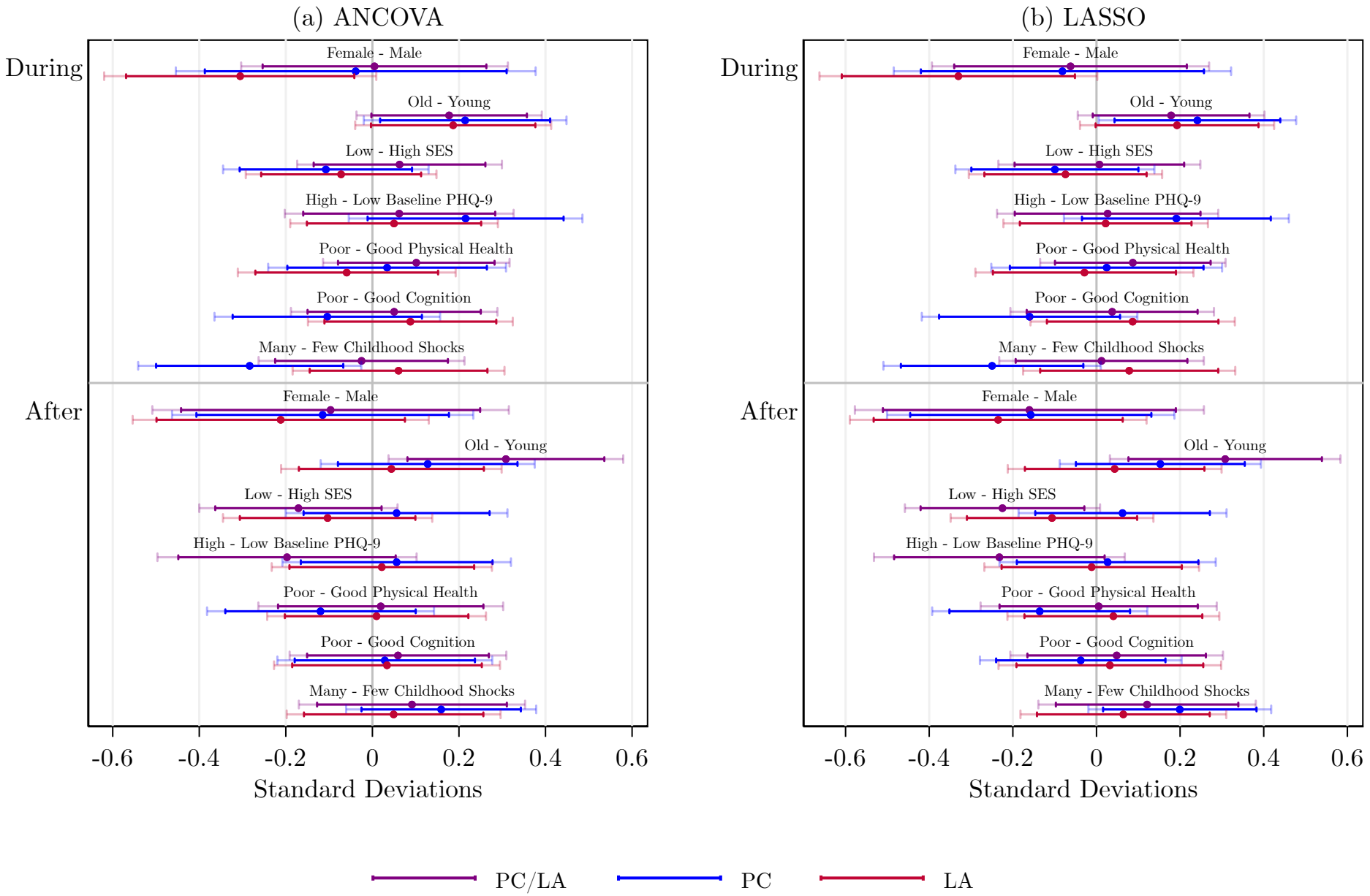

Figure B30: Heterogeneous Impacts on Cognitive Performance

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 positive and significant effect means that the first listed group has a larger increase in cognitive performance. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

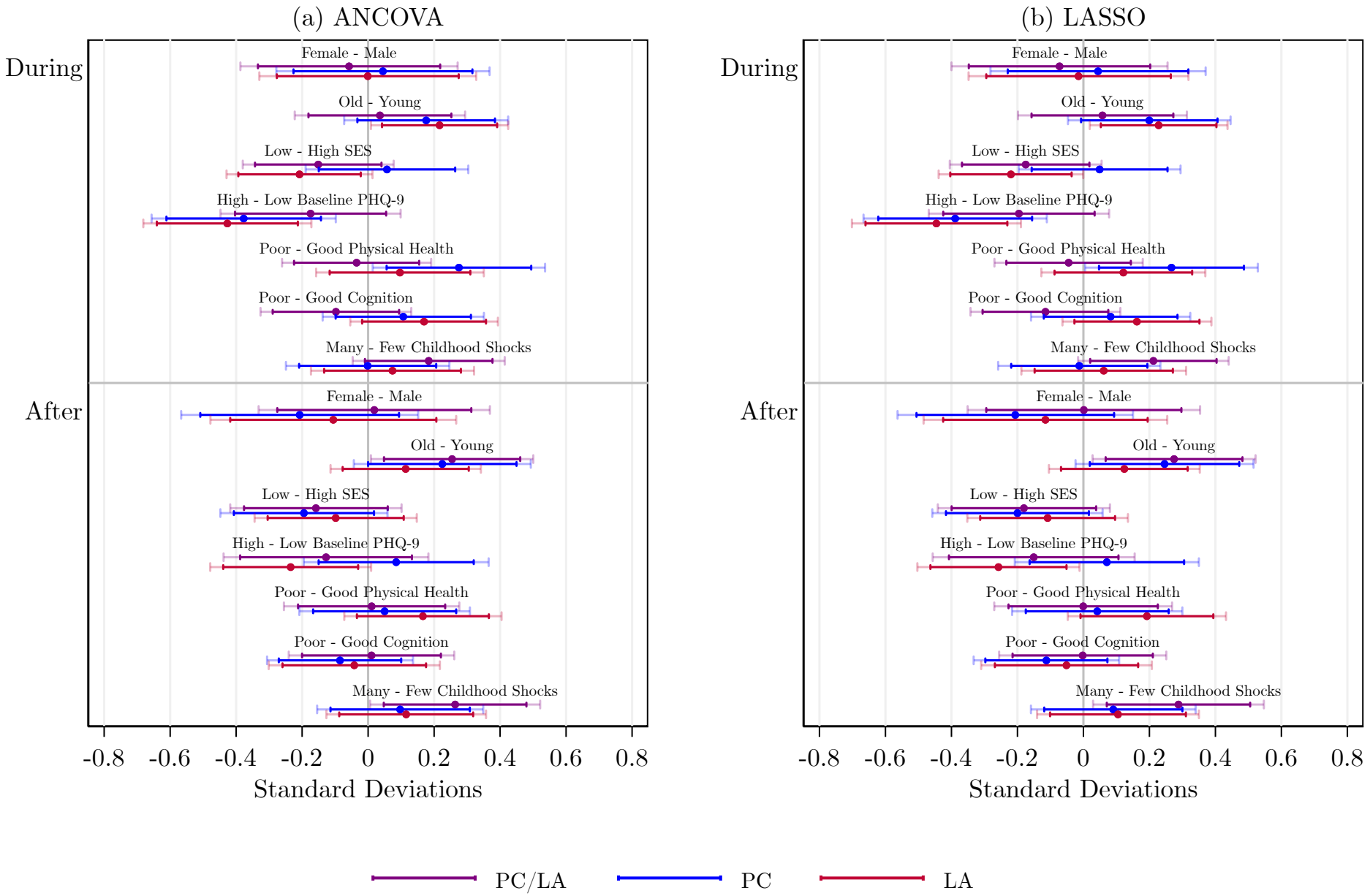

Figure B31: Heterogeneous Impacts on Participation in Household Decisions

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 positive and significant effect means that the first listed group has a larger increase in participation in household decisions. 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. Light bars indicate 95 percent confidence intervals and dark bars indicate 90 percent confidence intervals based on locality-clustered standard errors.

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