

# The Labor Market Impact of Mental Health Care in India

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## Abstract

Poor mental health is a persistent public health challenge in developing countries, where around 20 percent of adults experience depression but most never receive treatment. This study evaluates the separate and joint impacts of employment support and mental health treatment for adults with depression in Karnataka, India. We recruited a sample of 1000 depressed adults through community screening and cross-randomized participants to receive assistance with job training and placement and/or eight months of psychiatric care. While both interventions improved mental health, these gains did not translate into substantial labor market benefits. Evidence suggests that discrimination and stigma related to mental illness may have undermined the intervention impacts. We show that mental health care recipients self-isolated, which led to reductions in both work and non-work outside the home. This pattern was concentrated among households that were active in the marriage market, where mental health stigma is a particular concern. Our findings suggest that support for people with depression may have unintended consequences in high-stigma settings.

**JEL:** I15, I18, J22

**Keywords:** Depression, Labor Supply, Discrimination

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# 1 Introduction

Depression and other mental illnesses are ubiquitous and have large economic consequences in developing countries. Mental disorders account for 11 percent of the disease burden in poor countries (Patel 2007, Bruckner et al. 2011). Depression, which is the most common mental disorder, affects around 20 percent of adults worldwide. Depression is both a cause and a consequence of poverty. Poverty increases depression risk by exacerbating trauma, stress, and uncertainty. Depression may in turn influence socioeconomic outcomes via labor force participation, productivity, human capital investment, and other important decisions. Scholars have begun to explore the the psychological channels through which poverty may affect economic choices (Mullainathan and Shafir 2013, Haushofer and Fehr 2014, Schilbach et al. 2016). Depression may be an important pathway for these effects.

Treating mental illness in poor setting is a stubborn challenge because there is both low demand and low supply of treatment. Due to pervasive stigma, most people with mental disorders do not seek treatment. Many people associate depression with negative stereotypes like laziness, selfishness, and attention seeking (Kermode et al. 2009), or conflate depression with psychotic disorders that have more extreme symptoms. Being labeled with these stereotypes may foster discrimination in the labor or marriage markets. In conjunction, mental health resources are extremely scarce in developing countries. Bruckner et al. (2011) identify a shortage of 235,000 mental health providers across 58 low and middle income countries. There are just 0.2 psychiatrists per 100,000 people in India, compared on to 13.7 psychiatrists per 100,000 people in the US (Jacob et al. 2007). This pattern suggests that there may be a market failure in which the lack of care perpetuates stigma, which reinforces the low demand for care. Stigma is a fundamental challenge to mental health care provision because the act of diagnosis, which precipitates stigma, is integral to treatment.

This study evaluates the socioeconomic impact of two interventions intended to improve mental health in the community. We identified 1000 study participants with mild or moderate depression through door-to-door screening in three peri-urban taluks near Bangalore, India.

In collaboration with a research hospital and a local NGO, we offered some participants eight months of free psychiatric care (PC). In this intervention, psychiatrists diagnosed and treated patients with pharmacotherapy during monthly office hours, while medical and NGO staff monitored medication adherence, side effects, and patient welfare throughout the study period. 44 percent of participants complied with PC. The NGO concurrently offered some participants employment support (ES). Staff worked with participants to identify and pursue income-generating activities, including formal sector jobs and self-employment opportunities. This intervention led to placements for 42 percent of participants, with substantial shares in the manufacturing and agricultural sectors. We cross-randomized these interventions, so that some participants received both interventions (PC/ES), some received only one, and some received neither intervention. We measured impacts on mental health and socioeconomic outcomes after four, eight, and twelve months. We pre-registered and filed a pre-analysis plan for this study in the AEA RCT registry before collecting follow-up data.

These interventions generally succeed in improving mental health. After eight months, the combination of both interventions reduced both depression severity and anxiety severity by 0.35 standard deviations ( $p < 0.001$  in both cases). Mental health benefits persisted through the final follow-up wave, four months after the conclusion of psychiatric care. However we find unexpected *negative* impacts on labor supply and earnings. Participants in the PC arm worked 2.7 fewer hours per week ( $p = 0.02$ ). Employment support offset this impact, so that PC/ES participants had similar labor supply to the control group. The interventions did not significantly risk and time preferences, child investment, sanitation, subjective wellbeing, or intra-household bargaining power.

Next we investigate the possible explanations for this phenomenon. Participation in the PC intervention required participants to receive a mental health diagnosis and interact publicly with medical and NGO staff. Stigma might reduce work through three broad channels. Stigma could reduce labor demand through discrimination by employers (Kessler et al. 1999). Participants might also limit their activities to hide their diagnosis from the

community (Thara and Srinivasan 2000). This incentive is particularly strong within households that are active in the marriage market, where any family association with mental illness may hamper marriage placements (Thara et al. 2003). Finally, participants might “self-stigmatize” by applying negative depression stereotypes to themselves (Corrigan et al. 2006, Corrigan et al. 2009). In this model, people diagnosed with depression work less because they self-identify with laziness or other stereotypes.

Evidence suggests that the negative labor supply response arose through self-isolation. According to time-use diaries, PC recipients reduced both work and non-work activities outside the home but increased these activities inside the home. Marriage market concerns appear to drive these patterns. Both PC and ES led to marriage delays for unmarried members of participants’ households. This impact was particularly strong while the interventions were ongoing: intervention households retained 0.19 more unmarried females than control households ( $p = 0.03$ ). In a heterogeneity analysis, we divide the sample into households with and without marriage-eligible members. Respondents from marriage-eligible households entirely explain the negative labor supply response. PC participants from marriage-eligible households work 4.2 fewer hours per week ( $p < 0.001$ ), instead spending more time on child care, which leads them to earn Rs. 140 less per week ( $p < 0.001$ ). An examination of time use by location confirms that these respondents also self-isolate to the greatest extent.

Our findings have important implications for public health policy. The psychiatric intervention involved in this study is affordable and scalable. Depression screening, diagnosis, and treatment with off-patent antidepressants is a plausible way to address endemic depression in developing countries.<sup>1</sup> Our findings also point to a market failure for mental health care in developing countries. The provision of psychiatric care (a supply shock) was able to improve mental health but led to unintended consequences that reinforce the status quo. Policy solutions may be needed that jointly increase the supply and demand for care.

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<sup>1</sup>Pharmacotherapy and psychotherapy, the two primary depression treatment approaches, are similarly effective on average (Sava et al. 2009). However pharmacotherapy, which economizes on labor costs, is more scaleable and cost-effective than psychotherapy in developing countries (Chisholm et al. 2004).

## 2 Background

### 2.1 Mental Health Stigma and Discrimination

Since stigma research traverses multiple disciplines, and scholars have not adopted a uniform definition of the term. In our working definition, stigma arises when the community affixes negative stereotypes and socially ostracizes individuals with an undesirable trait.<sup>2</sup> Depression is associated with laziness, unreliability, weakness, and other negative stereotypes, which may have negative consequences for people who are labeled as depressed (Cox et al. 2012, Kermode et al. 2009). Many people also conflate depression and other forms mental illness with even stronger negative stereotypes, such as psychosis (Angermeyer et al. 2004). Stigma may also “spill over” to family members and others who are associated with the mentally ill person (Angermeyer et al. 2003). The nature and the extent of mental health stigma varies culturally and is a function of the availability of treatment (Littlewood 1998). The provision of high-quality care may ameliorate stigma by weakening negative stereotypes about people with mental illness.

Research demonstrates that stigma reduces the demand for mental health care. In Clement et al.’s (2015) meta-analysis, which primarily focused on developed countries, 21-23 percent of study participants identify stigma as a barrier to seeking care. While the majority of people with mood disorders (e.g. depression) eventually seek care, they wait an average of eight years before doing so (Thornicroft 2008). People base these decisions on their subjective expectations of stigma costs, which may diverge from realized stigma costs (Lasalvia et al. 2013). According to Angermeyer et al. (2004), 82 percent of people

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<sup>2</sup>According to Link and Phelan (2001, p. 367), “stigma exists when the following interrelated components converge. In the first component, people distinguish and label human differences. In the second, dominant cultural beliefs link labeled persons to undesirable characteristics - to negative stereotypes. In the third, labeled persons are placed in distinct categories so as to accomplish some degree of separation of ‘us’ from ‘them.’ In the fourth, labeled persons experience status loss and discrimination on access to social, economic, and political power that allows the identification of differences, the construction of stereotypes, the separation of labeled persons into distinct categories, and the full execution of disapproval, rejection, exclusion, and discrimination. Thus we apply the term stigma when elements of labeling, stereotyping, separation, status loss, and discrimination co-occur in a power situation that allows the components of stigma to unfold.”

with depression anticipated a loss of access to employment, while only 2 percent actually experienced this form of stigma. This research focuses on developed countries where mental health care is generally available. Little is known about how mental health stigma manifests in developing countries.

There are three broad ways in which stigma may affect people who are diagnosed with depression in our context. It may lead to labor market discrimination, in which employers reduce the demand for labor by depressed people. Employers and coworkers may shun people with depression due to stereotypes of laziness and unreliability. Although many people are self-employed or work in small enterprises, depression stigma may also reduce demand their output. Evidence suggests that many people perceive this concern, but that it may not be a large issue in practice (Angermeyer et al. 2004, Banerjee et al. 2009). Self-stigma is another possible impact of a depression diagnosis. Self-stigma occurs when people internalize negative stereotypes associated with mental illness and adopt in turn adopt these behaviors (Corrigan et al. 2009, Corrigan and Rao 2012). The authors describe the “why try” effect, in which people with depression lose self-efficacy and stop exerting effort at work and in other endeavors.

Finally, mental health stigma may have important ramifications in the marriage market. This channel is particularly relevant in India, where households must arrange matches with other households from nearby communities. Marriages are high-stakes decisions that often involve large dowry payments, the bride’s relocation to the groom’s household, and costly divorce (Srinivasan and Lee 2004, Pothan 1989). Asymmetric information is acute in this setting, and households have an incentive to conceal negative attributes that might worsen their marriage market prospects. Qualitative evidence suggests that it is typical for households to conceal mental illness from other households within a marriage (Thara et al. 2003). This form of stigma may easily spill over onto other household members. Since depression is heritable (Nestler et al. 2002), the families of potential spouses may be reluctant to match with someone whose relatives have depression. We are not aware of other research that

examines this stigma channel in detail.

The pervasiveness of stigma has important ramifications for mental health care provision and policy. The systematic undertreatment of depression is a major reason why depression contributes so substantially to the global burden of disease (Thornicroft et al. 2017). An aggressive approach to depression seems justifiable on these grounds. However the diagnostic process, which is inherent in the provision of care, may cause unintended consequences by inducing stigma. Policymakers can reduce stigma through mental health education and direct indirect contact with patients (Thornicroft et al. 2016), but this process is slow and indirect. It is not clear how best to approach depression treatment given these tradeoffs.

## **2.2 Depression in the Community**

Because it is so prevalence, depression may have important economic consequences. Burden of disease statistics indicate that depression is the nineteenth most common disease in the world (Thornicroft et al. 2017). However evidence from developing countries is limited because most mental health research focuses on developed countries. In light of these data limitations, we conducted a survey in Madhugiri Taluk, Karnataka to measure the prevalence of depression and the correlation of depression with socioeconomic status and other covariates. This taluk is adjacent to the study area and has similar demographic characteristics. Surveyors attempted to reach a representative sample of adults in this taluk. We selected 120 sample villages and wards from the 2011 census roster of 327 villages and wards. Within each village/ward, surveyors sampled every 25th household and selected two adults from the household roster to complete the questionnaire. Surveyors followed up a maximum of three times while attempting to reach the sampled individuals.

The questionnaire elicited depression severity using the PHQ-9 instrument (Kroenke et al. 2001), as in our intervention study below. We used several of the same surveyors for both data collections and administered the PHQ-9 using a similar survey approach to maximize the comparability of depression severity estimates across these two samples. The

survey also measured demographic and socioeconomic characteristics, as well as items that were used to determine eligibility for the intervention study (e.g. willingness to accept a job paying Rs. 3000-6000). Finally, surveyors elicited the exposure to recent negative life events (NLEs), including unemployment, loss of a business, serious illness, and natural disasters. NLEs are important determinants of depression risk in epidemiological models of depression (Kessler 1997).

To assess representativeness, we compare the demographic characteristics of our sample to the characteristics of Madhugiri in the 2011 Census of India. According to the census, the population of Madhugiri is 95 percent Hindu, 50 percent female, 24 percent SC/ST, and 63 percent literate. Our sample is 93 percent Hindu, 58 percent female, 53 percent SC/ST, and 65 percent literate. The gender and SC/ST imbalance may reflect the difficulty reaching some people who work away from home during the day. We reweight our sample to match the taluk characteristics in our analysis below, however depression prevalence estimates are nearly identical irrespective of the use of these weights.

Figure 1 (Panel A) shows the distribution of depression severity in the Madhugiri community sample. For this discussion we follow the threshold definitions for mild depression (scores of 5-10), moderate depression (scores of 11-20), and severe depression (scores of 21 or more). Our survey indicates that 23.6 percent of Madhugiri adults are at least mildly depressed (confidence interval: 21-26 percent), 7.7 percent are at least moderately depressed (confidence interval: 6-9 percent), and 0.2 percent are severely depressed (confidence interval: 0-0.5 percent). The PHQ-9 threshold for moderate depression corresponds loosely with the diagnosis of major depressive disorder (MDD), although the PHQ-9 scale is not a diagnostic instrument. Our findings are broadly consistent patterns in the World Mental Health Surveys (Thornicroft et al. 2017). Depression may have large economic ramifications because it is so pervasive.

Panel B of Figure 1 shows the relationship between depression and socioeconomic status in the community. The SES index is defined as the first principal component of non-SC/ST



status, schooling, literacy, savings, and house size (number of rooms). The x-axis of the figure shows percentiles of this index. There is a strong negative relationship between depression and SES. PHQ-9 scores are around 2 points higher in the bottom SES quartile than in the top SES quartile. Table 1 examines these factors in more detail. The table shows that depression is positively correlated with age and female gender. It is negatively correlated with socioeconomic status: depressed people have 0.5 fewer years of schooling ( $p < 0.01$ ) and lower literacy ( $p < 0.01$ ). However SC/ST status, house size, and savings are not significantly correlated with depression.

## 3 Study Design

### 3.1 Sampling and Recruitment

Our sampling frame is the set of villages and wards with at least 40 households in the taluks of Doddaballapur, Korategere, and Gauribidanur, Karnataka. In the 2011 Census of India, these taluks have a total population of 758,184. After eliminating 51 villages that were too small or remote, we identified 616 target villages and wards (urban districts). Hereafter, we refer collectively to villages and wards as “villages.” We randomized villages across four intervention arms (described below) before recruiting study participants. We constructed a village socioeconomic index using data from the 2011 census on average house quality, electrification, latrine use, and ownership of several durable goods. We stratified the randomization by taluk and terciles of this index, for a total of nine strata. Village randomization minimized the scope for social interaction across intervention arms and the potential for surveyors to violate the randomization by offering treatment to people with more severe depression.

Screening and enrollment took place from December 2016 through February 2017. Surveyors followed a door-skip pattern based on village population to target the recruitment of 1-2 study participants per sample village. Once at the household, surveyors randomly

chose an available adult and screened this person for study eligibility. The screening included the PHQ-9 depression severity score (Kroenke et al. 2001), as well as an assessment of the likelihood of taking up employment. Participants were required to have PHQ-9 scores of 9-20, indicating mild or moderate depression.<sup>3</sup> Following our IRB protocol, respondents with PHQ-9 scores of 21 or more (indicating severe depression) were referred for immediate treatment and were not enrolled in the study. In total, surveyors screened 6446 people in order to enroll a study sample of 1000 people across 506 villages. Study participants provided written informed consent before joining the study.

### 3.2 Interventions and Randomization

We coordinated with Grameena Abudaya Seva Samsthe (GASS), a local social service organization, to implement this study. GASS has 30 full-time staff and 30 part-time staff and volunteers. Since 2001, GASS has worked to provide health care and social support to people with physical and mental disabilities. We cross-randomized psychiatric care (PC) and employment support (ES) so that some participants received both interventions (PC/ES), some received only one intervention, and some received neither intervention. GASS was constrained in the number of recipients to whom it could deliver either intervention. We improved statistical power given this constraint by doubling the size of the control arm that received neither intervention. The PC arm included 207 participants, the ES arm included 205 participants, the PC/ES arm included 193 participants, and the control arm included 395 participants.

For the PC intervention, GASS and the Shridevi Institute of Medical Sciences and Research Hospital to provide eight months of free psychiatric care. GASS organized monthly office hours for psychiatrists and helped to transport participants to these appointments. During an initial 30-minute visit, psychiatrists diagnosed patients, explained the significance

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<sup>3</sup>Surveyors screened out respondents who were pregnant, physically disabled, currently earning more than Rs. 6000 per month, or who had child care duties requiring them to remain at home during the day. 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 study participants have baseline PHQ-9 scores of 7 or 8.

of mental illness, and proposed individualized courses of treatment. Doctors provided pharmacotherapy while medical and NGO staff monitored medication adherence, side effects, and patient welfare throughout the intervention. Patients returned for monthly follow-up visits for up to eight months. Figure 2 illustrates compliance with the PC intervention. 45 percent of eligible study participants attended at least one camp and 23 percent attended at least five camps. Participants who also received employment support participated in 0.22 additional camps on average ( $p = 0.45$ ).

While the intervention focused on depression treatment, some patients presented were also diagnosed with anxiety disorders and other illnesses (primarily pain and high blood pressure). Figure 3 illustrates the proportion of respondents who were treated for depression, anxiety, and other illnesses. Psychiatrists treated depression with off-patent SSRIs such as fluoxetine (Prozac), escitalopram (Lexapro), and paroxetine (Paxil). Psychiatrists have relied on these drugs, which have mild and well-understood side effects, to treat depression for decades (Cascade et al. 2009). Where appropriate, psychiatrists treated anxiety disorders with clonazepam (Klonopin) (Londborg et al. 2000, Dell’osso and Lader 2013). Due to the risk of dependency, doctors used this drug sparingly for maximum of six weeks. Dr. Anil Kumar, MD, MBBS, who is an associate professor of psychiatry at the Shridevi Institute of Medical Sciences and Research Hospital in Tumkur, Karnataka, oversaw this intervention with supervision from his institution’s IRB. We also obtained approval from several other IRBs associated with the funders and members of the study team.

For the ES intervention, GASS staff worked with participants to identify and pursue income-generating activities, including formal sector jobs and opportunities for self-employment. There are several dozen factories in the area, including plants making garments, cement, plastics, medicine, wristwatches, paint, and cosmetics. The intervention did not impose any time constraints on these employment arrangements. Alternatively, some participants received loans to start small businesses or received additional agricultural training. GASS sought to tailor this assistance to the participants’ particular needs. To en-

courage job retention and facilitate the transition to employment, GASS held monthly group meetings with people in this arm to discuss on-the-job challenges.<sup>4</sup> Figure 4 illustrates compliance with the ES intervention. 64 percent of eligible study participants attended at least one group meeting and 42 percent of eligible participants took up employment. The most common jobs were in manufacturing and petty trades, although substantial proportions also took up employment in agriculture and day labor. The figure shows that ES participation was higher among participants who did not also receive the PC intervention, suggesting that PC was stigmatizing for some participants.

Consistent with our IRB protocol, GASS staff visited all study participants (regardless of intervention arm) in their homes once per month in order to monitor mental health. For PC recipients, staff also monitored drug compliance and side effects. Our protocol directed us to refer any patients who developed severe depression ( $\text{PHQ-9} \geq 21$ ) for immediate inpatient psychiatric care, however this situation did not arise in practice. We pre-registered and filed a pre-analysis plan for this study in the AEA RCT registry before collecting follow-up data.

45 percent of eligible participants received psychiatric care and 42 percent of eligible participants took up employment. Table 2 assesses the selection into participation by comparing the Round 1 characteristics of compliers and non-compliers with both interventions. For each intervention, the table combines the PC/ES arm with the arms receiving only one intervention. Columns 1-3 show that psychiatric care recipients have more education, higher literacy, and higher household income. Men comprise a larger fraction of PC compliers than non-compliers. Compliance is not correlated with initial depression or anxiety, however compliers have somewhat fewer paid and child care hours. In Columns 4-6, employment recipients have lower household income and higher initial labor supply than non-recipients, however compliers and non-compliers are generally similar on other dimensions. Compliers with both interventions had lower attrition, suggesting that some participants remained in

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<sup>4</sup>This intervention may have provided a direct mental health benefit by distracting participants from their life circumstances. One goal of cognitive behavioral therapy (CBT), which is the primary non-pharmacological depression treatment approach, is to prevent patients from ruminating on their condition by occupying them with other activities (Piet and Hougaard 2011).

the study so they could continue to benefit from the interventions. These aspects of selection notwithstanding, the compliance rates suggest that multiplying the intent-to-treat estimates by 2.2 – 2.4 to obtain approximate “treatment-on-the-treated” impacts for compliers.

### 3.3 Data and Measurement

We measured mental health and a range of economic outcomes at baseline and over three follow-up waves, which were spaced roughly four months apart. Surveyors administered the Round 1 (baseline) survey immediately after identifying eligible participants and obtaining written informed consent. The Round 2 survey occurred midway through the PC intervention, by which time most ES placements had occurred. The Round 3 survey occurred at the conclusion of the PC intervention, and the Round 4 survey occurred four months after PC had ended.

We assess depression in the field using the PHQ-9 depression screening instrument (Kroenke et al. 2001). This nine-item instrument elicits how frequently the respondent has experienced several depression symptoms in the past two weeks.<sup>5</sup> The PHQ-9 score ranges from 0 to 27: scores of 5-10 indicate mild depression, scores of 11-20 indicate moderate depression, and scores of 21 or more indicate severe depression. The PHQ-9 has been widely validated internationally and specifically in India (Martin et al. 2006, Ganguly et al. 2013). Researchers have used this instrument both to screen for depression and to measure the response to therapy (Derogatis and Culppepper 2004, Löwe et al. 2006). Anxiety is a common comorbidity with depression (Hirschfeld 2001). We measure anxiety symptoms using the GAD-7 anxiety screening instrument, which follows the format of the PHQ-9 (Spitzer et al. 2006).

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<sup>5</sup>For each of nine depression symptoms, respondents indicate how often they have been bothered over the past two weeks. Symptoms include “little interest or pleasure in doing things”, “feeling down, depressed, or hopeless”, trouble falling or staying asleep, or sleeping too much”, “poor appetite or overeating”, “feeling bad about yourself, or that you are a failure or have let yourself or your family down”, trouble concentrating on things such as reading the newspaper or watching television”, “moving or speaking so slowly that other people could have noticed, or being so fidgety or restless that you have been moving around a lot more than usual”, and “thought you would be better off dead or of hurting yourself in some way.”

The survey measured an array of economic outcomes. Following our pre-analysis plan, labor supply and earnings are our primary outcomes. We measure labor supply by eliciting the number of hours the respondent has spent on paid work, unpaid work, and domestic work within the past seven days. We also measure the earnings from all jobs over this period. We construct the time spent on paid work, domestic work, child care, sleep, job search, and leisure from 24-hour time diaries. A detailed consumption module elicits household food consumption over the past seven days, individual food consumption over the previous day, household non-food consumption over the past 30 days, and household clothing expenditures over the past 60 days.

We measured time and risk preferences in order to explore possible mechanisms for treatment effects on labor supply. We elicited the time preference for leisure through a lentil sorting task using the “convex time budget” (CTB) methodology (Andreoni and Sprenger 2012), which requires respondents to allocate units of consumption between earlier and later periods on a continuous scale. We ask respondents to sort varying quantities of lentils (a tedious task requiring the respondent to forgo leisure) in exchange for \$2.20, half of which was paid up front and half of which was paid after six weeks. Respondents allocated lentils across 15 scenarios that varied in terms of the implicit interest rate, the definition of the earlier period, and the interval between the earlier and later periods.<sup>6</sup> We elicited risk preferences in three complementary ways. Respondents reported their general attitude toward risk on a Likert scale. We also used a modified DOSPRT scale to assess the perceived riskiness and likelihood of engaging in five risky behaviors (Blais and Weber 2006). Finally, we followed Eckel and Grossman (2008) and asked respondents to choose among six incentivized “coin-flip” lotteries with different variances and expected returns. The safest lottery in this exercise provided \$1.03 with certainty and the riskiest lottery had a 50 percent probability

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<sup>6</sup>Forgone leisure was an advantageous consumption good for this exercise because we could fully control when consumption occurred and prevent respondents from transferring the good to others. The implicit six-week interest rates were 50 percent, 75 percent, 125 percent, and 150 percent. To illustrate, sorting 10 grams earlier led to sorting 45 grams later under the 50 percent interest rate but led to sorting 135 grams later under the 150 percent interest rate. The earlier period was either defined as now or in three weeks. The interval between periods was either defined as in three or six weeks.

of providing either \$2.57 or \$0.07, for an expected payoff of \$1.32. Our analysis focuses on the first principal component of these risk preference measures.

Surveys included three incentivized cognition measurements. In each round, respondents completed eight Raven’s (1936) Progressive Matrix exercises, which measure abstract reasoning and fluid intelligence. Depression is associated with lower scores on this assessment (Kuzis et al. 1997, Moritz et al. 2002). We also included forward and backward digit span assessments, which require respondents to repeat back strings of digits in either forward or reverse order. Both exercises measure working memory; the backward digit span also measures short-term cognitive processing (St Clair-Thompson 2010). Our analysis relies on the first principal component of these outcomes.

We measure impacts on several other classes of outcomes. The subjective wellbeing index is the first principal component of several items that elicit agreement or disagreement with statements about life satisfaction. The bargaining power index measures the extent to which the respondent participates in household decision-making regarding labor supply and savings decisions. The physical health index is the first principal component of several “activities of daily living” measures, including the ability to do moderate and strenuous tasks and the level of physical pain. The sanitation index combines several surveyor observations of the extent of open defecation, garbage disposal, and respondent hygiene.

Our analysis below distinguishes between household with and without marriage-eligible members. The household roster elicits the marital status of each member in Round 1. We define someone as marriage-eligible if he or she is old enough to marry but is not yet married. Following demographic patterns in marriage ages in this setting, we define this window as ages 12-30 for women and 18-30 for men. We distinguish between households with any eligible members (52 percent of respondents) and no eligible members (48 percent of respondents). It is customary for women to reside with their husbands after marriage. Since subsequent survey rounds do not elicit marital status directly, we infer the marital status of baseline-unmarried women according to their subsequent presence or absence from

the household roster.

## 4 Empirical Analysis

### 4.1 Identification Strategy

Our analysis relies on the random assignment (by village) of participants to intervention arms. We estimate “intent-to-treat” effects by incorporating the outcomes of all respondents within each arm regardless of compliance. We estimate the following empirical specification by OLS and cluster standard errors by village throughout our analysis.

$$Y_{ijt} = \beta_0 + \beta_1 PC/ES_j + \beta_2 PC_j + \beta_3 ES_j + \beta_4 Y_{ij}^1 + \gamma_t + S_j + \varepsilon_{ijt} \text{ for } t \in \{2, 3, 4\} \quad (1)$$

In this expression,  $PC/ES$  is an indicator for the intervention arm that received both interventions,  $PC$  is an indicator for the arm that only received  $PC$ , and  $ES$  is an indicator for the arm that only received  $ES$ . All impacts are measured relative to the control arm. Following the standard ANCOVA specification, regressions control for the Round 1 dependent variable  $Y^1$ . Regressions include round indicators ( $\gamma$ ) and strata indicators ( $S$ ). We estimate this model by pooling the three rounds of follow-up data and then analyze impacts by round. Tables also report estimates of the interaction effect,  $\hat{\beta}_1 - \hat{\beta}_2 - \hat{\beta}_3$ , which provides the differential impact of receiving both interventions rather than only  $PC$  or  $ES$ .

Table 3 shows Round 1 means of key outcome variables and covariates by intervention arm. We report the arm-specific mean of each variable and the p-value indicating the joint significance of the differences in means. P-values are based on OLS regressions with village-clustered standard errors. Columns 1-5 show that most outcomes are balanced across intervention arms in Round 1. The joint p-value for the covariates in the table is 0.49, which indicates that although several variables show significant differences, the arms are balanced overall. However the table shows an imbalance in PHQ-9 scores. This pattern is problem-



atic because it may spuriously contribute to follow-up differences in this or other outcomes. To address this concern, Columns 6-10 use entropy weights, which are similar to inverse propensity weights, to impose balance across arms in the first three moments of the PHQ-9 distribution (Hainmueller 2012, Hainmueller and Xu 2013). These weights further reduce the differences across arms. We explore the sensitivity of our estimates to employing these weights in our regressions below. In practice, estimates are similar regardless of whether weights are used.

## 5 Primary Results

### 5.1 Mental Health Impacts

Table 4 shows the impact of the interventions on depression and anxiety symptoms. In Panel A shows estimates that pool Rounds 2-4. In Columns 1 and 3, PC/ES reduced depression severity by 1.33 points (0.28 standard deviations,  $p < 0.001$ ) and anxiety severity by 0.87 points (0.22 standard deviations,  $p < 0.001$ ). PC alone reduced depression severity by 0.61 points (0.13 standard deviations,  $p = 0.06$ ) and anxiety severity by 0.32 points (0.08 standard deviations,  $p = 0.25$ ). ES alone reduced depression severity by 0.41 points (0.09 standard deviations,  $p = 0.27$ ) and anxiety severity by 0.14 points (0.04 standard deviations,  $p = 0.63$ ). The negative but statistically insignificant interaction effects for both outcomes suggest that receiving both interventions is more effective than receiving either intervention alone. We may worry that these estimates reflect the Round 1 imbalance in PHQ-9 scores. Columns 2 and 4 reproduce these estimates while reweighting to balance by Round 1 PHQ-9 scores. The similarity of the weighted and unweighted estimates further indicates that the PHQ-9 imbalance is not a serious confound in practice. We proceed by relying on weighted estimates and note any instances in which results are sensitive to weighting.

Figure 5 illustrates the treatment effects on the PHQ-9 and GAD-7 distributions. The figure pools Rounds 2-4 to plot the distributions of these variables by intervention arm.

PC/ES (shown in purple) is shifted to the left of the other curves and is more dispersed in both cases. A comparison of the PC and ES curves with control indicates a smaller but qualitatively similar shift to the left. More generally, the figure indicates that impacts on mental health arise through improvements throughout the distribution rather than for particular levels of depression and anxiety severity.

Figure 6 illustrates mental health impacts by survey round. Impacts generally strengthen over time, with the PC/ES impact on depression severity rising from 0.95 points (0.21 standard deviations) in Round 2 to 1.69 points (0.34 standard deviations) in Round 4. The strongly significant mental health impacts in Round 4 are striking since this round occurred four months after the conclusion of the PC intervention. This pattern suggests that PC/ES may have lasting mental health benefits for recipients.

## 5.2 Socioeconomic and Other Impacts

Figure 7 summarizes the impacts of each intervention on all outcomes specified in our pre-analysis plan. We express all impacts in standard deviations and indicate in bold estimates that are statistically significant at the 10 percent threshold. In addition to the results we discussed above, PC increased sleep time and reduces risk preferences, cognition, subjective wellbeing, and subjective physical health. ES reduced domestic work time and subjective wellbeing but increased household clothing expenditures. PC/ES reduced cognition and increased subjective physical health. The confidence intervals in these figures do not adjust for multiple hypothesis testing, although we expect to implement this correction in the future. These figures provide some of the first evidence of the impact of depression treatment on this array of economic outcomes.

Table 5 considers the socioeconomic impacts of the intervention. Columns 1-3 show impacts on weekly work time, distinguishing between paid work, unpaid work, and child care. Columns 4 and 5 show impacts on weekly earnings and per-capita household income. Panel A (Column 1) indicates that all interventions *reduced* paid work time. PC reduced

paid work time by 2.8 hours per week (21 percent,  $p = 0.02$ ), while ES reduced paid work time by 1.2 hours per week (9 percent,  $p = 0.33$ ), and PC/ES reduced paid work time by 0.3 hours per week (2 percent,  $p = 0.83$ ). Because of the relatively large negative effects of both PC and ES, receiving both P and ES increases labor supply by 3.7 hours (28 percent,  $p = 0.04$ ) relative to receiving either intervention alone. Columns 2 and 3 show small and insignificant impacts on unpaid work and child care. Columns 4-5 show impacts on earnings and household income that are consistent with the paid work time results in Column 1. In particular, PC reduced weekly earnings by Rs. 74 (20 percent,  $p = 0.05$ ). Due to the negative impacts of PC and ES, the interaction effects are positive and significant for both of these outcomes. Figure 10 illustrates the socioeconomic impacts by survey round. PC reduced paid work time and earnings by a similar degree in Rounds 2-4, while the negative impact of ES disappeared by Round 4.

The estimates in Panel A may be difficult to interpret because they do not distinguish between men and women. Consistent with the prevailing gender norms, men spent 52 percent more time in the paid workforce than women in our sample (19.3 versus 12.7 weekly hours in the control group over Rounds 2-4). Panel B distinguishes between impacts for women and men to clarify the contributions of men and women to the overall results. The male estimates are underpowered since men make up only 14 percent of the sample. Estimates are qualitatively similar for men and women. In Column 1, PC reduced paid employment by 2.1 hours (17 percent,  $p = 0.09$ ) for women and by 7.1 hours (37 percent,  $p = 0.08$ ) for men. These estimates clarify that effects for women, who predominate in our sample, are reasonable despite their lower labor force participation in general.

To explore the labor market impacts further, Figure 8 distinguishes between the extensive and intensive margins of paid work time. Panel A shows that PC participants were 6 percentage points less likely to report any paid work hours than control participants ( $p = 0.05$ ). In Panel B, both PC and ES participants with positive hours reported 2-3 fewer hours, but these differences were not statistically significant ( $p = 0.24$  for PC vs. C and

$p = 0.11$  for ES vs. C). Next we consider possible impacts on wages. Figure 9 plots the densities of wages for the intervention arms at follow-up. These distributions look similar and are not statistically different, which suggests that wages were not an important channel for the observed results.

Finally, Table 6 examines impacts on paid work time by sector of employment. We distinguish between agricultural, non-agricultural, and casual employment. Agriculture includes the cultivation of own crops as well as wage labor for others. It also includes animal husbandry and flower cultivation. Non-agriculture includes other employment for wages or a salary. Casual labor includes artisan or independent work, running a petty shop, domestic work for another household, and odd jobs. The table shows that the impact on work time occurs primarily in the non-agricultural sector. In Columns 3 and 4, PC reduced non-agricultural work time by 2.52 hours ( $p < 0.01$ ) and non-agricultural earnings by Rs. 56 ( $p = 0.03$ ). Other results in the table are not statistically significant, aside from a possible positive impact of PC/ES on casual earnings in Column 6.

## 6 Interpretation

Several of the results in Section 5 require additional explanation. The negative impact of PC on paid work time is unexpected, but could arise if PC recipients experienced negative physical side effects or office hour attendance crowded out work time. However only 10 percent of PC compliers reported experiencing side effects. Office hours were held on Sundays, which is typically a day of rest. The negative (though insignificant) impact of ES on paid work time is also puzzling since this intervention directly targeted the employment prospects of recipients. It is also surprising that PC reduces subjective physical health and cognition, and that both PC and ES reduce subjective wellbeing.

One explanation for this pattern is that, while PC and ES are directly beneficial, participation also imposes costs by stigmatizing participants. GASS, the implementing partner, was known throughout the study area for prior work rehabilitating people with serious men-

tal illness. To administer the intervention, GASS staff interacted with participants regularly in ways that were visible to others in the community. We may expect the PC intervention to be particularly stigmatizing because the provision of medical care sends the signal that the recipient’s illness is serious (Bharadwaj et al. 2017). Moreover, psychiatrists diagnosed patients and provided psycho-education during the initial psychiatric visit, which may have led patients to self-stigmatize (Corrigan et al. 2009, Corrigan and Rao 2012). The compliance pattern in Figure 4 supports the interpretation that PC caused stigma. The figure shows that ES participation was significantly higher for people who did not also receive PC. Negative impacts on cognition and subjective physical health are also consistent with stigma. Stigma and self-stigma are generally associated with diminished self-esteem and self-efficacy, which may have hampered performance on the cognitive tests and led respondents to be more pessimistic about their physical abilities.

Section 2.1 outlines three primary channels through which stigma may reduce labor supply. Stigma may result in discrimination by employers or other coworkers against participants, effectively reducing their labor demand. Self-stigma may lead participants to perceive themselves to have less ability because of their illness. Relatedly, participants may adopt ‘sick-role behavior’ by relying on others to work on their behalf. Finally, concerns about stigma may lead participants to sequester themselves to limit the spread of information about their condition. This phenomenon is particularly plausible for households that are active in the arranged marriage market, in which any aspersion about the household may substantially limit marriage market prospects. A forthcoming data collection will allow us to examine all of these aspects in detail. The following subsection provides evidence for the marriage market channel.

## 6.1 Stigma and the Marriage Market

A mental illness diagnosis may be particularly problematic for households that are active in the marriage market. As elsewhere in India, communities in the study area practice ar-

ranged marriage in which the households broker matches between eligible partners. Although providing dowry is technically illegal, the bride’s family typically makes a large transfer of money, jewelry, livestock, or other assets to the groom’s family. Research suggests that the size of the dowry partially reflects the “market-clearing price” of the match (Anukriti et al. 2016).

To begin, we investigate whether study participation had an effect on marriage timing. We observe the marital status of all household members in Round 1. Since wives universally colocate with their husbands at marriage, we can infer the marital status of initially-unmarried women in Rounds 2-4 according to their presence or absence in the household (Mullatti 1995). We define a female household member as “marriage-eligible” if she is has never been married as of Round 1 and is between 12-30 years old.<sup>7</sup> The number of marriage-eligible females per household may increase or decrease as people leave or join households and age in or out. Since only 6 percent of female study participants are marriage-eligible (most are already married), variation in this outcome arises primarily through other household members. Figure 11 examines the impact of the interventions on marriage timing. We combine the PC, ES, and PC/ES interventions to compare households that received “any intervention” and “no intervention.” The figure plots the average number of marriage-eligible females by survey round. While there are similar concentrations of unmarried females in Round 1, “any intervention” households retain significantly more unmarried females in Round 2. While this pattern dissipates by Round 3, the difference in Round 2 suggests that households in the intervention arms initially had difficulty placing their daughters in marriages.

In response to marriage market stigma, households may wish to limit the activities of study participants in order to minimize the spread of information about their mental health diagnoses. Under this mechanism, the negative impacts on labor supply and other

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<sup>7</sup>While the late teens is a typical marriage age in this setting, we define the window in this way because girls may marry as soon as they begin to menstruate (Desai and Andrist 2010). Since men do not move out when they marry, we lack the data to examine the impact on marriage patterns for males.

socioeconomic outcomes should be concentrated among households with marriage-eligible members. We divide the sample into subgroups with and without marriage-eligible members (regardless of gender) in Round 1. 52 percent of respondents live in household with marriage-eligible members. Table 7 compares the baseline characteristics of respondents with and without marriage-eligible household members. Depression severity, paid work time, and earnings are uncorrelated with household marriage eligibility. However respondents from marriage-eligible households are older, have less schooling, and lower literacy. Panel C shows some differences in the household composition of these respondents. Marriage-eligible households have additional young females and older males.

Table 8 examines the impacts on socioeconomic outcomes by household marriage eligibility. Negative impacts of PC on paid work time, earnings, per capita household income, and per capita household consumption are concentrated entirely among respondents from marriage-eligible households. The odd columns of the table show that for this subgroup, paid work time fell by 5.1 hours per week (35 percent,  $p = 0.001$ ), weekly earnings fell by Rs. 152 (37 percent,  $p = 0.002$ ), and per capita household income fell by Rs. 69 (13 percent,  $p = 0.009$ ) The impact of ES for this group was smaller but was qualitatively similar. Moreover, respondents from marriage-eligible households increased child care time by 1.3 hours per week (95 percent,  $p = 0.03$ ). By contrast, respondents without marriage-eligible people in their households did not exhibit these patterns. Impacts on paid work time, earnings, and household income are positive but insignificant.

One concern with this heterogeneity analysis is that characteristics that are correlated with household marriage eligibility could spuriously explain this pattern. The even columns of Table 8 control for the interaction of PC/ES, PC, and ES with all of the baseline covariates in Table 7. If this pattern arises through an imbalance in one of these covariates, including these controls should attenuate the interaction with household marriage eligibility. These covariates are highly jointly significant for all three outcomes. A comparison of odd and even columns shows that controlling for treatment  $\cdot$  covariates does not attenuate the dif-

ferences between respondents from marriage-eligible and ineligible households. PC · eligible estimates actually become somewhat larger in absolute value. These findings suggest that the interaction with household marriage eligibility is not spurious.

To explore this pattern further, we examine impacts on time use by location and activity in the 24-hour time diary. We distinguish between work and non-work activities that occur either within or outside of the home. The figure multiplies these values by 7 to make them comparable with prior work time estimates. Consistent with earlier paid work time estimates, PC/ES and PC respondents spent less time working outside the home. However they also spent less time on non-work activities outside the home. By contrast, these respondents spent more time on both work and non-work activities inside the home. These effects are particularly strong for respondents from marriage-eligible households, while we do not find this pattern for marriage ineligible households. These estimate further support the premise that labor supply declined because PC and (to a lesser extent) other intervention recipients isolated themselves from others in the community.

## 7 Conclusion

This study evaluates the impact of psychiatric care and employment support to address depression within the community. Our community survey demonstrates that depression is a pervasive illness in this setting, highlighting the potential economic consequences of providing mental health care. It is unclear how best to provide mental health care in this context, considering the dearth of trained mental health professionals. Pharmacotherapy is a relatively inexpensive way to deliver depression treatment in settings with scarce human capital. We show that providing pharmacotherapy within the community is feasible and can reduce the severity of depression and anxiety symptoms.

The unexpected labor market and socioeconomic consequences of the interventions suggests an additional challenge for providing treatment in this setting. In settings with a high degree of stigma, patients bear an additional cost of receiving a mental health diagnosis.



This cost may offset the direct mental health benefits of treatment, so that patients report lower subjective wellbeing despite feeling better. Secondly, patients and their families may respond to stigma in ways that minimize the stigma costs, such as avoiding interaction in the community. These responses may have unintended consequences such as the decline in labor supply that we observe here.

Table 1: Healthy and Depressed Adults in the Madhugiri Community Sample

	Sample		P-Value
	Healthy (1)	Depressed (2)	(1) vs. (2) (3)
PHQ-9	1.7	13.1	0.00***
Age	34.5	37.9	0.00***
Female	0.49	0.56	0.12
Scheduled caste/tribe	0.24	0.27	0.39
Schooling (years)	7.5	4.4	0.00***
Literacy (1-3)	2.2	1.7	0.00***
Any household savings	0.50	0.55	0.44
Bedrooms (number)	1.5	1.4	0.21
Negative life events (Holmes and Rhae)	38.7	57.4	0.00***
Negative life events (count: 0 - 6)	0.83	1.18	0.00***
Observations	1335	170	—

Note: the tables reports means for representative adults (aged 18-50) in Madhugiri, Karnataka. Estimates are weighted to match Madhugiri characteristics (religion, literacy, SC/ST status, and gender) in the 2011 Census of India. Members of the healthy subsample (Column 1) have PHQ-9 scores below 9 while members of the depressed subsample (Column 2) have PHQ-9 scores of 9 or more. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 2: Baseline Characteristics by Intervention Compliance

Compliance:	Psychiatric Care			Employment Support		
	Yes	No	P-value	Yes	No	P-value
	(1)	(2)	(3)	(4)	(5)	(6)
<i>A: Respondent Characteristics</i>						
Female	0.75	0.90	0.00***	0.82	0.86	0.27
Married	0.76	0.79	0.53	0.76	0.78	0.71
Schooling (years)	5.7	4.5	0.02**	5.3	5.1	0.67
Literacy (1-3)	2.0	1.8	0.05**	1.9	2.0	0.40
PHQ-9 depression scale (0-27)	13.6	13.6	0.93	13.4	13.8	0.26
GAD-7 anxiety scale (0-20)	10.6	10.9	0.59	10.4	10.9	0.22
Early-life shocks (0-6)	1.4	1.3	0.61	1.4	1.1	0.02**
Weekly paid work hours	5.2	7.8	0.06*	8.4	5.8	0.08*
Weekly unpaid work hours	3.8	3.4	0.72	2.8	3.1	0.73
Weekly child care hours	7.0	10.1	0.11	8.9	8.8	0.94
Weekly earnings (Rs.)	214	189	0.63	314	169	0.12
Weekly non-home activities	8.7	7.3	0.28	9.9	7.0	0.03**
<i>B: Household Characteristics</i>						
Household size	4.1	4.3	0.29	4.2	4.1	0.35
Marriage-eligible females (count)	0.6	0.7	0.30	0.6	0.6	0.43
Marriage-eligible males (count)	0.19	0.08	0.04**	0.16	0.10	0.29
Monthly income per capita (Rs.)	2159	1765	0.03**	1710	2032	0.06*
Monthly expenditure per capita (Rs.)	829	804	0.54	812	799	0.67
Net worth (1000 Rs.)	-34.4	-42.4	0.41	-43.3	-29.4	0.20
House quality (1-3)	1.9	1.8	0.52	1.9	1.8	0.46
Has a toilet	0.66	0.56	0.06*	0.57	0.58	0.88
Attrition by Round 4	0.14	0.23	0.03**	0.14	0.20	0.09*
Joint p-value	—	—	0.00***	—	—	0.02**
Observations	179	221	—	169	229	—

Note: Columns 1-3 pool participants in the PC/ES and PC arms while Columns 3-6 pool participants in the PC/ES and ES arms. To comply with PC, a participant must attend at least one mental health camp. To comply with ES, a participant must be placed in a job. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 3: Baseline Characteristics by Intervention Arm

	Unweighted					Weighted				
	PC/ES	PC	ES	C	P-value	PC/ES	PC	ES	C	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>A: Respondent Characteristics</i>										
Female	0.83	0.84	0.85	0.90	0.07*	0.83	0.84	0.85	0.90	0.11
Married	0.78	0.78	0.75	0.78	0.83	0.78	0.77	0.75	0.78	0.93
Schooling (years)	5.3	4.7	5.0	5.0	0.67	5.3	4.8	5.1	5.0	0.72
Literacy (1-3)	1.9	1.9	1.9	1.9	0.84	1.9	1.9	1.9	1.9	0.82
PHQ-9 depression scale (0-27)	13.6	13.9	13.6	14.4	0.04**	13.6	13.6	13.6	13.6	0.99
GAD-7 anxiety scale (0-20)	10.8	11.0	10.7	11.3	0.33	10.8	10.7	10.7	10.7	0.99
Early-life shocks scale	90.7	100.0	85.5	92.5	0.59	90.7	98.1	86.7	91.7	0.76
Weekly paid work hours	7.3	6.1	6.5	5.8	0.70	7.3	6.0	6.6	6.5	0.86
Weekly earnings (Rs.)	213	187	242	123	0.02**	213	187	248	141	0.07*
Weekly child care hours	9.1	8.4	8.7	8.7	0.98	9.1	8.5	8.6	8.5	0.98
Weekly non-home activities	8.2	7.7	8.1	7.4	0.88	8.2	7.7	8.3	7.6	0.91
<i>B: Household Characteristics</i>										
Household size	4.2	4.2	4.0	4.2	0.38	4.2	4.2	4.0	4.2	0.49
Marriage-eligible females (count)	0.64	0.68	0.56	0.65	0.49	0.64	0.68	0.55	0.63	0.44
Marriage-eligible males (count)	0.15	0.10	0.10	0.05	0.04**	0.15	0.10	0.11	0.05	0.03**
Monthly income per capita (Rs.)	2052	2090	2045	1860	0.53	2052	2105	2013	1918	0.78
Weekly food expenditure per capita (Rs.)	810	821	795	817	0.82	810	820	804	812	0.82
Net worth (1000 Rs.)	-38.7	-38.2	-30.0	-47.5	0.33	-38.7	-38.9	-32.1	-47.5	0.53
House quality (1-3)	1.8	1.9	1.9	1.8	0.90	1.8	1.8	1.9	1.8	0.92
Has a toilet	0.62	0.60	0.53	0.61	0.24	0.62	0.60	0.53	0.62	0.25
Recent shocks scale	92.7	95.3	94.6	95.7	0.97	92.7	94.1	95.9	94.7	0.97
Attrition by Round 4	0.20	0.18	0.15	0.17	0.52	0.20	0.18	0.14	0.17	0.52
Joint p-value	—	—	—	—	0.49	—	—	—	—	0.67
Observations	193	207	205	395	—	193	207	205	395	—

Note: PC = psychiatric care, ES = employment support, C = control. The table reports Round 1 means of key demographic and outcome variables. Columns 1-4 provide unweighted means while Columns 6-9 use entropy weights to restore balance in the PHQ-9 depression scale. P-values, which are based on regressions with village-clustered standard errors, test whether the four arms are jointly significantly different. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 4: Impacts on Depression and Anxiety Severity

	PHQ-9 Depression Scale		GAD-7 Anxiety Scale	
	(1)	(2)	(3)	(4)
PC/ES	-1.33*** (0.34)	-1.32*** (0.34)	-0.87*** (0.27)	-0.86*** (0.27)
PC	-0.61* (0.33)	-0.59* (0.34)	-0.32 (0.27)	-0.30 (0.28)
ES	-0.41 (0.36)	-0.30 (0.36)	-0.14 (0.30)	-0.054 (0.29)
Interaction effect	-0.32 [0.54]	-0.43 [0.42]	-0.41 [0.33]	-0.50 [0.24]
Weights	No	Yes	No	Yes
Observations	2651	2651	2651	2651
Control mean	9.60	9.40	7.64	7.54

Note: village-clustered standard errors appear in parentheses and interaction effect p-values appear in brackets. The interaction effect ( $\hat{\beta}^{PC/ES} - \hat{\beta}^{PC} - \hat{\beta}^{ES}$ ) is the differential impact of receiving both interventions. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 5: Impacts on Weekly Work Time, Earnings, and Income

	Work Hours			Earnings	HH PC Income
	Paid	Unpaid	Child Care		
	(1)	(2)	(3)	(4)	(5)
<i>A: Pooled Estimates</i>					
PC/ES	-0.32 (1.31)	0.32 (0.78)	0.40 (0.59)	-38.5 (38.3)	24.6 (23.9)
PC	-2.83** (1.20)	0.21 (0.82)	-0.056 (0.53)	-74.1** (37.3)	-31.7 (21.9)
ES	-1.21 (1.22)	0.048 (0.77)	0.24 (0.50)	-40.5 (38.2)	-6.89 (22.5)
Interaction effect	3.72 [0.04]	0.06 [0.96]	0.21 [0.79]	76.1 [0.18]	63.2 [0.07]
Control mean	13.4	4.3	3.6	370	530
<i>B: Estimates by Gender</i>					
PC/ES · female	0.19 (1.42)	-0.049 (0.81)	0.54 (0.67)	-27.3 (39.6)	30.5 (25.8)
PC · female	-2.15* (1.27)	-0.35 (0.87)	-0.094 (0.60)	-67.5* (38.6)	-36.5 (22.2)
ES · female	-1.28 (1.26)	0.29 (0.87)	0.25 (0.56)	-41.6 (40.1)	0.22 (23.6)
PC/ES · male	-3.81 (4.12)	2.75 (2.11)	-0.37 (0.71)	-109.0 (137.9)	-12.7 (48.2)
PC · male	-7.14* (4.12)	3.57 (2.18)	0.039 (0.85)	-121.0 (136.4)	-15.8 (53.2)
ES · male	-1.57 (4.60)	-0.94 (1.83)	0.11 (0.84)	-46.2 (141.0)	-54.9 (46.1)
Interaction effect (F)	3.6 [0.07]	0.01 [0.99]	0.38 [0.68]	82 [0.17]	67 [0.06]
Interaction effect (M)	4.9 [0.41]	0.12 [0.97]	-0.52 [0.64]	58 [0.76]	58 [0.43]
Control mean (F)	12.7	4.2	3.9	338	537
Control mean (M)	19.3	4.9	1.6	628	467
Observations	2645	2645	2645	2645	2645

Note: village-clustered standard errors appear in parentheses and interaction effect p-values appear in brackets. The interaction effect ( $\hat{\beta}^{PC/ES} - \hat{\beta}^{PC} - \hat{\beta}^{ES}$ ) is the differential impact of receiving both interventions. Earnings and income are winsorized at 5 percent. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 6: Impacts by Employment Sector

	Agriculture		Non-Agriculture		Casual	
	Hours	Earnings	Hours	Earnings	Hours	Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
PC/ES	-0.63 (0.89)	-17.9 (15.7)	-0.69 (0.90)	-18.8 (24.2)	1.03 (0.64)	18.8* (10.1)
PC	-0.44 (0.86)	-8.41 (15.9)	-2.52*** (0.89)	-56.0** (25.8)	0.075 (0.56)	3.80 (8.11)
ES	-0.79 (0.72)	-14.6 (14.0)	-0.15 (1.04)	-4.90 (29.1)	-0.30 (0.54)	-4.39 (7.16)
Interaction effect	0.61 [0.60]	5.1 [0.81]	2.0 [0.15]	42.2 [0.29]	1.3 [0.15]	19.4 [0.13]
Control mean	5.3	99	6.1	167	2.0	33
Observations	2645	2645	2645	2645	2645	2645

Note: village-clustered standard errors appear in parentheses and interaction effect p-values appear in brackets. The interaction effect ( $\hat{\beta}^{PC/ES} - \hat{\beta}^{PC} - \hat{\beta}^{ES}$ ) is the differential impact of receiving both interventions. Earnings are winsorized at 5 percent. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 7: Baseline Characteristics by Household Marriage Eligibility

	Eligible (1)	Ineligible (2)	P-value (3)
<i>A: Respondent Characteristics</i>			
Age	36.6	33.8	0.00***
Female	0.85	0.86	0.77
Married	0.73	0.82	0.00***
Schooling (years)	4.4	5.7	0.00***
Literacy (1-3)	1.8	2.1	0.00***
PHQ-9 depression scale (0-27)	13.6	13.6	0.94
GAD-7 anxiety scale (0-20)	10.7	10.8	0.88
Early-life shocks (0-6)	1.4	1.2	0.18
Weekly paid work hours	7.0	6.6	0.70
Weekly unpaid work hours	3.5	3.2	0.63
Weekly child care hours	5.9	12.5	0.00
Weekly earnings (Rs.)	166	179	0.63
<i>B: Household Characteristics</i>			
Household size	4.5	3.8	0.00***
Marriage-eligible females (count)	0.82	0	0.00***
Marriage-eligible males (count)	0.73	0.	0.00***
Monthly income per capita (Rs.)	451	409	0.06*
Net worth per capita (Rs.)	-9506	-8719	0.49
House quality (1-3)	1.82	1.88	0.12
Has a toilet	0.60	0.58	0.53
<i>C: Household Composition</i>			
Females 0-20	0.96	0.60	0.00***
Females 21-40	0.89	0.97	0.04
Females 41-60	0.45	0.39	0.08*
Females 61+	0.13	0.16	0.26
Males 0-20	0.75	0.77	0.46
Males 21-40	0.75	0.68	0.17
Males 41-60	0.63	0.38	0.00***
Males 61+	0.10	0.13	0.23
Attrition by Round 4	0.16	0.19	0.20
Joint p-value	—	—	0.00***
Observations	522	478	—

Note: the table reports means in Round 1 for respondents from marriage-eligible and marriage-ineligible households. P-values in Column 3 are based on regressions with village-clustered standard errors. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



Table 8: Estimates by Household Marriage Eligibility

	Paid Work Hours		Earnings		HH PC Income	
	(1)	(2)	(3)	(4)	(5)	(6)
PC/ES · eligible	-1.88 (1.85)	-1.28 (1.76)	-83.3 (56.3)	-75.8 (56.1)	38.9 (32.0)	39.1 (31.9)
PC · eligible	-5.12*** (1.55)	-6.37*** (1.50)	-151.9*** (48.8)	-169.5*** (49.0)	-68.6*** (26.1)	-84.5*** (26.2)
ES · eligible	-1.69 (1.75)	-1.29 (1.68)	-56.7 (59.5)	-29.5 (54.9)	-22.1 (28.1)	-9.79 (25.6)
PC/ES · ineligible	1.42 (1.76)	1.47 (1.96)	11.5 (49.5)	28.7 (54.7)	9.41 (31.6)	12.9 (31.9)
PC · ineligible	0.013 (1.92)	0.48 (2.10)	21.4 (59.8)	29.3 (65.0)	19.2 (31.4)	20.0 (32.1)
ES · ineligible	-0.61 (1.63)	-2.09 (1.89)	-19.4 (49.3)	-55.4 (59.4)	8.58 (31.4)	19.1 (29.0)
Control for treatment · covariates	No	Yes	No	Yes	No	Yes
Control mean (eligible)	14.5	14.5	406	406	544	544
Control mean (ineligible)	12.2	12.2	330	330	514	514
Treatment · covariates (joint p-value)	—	0.00	—	0.00	—	0.00
Eligible = ineligible (joint p-value)	0.18	0.06	0.15	0.10	0.03	0.05
Observations	2645	2645	2645	2645	2645	2645

Note: village-clustered standard errors appear in parentheses. “Eligible” households have  $\geq 1$  marriage-eligible members while “ineligible” households have zero marriage-eligible members. All outcomes are measured on a weekly basis. Even columns control for the interaction of treatment with all baseline covariates in Table 3 as well as household composition indicators. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

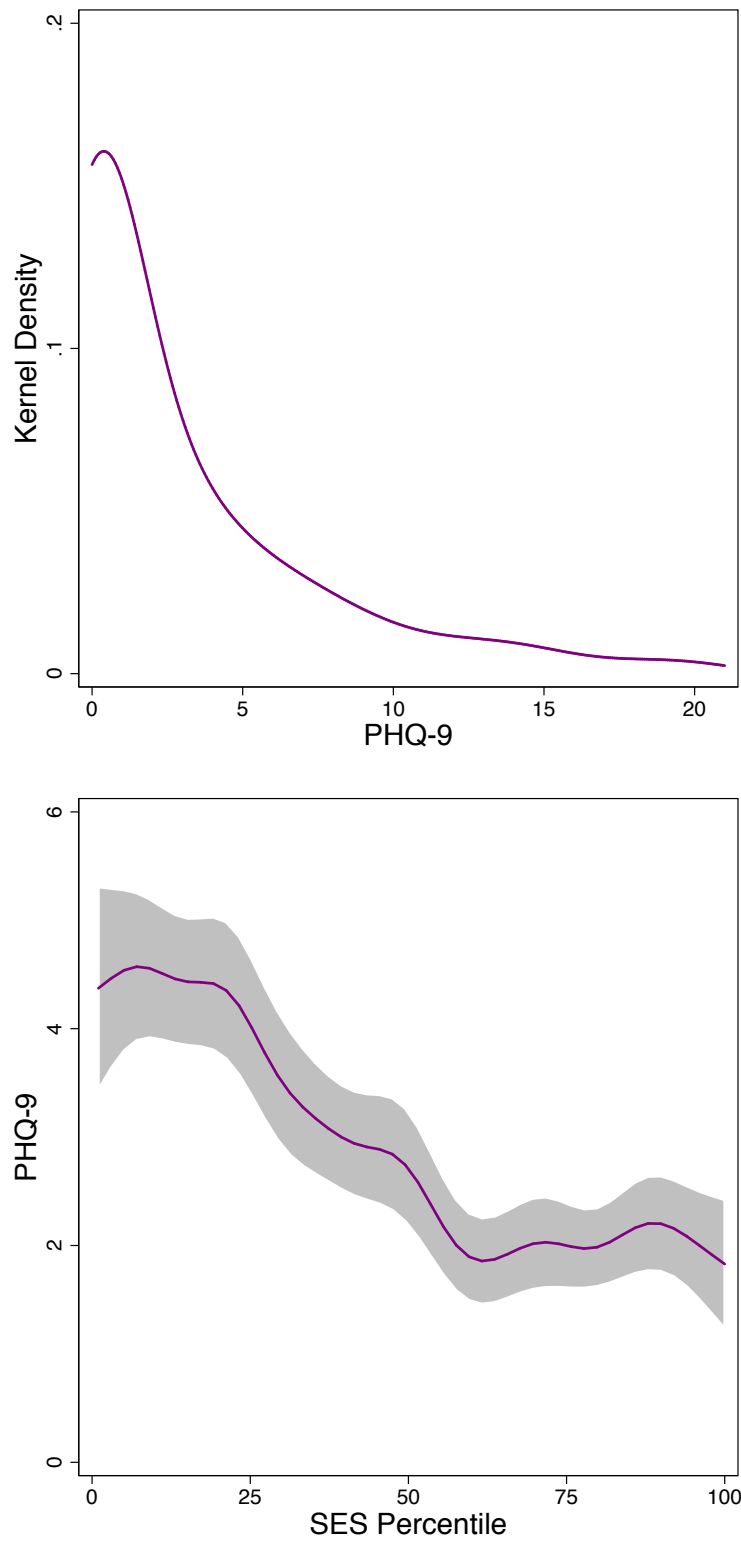


Figure 1: The Distribution of PHQ-9 Scores (Panel A) and the SES Gradient of PHQ-9 Scores (Panel B) in the Madhugiri Community Sample

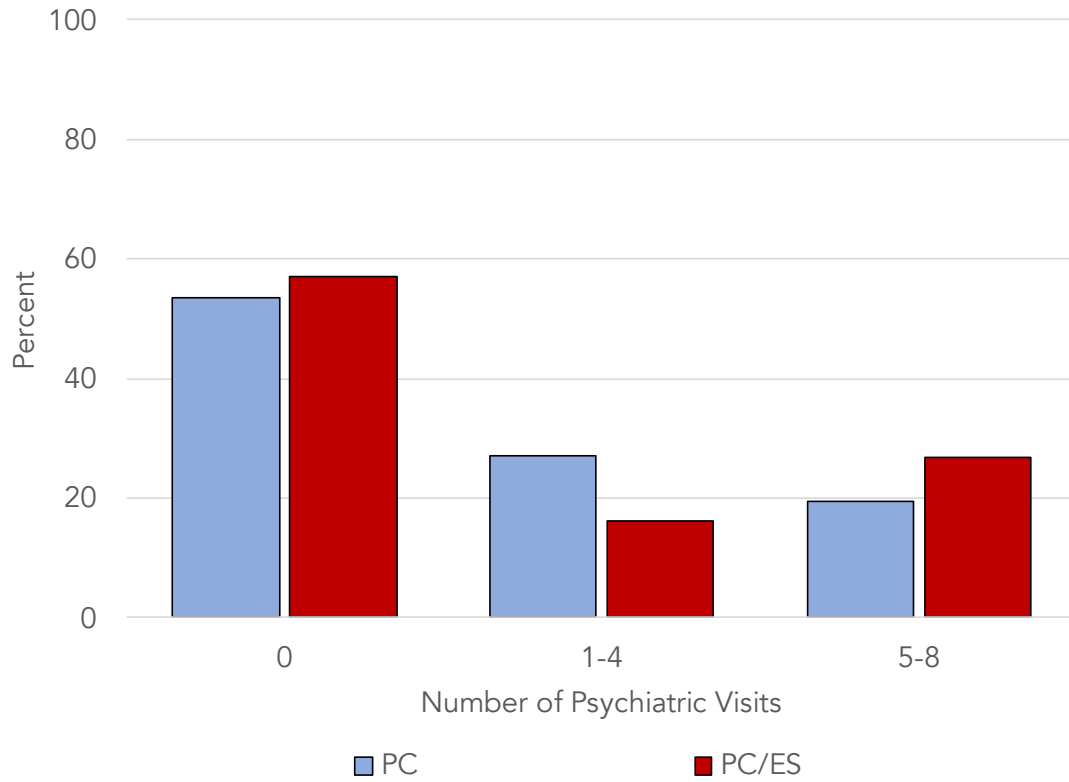


Figure 2: Compliance with the Psychiatric Care Intervention

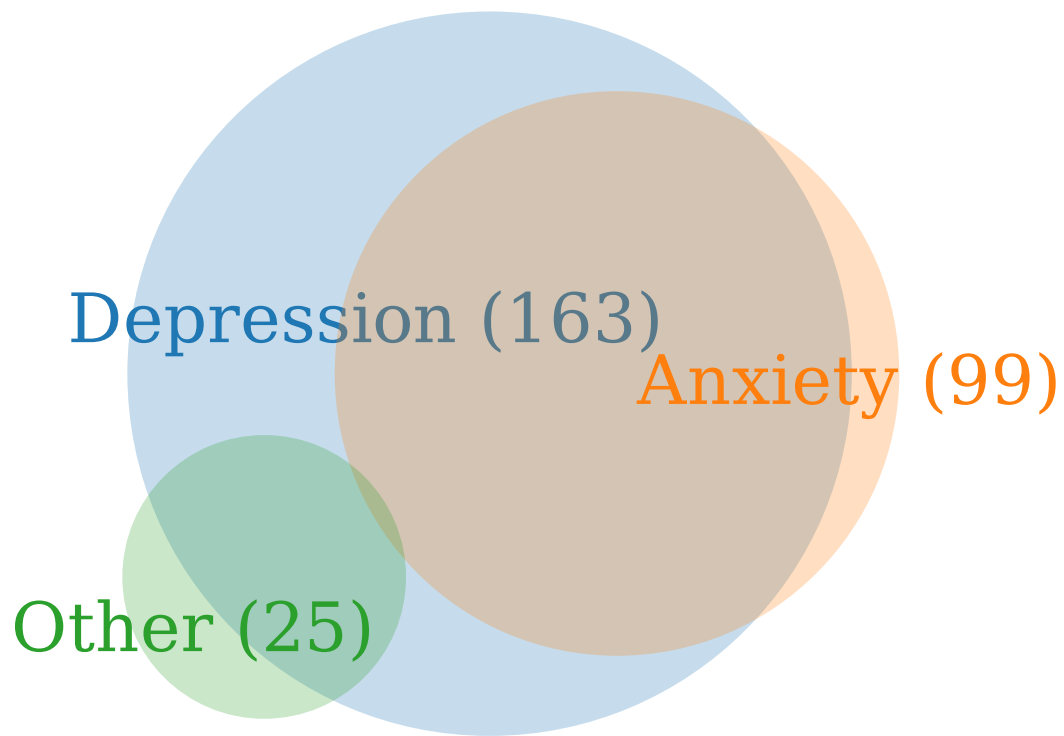


Figure 3: Treatments Provided the Psychiatric Care Intervention

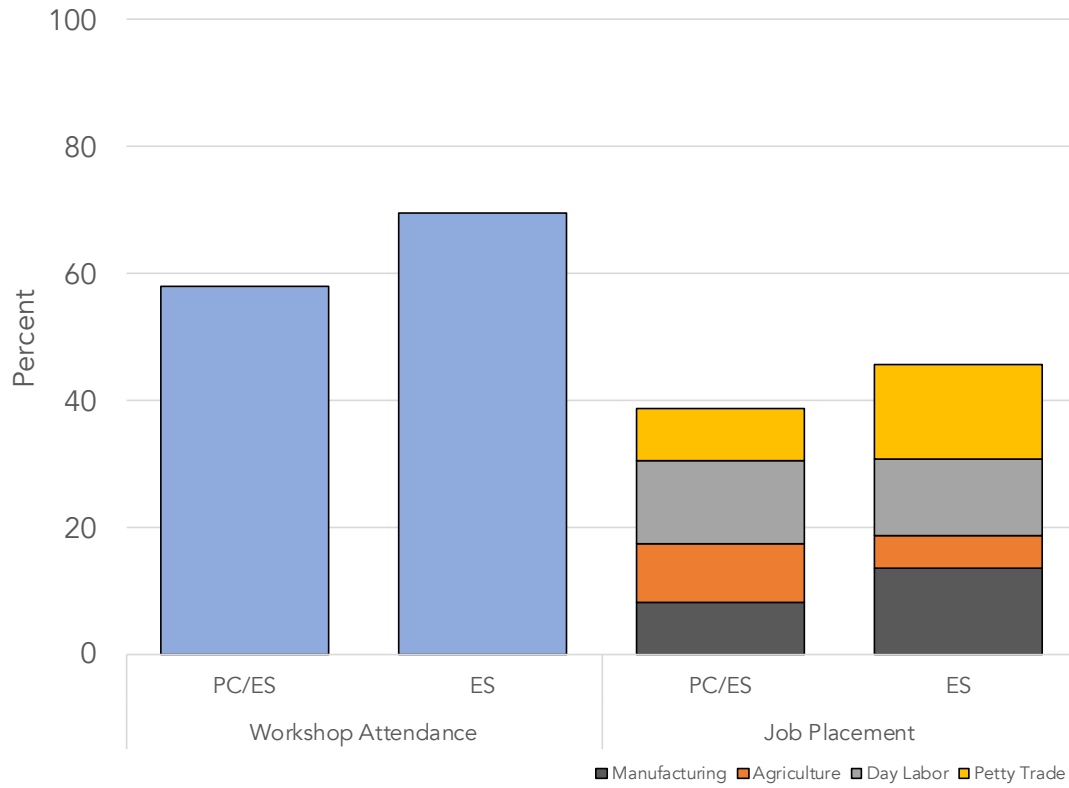


Figure 4: Compliance with the Employment Support Intervention

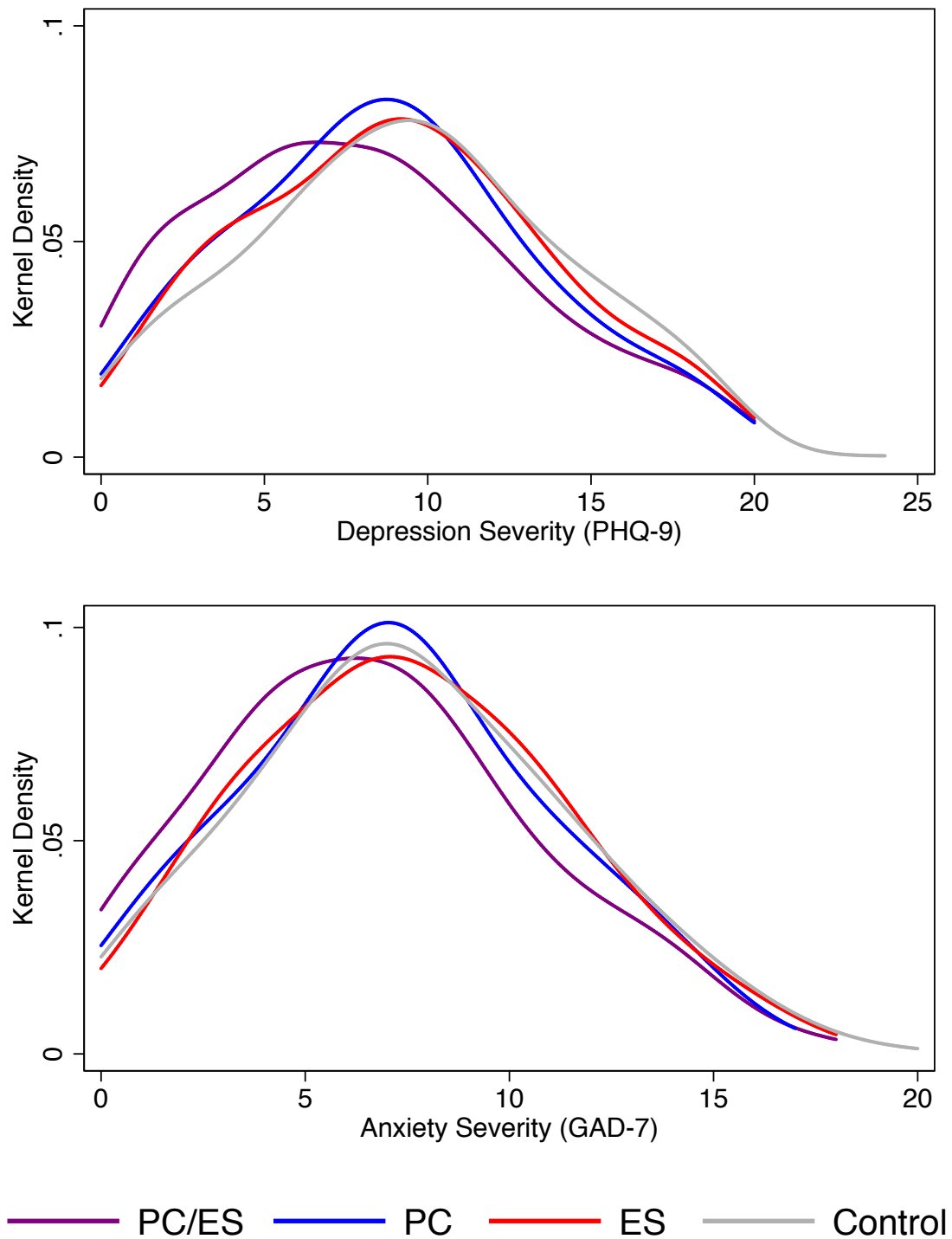


Figure 5: Depression and Anxiety Severity at Follow-Up by Intervention Arm

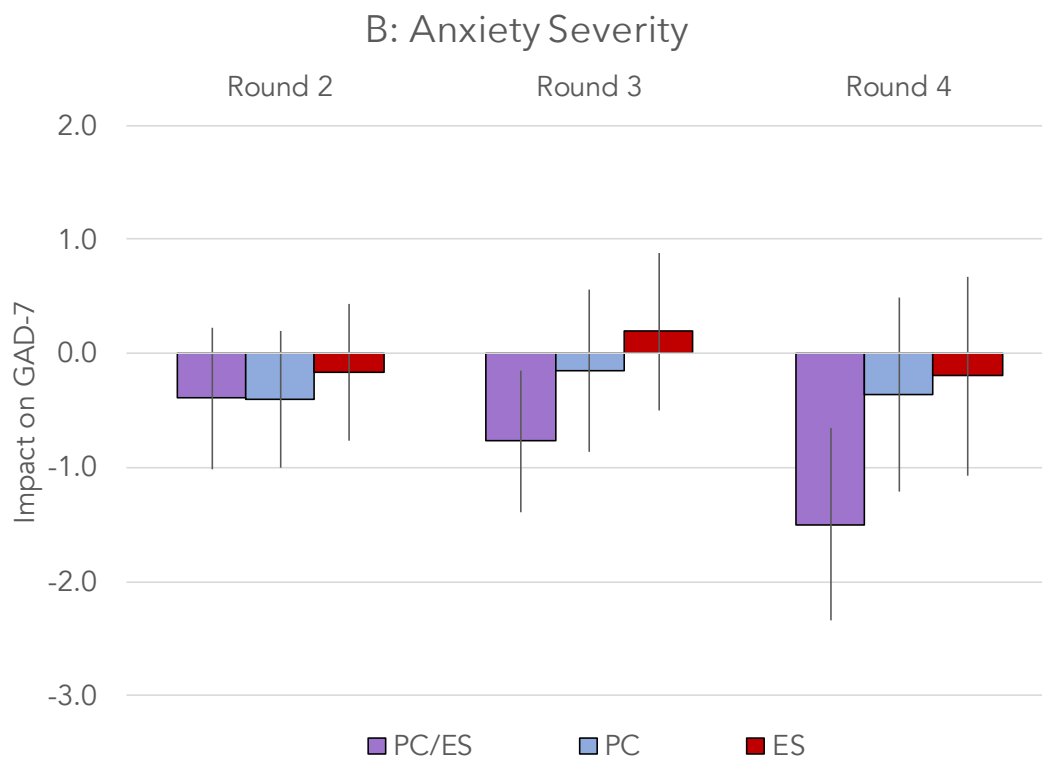
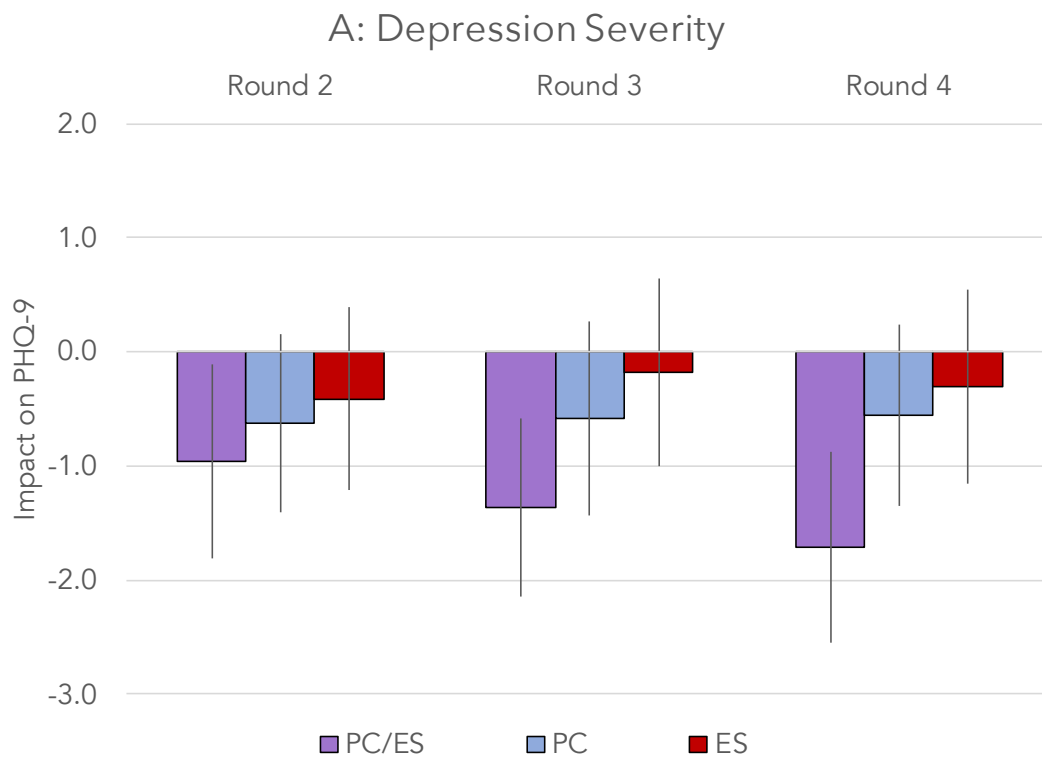


Figure 6: Mental Health Impacts by Round (with 90% CIs)

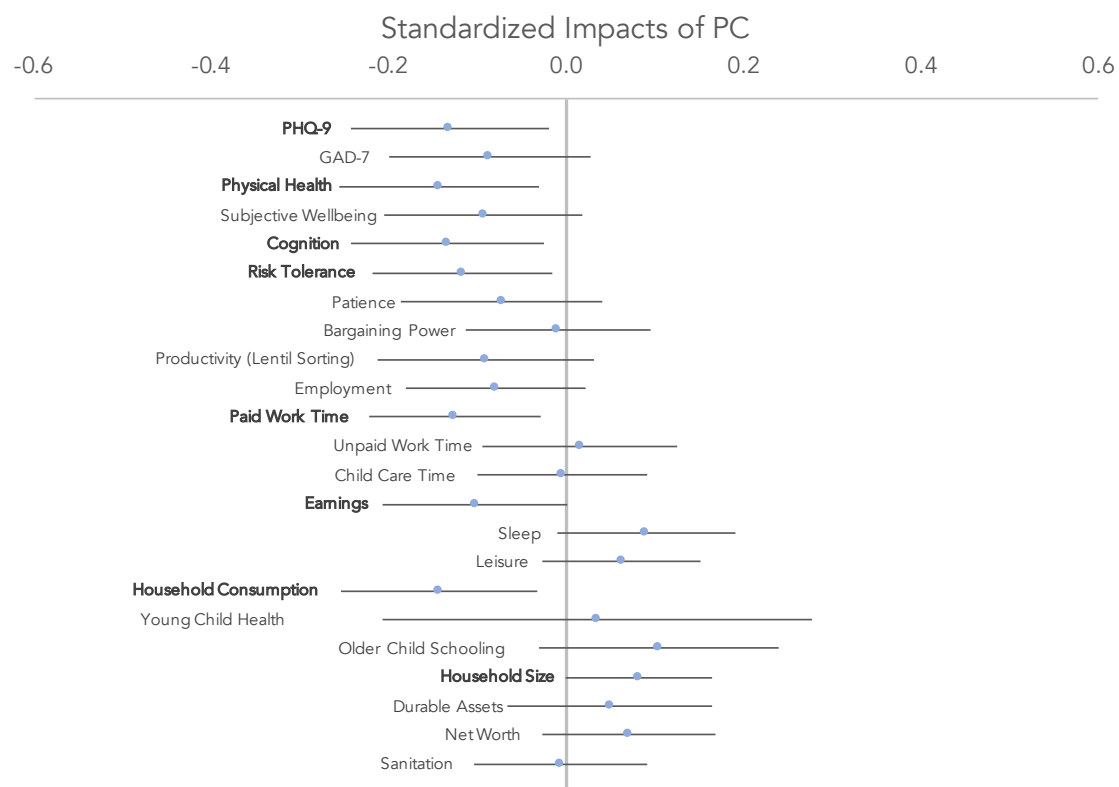
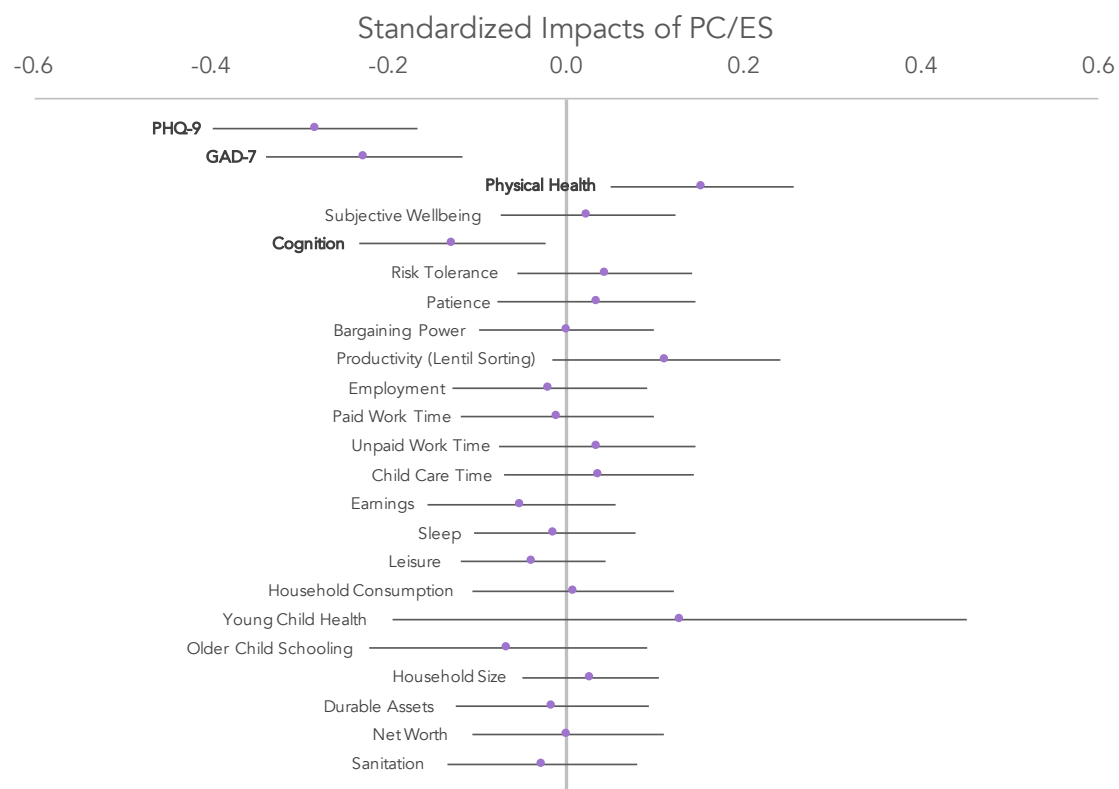


Figure 7: Standardized Impacts on Pre-Specified Outcomes (with 90% CIs)



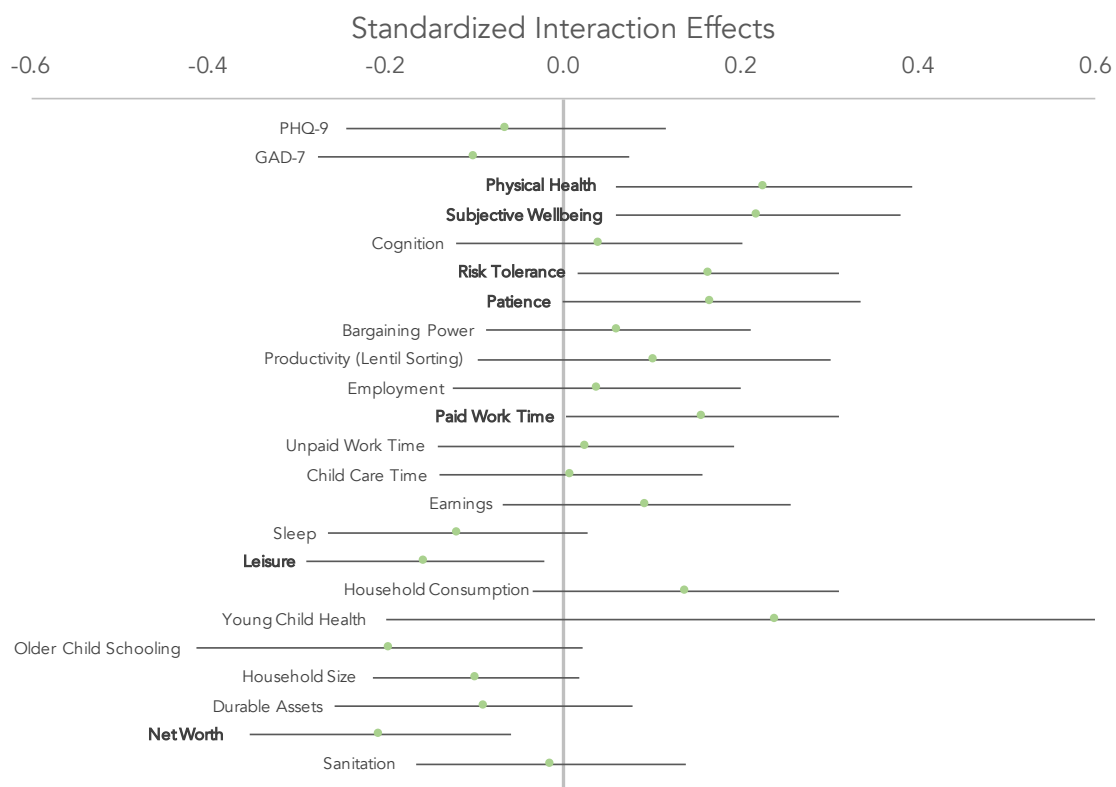
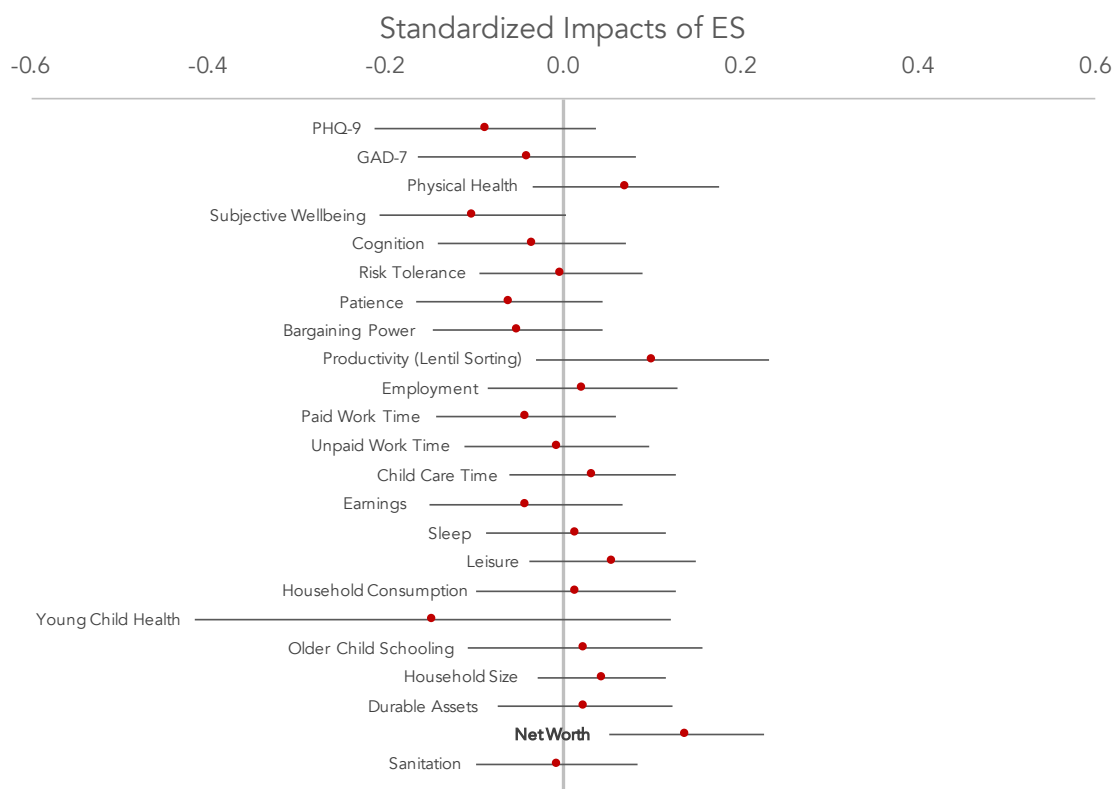


Figure 7 (Continued): Standardized Impacts on Pre-Specified Outcomes (with 90% CIs)

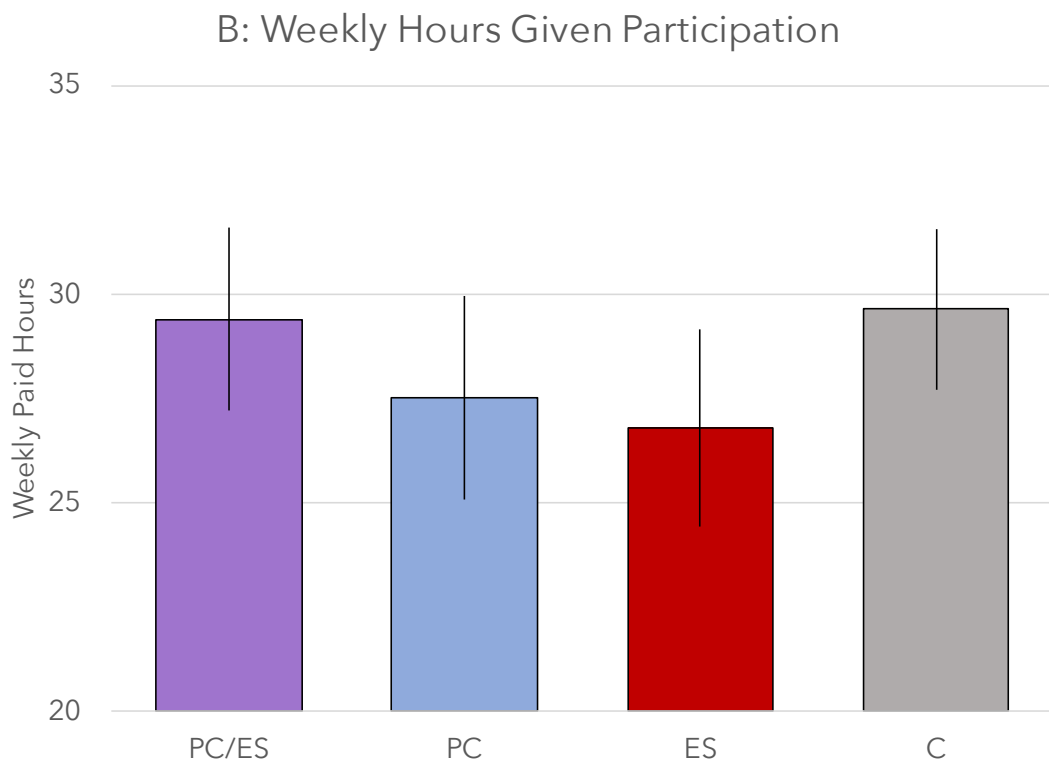
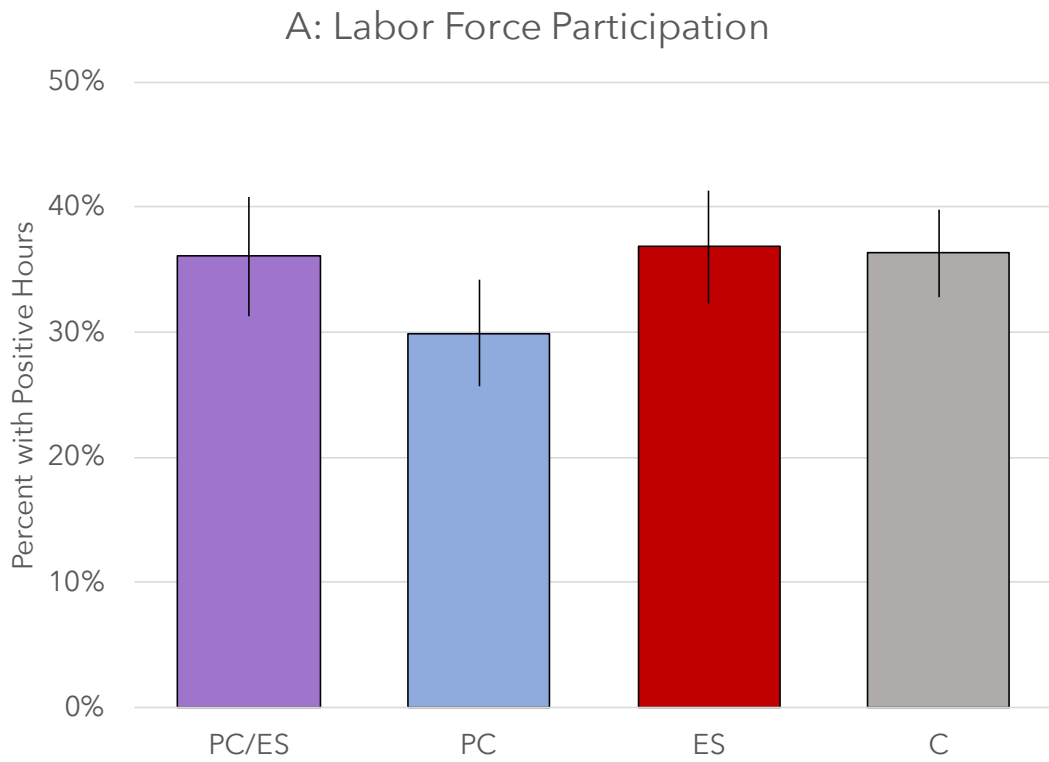


Figure 8: Extensive and Intensive Margins of Paid Work Time (with 90% CIs)

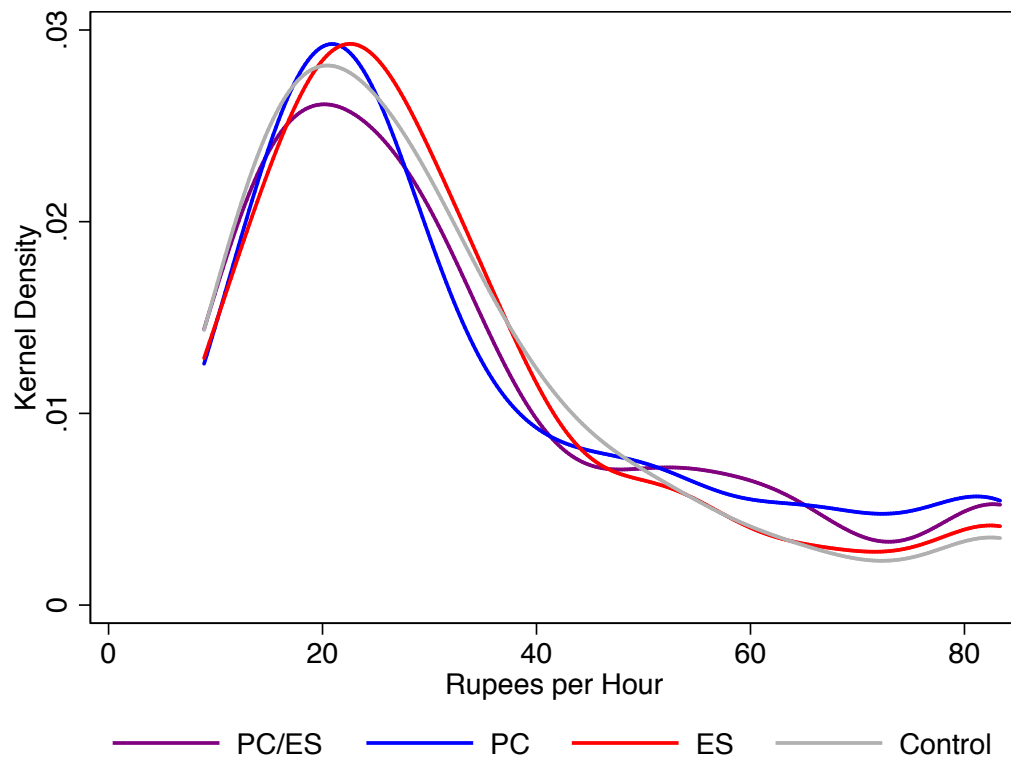


Figure 9: The Wage Distribution by Intervention Arm

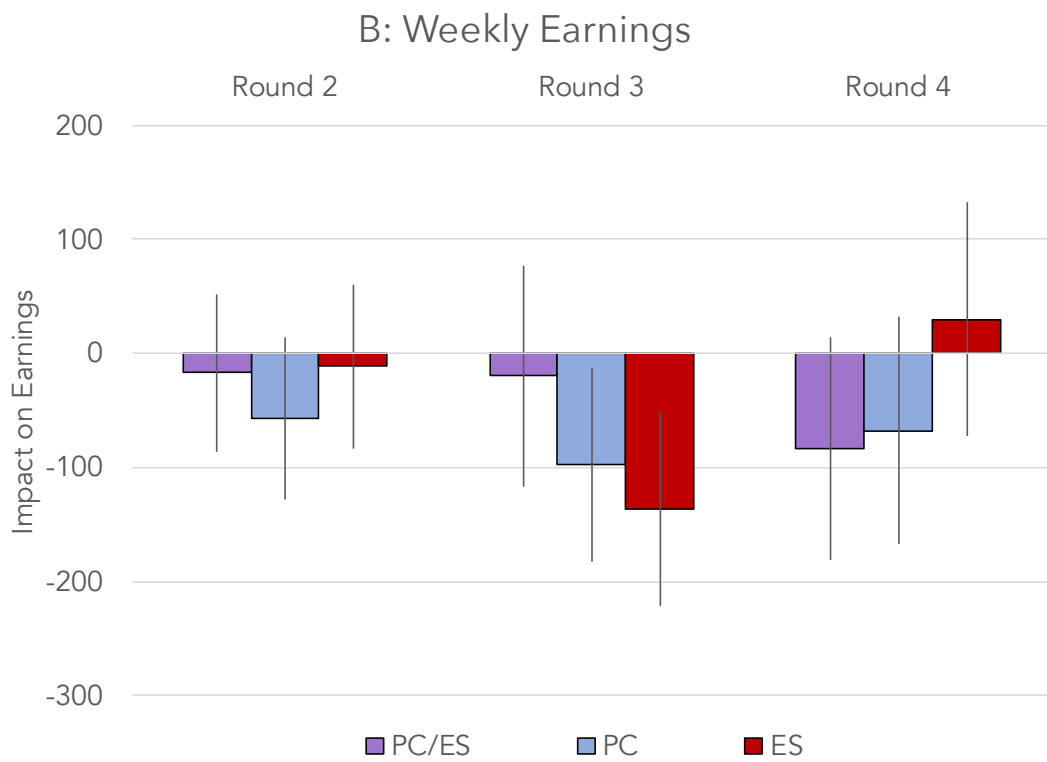
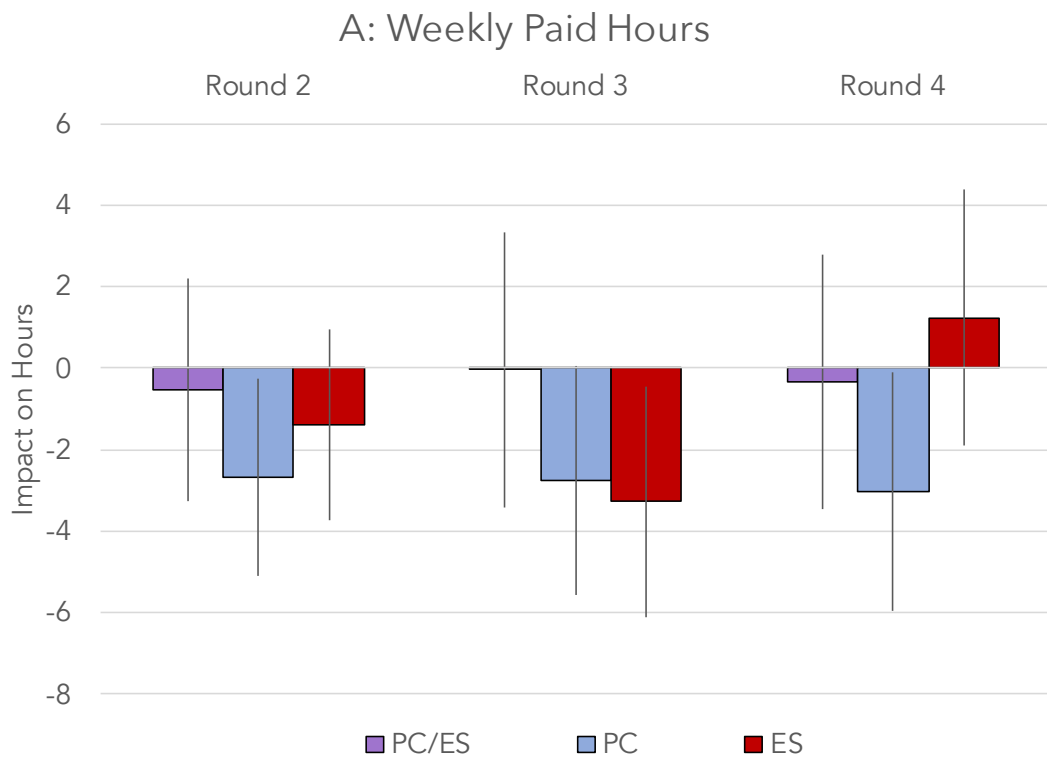


Figure 10: Labor Market Impacts by Round (with 90% CIs)

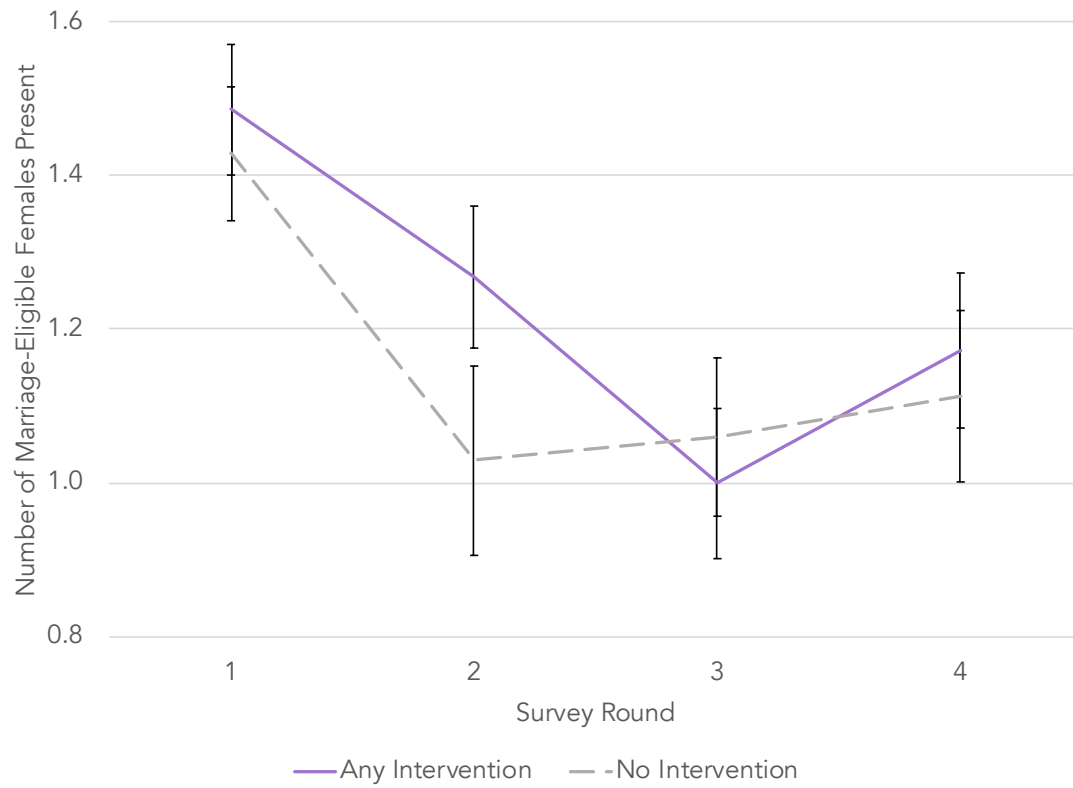


Figure 11: Marriage-Eligible Female Household Members by Survey Round

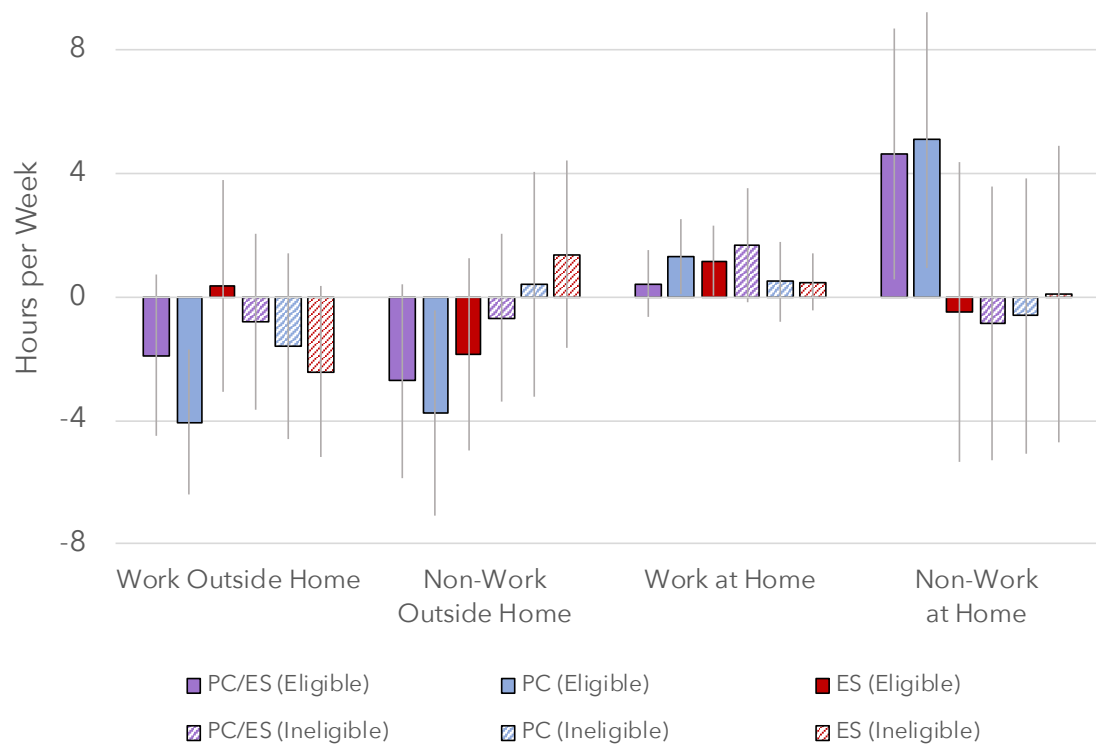


Figure 12: Impacts on Time Use by Activity Type and Location

## References

- Andreoni, James and Charles Sprenger**, “Estimating Time Preferences from Convex Budgets,” *American Economic Review*, 2012, *102* (7), 3333–3356.
- Angermeyer, Matthias C, Beate Schulze, and Sandra Dietrich**, “Courtesy Stigma,” *Social Psychiatry and Psychiatric Epidemiology*, 2003, *38* (10), 593–602.
- , **Michael Beck, Sandra Dietrich, and Anita Holzinger**, “The Stigma of Mental Illness: Patients’ Anticipations and Experiences,” *International Journal of Social Psychiatry*, 2004, *50* (2), 153–162.
- Anukriti, S, Sungoh Kwon, and Nishith Prakash**, “Dowry: Household Responses to Expected Marriage Payments,” 2016. Unpublished Manuscript.
- Banerjee, Abhijit, Marianne Bertrand, Saugato Datta, and Sendhil Mulainathan**, “Labor Market Discrimination in Delhi: Evidence from a Field Experiment,” *Journal of Comparative Economics*, 2009, *37* (1), 14–27.
- Bharadwaj, Prashant, Mallesh M Pai, and Agne Suziedelyte**, “Mental Health Stigma,” *Economics Letters*, 2017, *159*, 57–60.
- Blais, Ann-Renee and Elke Weber**, “A Domain-Specific Risk-Taking (DOSPERT) scale for adult populations,” *Judgment and Decision Making*, July 2006, *1* (1), 33–47.
- Bruckner, Tim A, Richard M Scheffler, Gordon Shen, Jangho Yoon, Dan Chisholm, Jodi Morris, Brent D Fulton, Mario R Dal Poz, and Shekhar Saxena**, “The mental health workforce gap in low-and middle-income countries: a needs-based approach,” *Bulletin of the World Health Organization*, 2011, *89*, 184–194.
- Cascade, Elisa, Amir H Kalali, and Sidney H Kennedy**, “Real-World Data on SSRI Antidepressant Side Effects,” *Psychiatry*, 2009, *6* (2), 16.
- Chisholm, Dan, Kristy Sanderson, Jose Luis Ayuso-Mateos, and Shekhar Saxena**, “Reducing the global burden of depression: population-level analysis of intervention cost-effectiveness in 14 world regions,” *The British Journal of Psychiatry*, 2004, *184* (5), 393–403.
- Clair-Thompson, Helen L St**, “Backwards Digit Recall: A Measure of Short-Term Memory or Working Memory?,” *European Journal of Cognitive Psychology*, 2010, *22* (2), 286–296.
- Clement, Sarah, Oliver Schauman, T Graham, F Maggioni, Sara Evans-Lacko, N Bezborodovs, C Morgan, N Rüsch, JSL Brown, and G Thornicroft**, “What is the impact of mental health-related stigma on help-seeking? A systematic review of quantitative and qualitative studies,” *Psychological Medicine*, 2015, *45* (1), 11–27.
- Corrigan, Patrick and Deepa Rao**, “On the Self-Stigma of Mental Illness: Stages, Disclosure, and Strategies for Change,” *Canadian Journal of Psychiatry*, 2012, *57* (8), 464–469.

- , **Jonathan Larson**, and **Nicolas Rusch**, “Self-sigma and the “why try” effect: impact on life goals and evidence-based practices,” *World Psychiatry*, 2009, 9 (8), 75–81.
- Corrigan, Patrick W**, **Amy C Watson**, and **Leah Barr**, “The Self-Stigma of Mental Illness: Implications for Self-Esteem and Self-Efficacy,” *Journal of Social and Clinical Psychology*, 2006, 25 (8), 875–884.
- Cox, William TL**, **Lyn Y Abramson**, **Patricia G Devine**, and **Steven D Hollon**, “Stereotypes, Prejudice, and Depression: The Integrated Perspective,” *Perspectives on Psychological Science*, 2012, 7 (5), 427–449.
- Dell’osso, Bernardo** and **Malcolm Lader**, “Do benzodiazepines still deserve a major role in the treatment of psychiatric disorders? A critical reappraisal,” *European Psychiatry*, 2013, 28 (1), 7–20.
- Derogatis, Leonard R** and **William J Culpepper**, “Screening for Psychiatric Disorders,” in “The Use of Psychological Testing for Treatment Planning and Outcomes Assessment, 3rd Edition,” Rutledge, 2004, chapter 2.
- Desai, Sonalde** and **Lester Andrist**, “Gender Scripts and Age at Marriage in India,” *Demography*, 2010, 47 (3), 667–687.
- Eckel, Catherine** and **Philip Grossman**, “Forecasting risk attitudes: An experimental study using actual and forecast gamble choices,” *Journal of Economic Behavior and Organization*, 2008, 68, 1–17.
- Ganguly, Samrat**, **Moumita Samanta**, **Prithwish Roy**, **Sukanta Chatterjee**, **David W Kaplan**, and **Bharati Basu**, “Patient health questionnaire-9 as an effective tool for screening of depression among Indian adolescents,” *Journal of Adolescent Health*, 2013, 52 (5), 546–551.
- Hainmueller, Jens**, “Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies,” *Political Analysis*, 2012, 20, 25–45.
- and **Yiqing Xu**, “ebalance: A Stata Package for Entropy Balancing,” *Journal of Statistical Software*, 2013, 54 (7).
- Hammen, Constance**, “Stress and Depression,” *Annual Review of Clinical Psychology*, 2005, 1, 293–319.
- Haushofer, Johannes** and **Ernst Fehr**, “On the psychology of poverty,” *Science*, 2014, 344 (6186), 862–867.
- Hirschfeld, Robert MA**, “The Comorbidity of Major Depression and Anxiety Disorders: Recognition and Management in Primary Care,” *Primary Care Companion to the Journal of Clinical Psychiatry*, 2001, 3 (6), 244.



- Hoffmann, Vivian, Jacob R Fooks, and Kent D Messer**, “Measuring and Mitigating HIV Stigma: A Framed Field Experiment,” *Economic Development and Cultural Change*, 2014, 62 (4), 701–726.
- Holmes, Thomas and Richard Rahe**, “The Social Readjustment Rating Scale,” *Journal of Psychosomatic Research*, 1967, 11, 213–218.
- Jacob, KS, P Sharan, I Mirza, M Garrido-Cumbrera, Soraya Seedat, Jair Jesus Mari, V Sreenivas, and Shekhar Saxena**, “Mental health systems in countries: where are we now?,” *The Lancet*, 2007, 370 (9592), 1061–1077.
- Kermode, Michelle, Kathryn Bowen, Shoba Arole, Soumitra Pathare, and Anthony F Jorm**, “Attitudes to people with mental disorders: a mental health literacy survey in a rural area of Maharashtra, India,” *Social psychiatry and psychiatric epidemiology*, 2009, 44 (12), 1087–1096.
- Kessler, Ronald C**, “The Effects of Stressful Life Events on Depression,” *Annual Review of Psychology*, 1997, 48 (1), 191–214.
- , **Kristin D Mickelson, and David R Williams**, “The Prevalence, Distribution, and Mental Health Correlates of Perceived Discrimination in the United States,” *Journal of Health and Social Behavior*, 1999, pp. 208–230.
- Kroenke, Kurt, Robert Spitzer, and Janet Williams**, “The PHQ-9: Validity of a Brief Depression Severity Measure,” *Journal of General Internal Medicine*, September 2001, 16 (9), 606–613.
- Kuzis, Gabriela, Liliana Sabe, Cecilia Tiberti, Ramón Leiguarda, and Sergio E Starkstein**, “Cognitive Functions in Major Depression and Parkinson Disease,” *Archives of neurology*, 1997, 54 (8), 982–986.
- Lasalvia, Antonio, Silvia Zoppei, Tine Van Bortel, Chiara Bonetto, Doriana Cristofalo, Kristian Wahlbeck, Simon Vasseur Bacle, Chantal Van Audenhove, Jaap Van Weeghel, Blanca Reneses et al.**, “Global pattern of experienced and anticipated discrimination reported by people with major depressive disorder: a cross-sectional survey,” *The Lancet*, 2013, 381 (9860), 55–62.
- Link, Bruce G and Jo C Phelan**, “Conceptualizing Stigma,” *Annual Review of Sociology*, 2001, 27 (1), 363–385.
- Littlewood, Roland**, “Cultural variation in the stigmatisation of mental illness,” *The Lancet*, 1998, 352 (9133), 1056–1057.
- Londborg, Peter D, Ward T Smith, Vincent Glaudin, and John R Painter**, “Short-term cotherapy with clonazepam and fluoxetine: anxiety, sleep disturbance and core symptoms of depression,” *Journal of Affective Disorders*, 2000, 61 (1-2), 73–79.

- Löwe, Bernd, Irini Schenkel, Caroline Carney-Doebbeling, and Claus Göbel,** “Responsiveness of the PHQ-9 to psychopharmacological depression treatment,” *Psychosomatics*, 2006, *47* (1), 62–67.
- Martin, Alexandra, Winfried Rief, Antje Klaiberg, and Elmar Braehler,** “Validity of the Brief Patient Health Questionnaire Mood Scale (PHQ-9) in the General Population,” *General Hospital Psychiatry*, 2006, *28* (1), 71–77.
- Moritz, Steffen, Christiane Birkner, Martin Kloss, Holger Jahn, Iver Hand, Christian Haasen, and Michael Krausz,** “Executive Functioning in Obsessive-Compulsive Disorder, Unipolar Depression, and Schizophrenia,” *Archives of Clinical Neuropsychology*, 2002, *17* (5), 477–483.
- Mullainathan, Sendhil and Eldar Shafir,** *Scarcity: Why having too little means so much*, Macmillan, 2013.
- Mullatti, Leela,** “Families in India: Beliefs and Realities,” *Journal of Comparative Family Studies*, 1995, pp. 11–25.
- Nestler, Eric J, Michel Barrot, Ralph J DiLeone, Amelia J Eisch, Stephen J Gold, and Lisa M Monteggia,** “Neurobiology of Depression,” *Neuron*, 2002, *34* (1), 13–25.
- Patel, Vikram,** “Mental health in low-and middle-income countries,” *British Medical Bulletin*, 2007, *81* (1), 81–96.
- Piet, Jacob and Esben Hougaard,** “The effect of mindfulness-based cognitive therapy for prevention of relapse in recurrent major depressive disorder: a systematic review and meta-analysis,” *Clinical Psychology Review*, 2011, *31* (6), 1032–1040.
- Pothen, S,** “Divorce in Hindu society,” *Journal of Comparative Family Studies*, 1989, pp. 377–392.
- Raven, JC,** “The Performances of Related Individuals in Tests Mainly Educative and Mainly Reproductive Mental Tests Used in Genetic Studies.” PhD dissertation, University of London (King’s College) 1936.
- Sava, Florin A, Brian T Yates, Viorel Lupu, Aurora Szentagotai, and Daniel David,** “Cost-effectiveness and cost-utility of cognitive therapy, rational emotive behavioral therapy, and fluoxetine (prozac) in treating depression: a randomized clinical trial,” *Journal of Clinical Psychology*, 2009, *65* (1), 36–52.
- Schilbach, Frank, Heather Schofield, and Sendhil Mullainathan,** “The Psychological Lives of the Poor,” *American Economic Review*, 2016, *106* (5), 435–40.
- Spitzer, Robert, Kurt Kroenke, Janet Williams, and Bernd Lowe,** “A Brief Measure for Assessing Generalized Anxiety Disorder,” *Archives of Internal Medicine*, May 22 2006, *166*, 1092–1097.

- Srinivasan, Padma and Gary R Lee**, “The Dowry System in Northern India: Women’s Attitudes and Social Change,” *Journal of Marriage and Family*, 2004, *66* (5), 1108–1117.
- Thara, Rangaswamy and TN Srinivasan**, “How Stigmatising is Schizophrenia in India?,” *International Journal of Social Psychiatry*, 2000, *46* (2), 135–141.
- , **Shanta Kamath, and Shuba Kumar**, “Women with Schizophrenia and Broken Marriages-Doubly Disadvantaged? Part II: Family Perspective,” *International Journal of Social Psychiatry*, 2003, *49* (3), 233–240.
- Thornicroft, Graham**, “Stigma and discrimination limit access to mental health care,” *Epidemiology and Psychiatric Sciences*, 2008, *17* (1), 14–19.
- , **Nisha Mehta, Sarah Clement, Sara Evans-Lacko, Mary Doherty, Diana Rose, Mirja Koschorke, Rahul Shidhaye, Claire O’Reilly, and Claire Henderson**, “Evidence for effective interventions to reduce mental-health-related stigma and discrimination,” *The Lancet*, 2016, *387* (10023), 1123–1132.
- , **Somnath Chatterji, Sara Evans-Lacko, Michael Gruber, Nancy Sampson, Sergio Aguilar-Gaxiola, Ali Al-Hamzawi, Jordi Alonso, Laura Andrade, Guilherme Borges et al.**, “Undertreatment of people with major depressive disorder in 21 countries,” *The British Journal of Psychiatry*, 2017, *210* (2), 119–124.