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DISCUSSION PAPER SERIES

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Manuela Angelucci
University of Texas at Austin and IZA

Daniel Bennett
University of Southern California

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Depression, Pharmacotherapy, and the Demand for a Novel Health Product*

Depression, a common and serious illness that is more prevalent among the poor, may limit the demand for health products and other beneficial technologies. To investigate, we evaluate the impact of depression treatment on the demand for a novel health product, hand sanitizer, in India. We cross-randomize depression treatment (pharmacotherapy) and free distribution of the product, and measure impacts on subsequent willingness to pay using the Becker-Degroot-Marschak mechanism, as well as product use. Depression treatment improves mental health and increases willingness to pay by 5 percent, implying that having major depression reduces willingness to pay by 26 percent. However, depression treatment does not affect product use, which is high after free distribution for all recipients. We investigate several pathways that may explain this pattern. These results are consistent with an effect of depression on the decision costs associated with a novel purchase. Our findings suggest that policymakers should use free distribution and other approaches that minimize decision costs to encourage the adoption of health products in high-depression settings.

JEL Classification: I15, I18
Keywords: depression, health, poverty

Corresponding author:
Manuela Angelucci
Department of Economics
University of Texas at Austin
Austin, TX 78712
USA
E-mail: mangeluc@utexas.edu

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1 Introduction

Preventative health products like anti-malarial bed nets, water purification tablets, and soap could be instrumental in improving the health and welfare of the poor. However, studies commonly find that few consumers are willing to pay full price for these ostensibly beneficial products, and that demand is highly elastic. Understanding the reasons for low demand is important to encourage the adoption and use of these products. Studies have found that subsidies relax financial constraints and that free distribution encourages experiential learning, both of which increase demand for these products. Limited information, the low salience of health prevention, and behavioral biases of consumers may also limit demand.[1]

Pervasive depression among poor people may contribute to the low demand for preventative health products. Depression is the most common mental disorder: 15-20 percent of adults experience depression at least once in their lives, and many more face sub-clinical psychological distress (Moussavi et al. 2007, Ferrari et al. 2013, Hasin et al. 2018). Depression is particularly common among the poor (Ridley et al. 2020). For example, while Sagar et al. (2020) estimate that the cross-sectional prevalence of depression is 3-4 percent in India, 10 percent of adults in our low-income study area have symptoms consistent with major depression and 24 percent of adults have at least some depression symptoms.

Depression may influence the demand for health products through several pathways. Symptoms of depression include indecisiveness, anhedonia, and pessimism, which may increase the decision cost of adoption and reduce the marginal utility of these products. Depression may interfere with learning about the benefits of unfamiliar products by affecting cognition. By changing risk and time preferences, depression could reduce the value of prevention. By reducing labor supply and productivity, it could diminish purchasing power. An effect of depression on intra-household bargaining power could also influence demand.

We study the relationship between depression and the demand for a preventative health product, liquid hand sanitizer, through a field experiment in Karnataka, India. Hand sanitizer is a useful alternative to soap when infectious diseases are common and people have

[1] For instance, see Devoto et al. (2012), Fink and Masiye (2012), Fink and Masiye (2015), Tarozzi et al. (2014), Dupas (2014a), Cohen et al. (2015), Dupas and Robinson (2013), and Kremer and Glennerster (2011). Evidence on the impact of providing information is mixed (Ashraf et al. 2013, Sylvia et al. 2022, Meredith et al. 2013). Dupas and Miguel (2017) summarize this literature.

few opportunities to wash their hands (Singh et al. 2020, Ranabhat et al. 2021). While hand sanitizer is available for sale in local shops, this product is novel in the sense that most people in the study area were unfamiliar with it and did not use it before our intervention.

We used community-based screening to recruit low-income adults with mild or moderate depression symptoms and randomly offered some participants free pharmacotherapy. While depression treatment was underway, we cross-randomized the free distribution of hand sanitizer to some participants. One year after free distribution, we measured product demand by using the Becker-Degroot-Marschak (BDM, 1964) mechanism to elicit willingness to pay (WTP). This design allows us to measure how depression affects both the willingness to pay for a novel preventative health product and the use of the product under free distribution. Demand was almost 100 percent at low prices but decreased rapidly, so that only 23 percent of control participants were willing to pay the retail price. The pattern of high demand at low prices and high price elasticity of demand characterizes many preventative health products (Dupas and Miguel 2017).

Both interventions achieved their goals. Offering depression treatment led to 48 percent take up and decreased the proportion of people with major depression symptoms by 19 percent. Free distribution led to 100 percent adoption and high use: after one year, 92 percent of free distribution recipients had used at least half of the product and 61 percent had depleted it.

Our first main finding is that depression treatment increases the WTP for hand sanitizer by 5 percent, implying that having major depression decreases WTP by 26 percent in our sample. This result suggests that depression may contribute to low demand for health products. Impacts are larger at higher prices: depression treatment increases demand by 50 percent at the market price of 80 rupees. Conversely, free distribution does not affect WTP.

Our second main finding is that, despite boosting demand, depression treatment does not increase product use, which is high after free distribution regardless of whether people were also offered depression treatment. This result suggests that depression does not limit the impact of free distribution on product adoption and use.

This finding also helps to distinguish between potential pathways that could contribute to the effect of depression treatment on demand. Most possible explanations, including changes in anhedonia, pessimism, risk and time preference, income, time use, cognition, and intrahousehold bargaining, should increase product use as well as WTP. In addition, depression treatment does not amplify the effect of free distribution on WTP or use, which suggests that the impact does not arise through learning. The positive effect on WTP and the null effect on product use are consistent with a decision cost pathway: deviating from the status quo to buy a novel product like hand sanitizer has a psychic cost, while use of the product conditional on ownership may not. By making a person more indecisive, depression may magnify this cost and thereby reduce WTP without affecting use conditional on ownership. While other explanations are also possible, several additional results support this interpretation. For instance, DT does not increase the demand for a familiar product, which is likely to have lower decision costs. It also has no effect on health-related consumption more broadly, which helps to rule out an effect through health preferences or salience.

These findings have direct policy implications. For products with highly elastic demand, depression may increase the scope for free distribution. A concern is that free distribution schemes may wastefully provide the product to many non-users. Free distribution to people with depression may not necessarily cause widespread wastage because depression decouples demand from use. For example, for our product, free distribution leads to high use regardless of depression treatment. Therefore, policymakers may favor free distribution over cost sharing to foster technology adoption in areas where poor mental health is endemic. For hand sanitizer, free distribution at point-of-use, such as through sanitizer stations near latrines, may be a cost-saving approach.

The links between depression, decision costs, and product demand may have additional policy implications. First, if depression amplifies decision costs, depressed people may be especially sensitive to smart defaults. Requirements to opt out rather than opt in may disproportionately encourage participation by people with depression. Secondly, the effectiveness of monetary incentives may depend on how decision costs vary with the size of a purchase. If large purchases have higher decision costs, then depressed people may be especially responsive to price subsidies, which also reduce decision costs. Both implications are speculative and beyond the scope of this study. However, Arulsamy and Delaney (2022) and Dupas et al. (2020) find evidence that is consistent with these conjectures.

This study contributes to multiple areas of research, including the literatures on the low demand for preventative health products (Dupas and Miguel 2017) and barriers to technology adoption more broadly (Foster and Rosenzweig 2010). Our findings have implications for the policy debates about whether to recoup program expenses through cost sharing (Kremer and Miguel 2007), target high-value users through ordeal mechanisms (Dupas et al. 2016, Dupas et al. 2020, Sylvia et al. 2022), or use smart defaults to enhance technology adoption (Choi et al. 2003, Bergman et al. 2020).

We contribute to the emerging literature that links depression to economic decision-making (Angelucci and Bennett 2022, Baranov et al. 2020, Bhat et al. 2022). By distinguishing between alternative pathways that link depression to WTP, we shed light on the ways that depression may affect economic behavior more broadly. These results are relevant for understanding the psychology of poverty (e.g., Mani et al. 2013, Mullainathan and Shafir 2013, Haushofer and Fehr 2014, Haushofer and Shapiro 2016). Depression, which is more common among poor people, may be a channel through which poverty affects decision-making. We also provide new evidence of a link between mental and physical health (Serena 2021). Lastly, the finding that depression may exacerbate decision costs has important behavioral economic implications. This pathway may explain why people with psychological distress are especially prone to making choices that are presented as the default option (Arulsamy and Delaney 2022, Bhat et al. 2022).

2 Study Design and Implementation

2.1 Treatments

We study the impacts of two interventions: depression treatment (DT) and free distribution of hand sanitizer (FD). Depression treatment consisted of up to eight monthly visits with a psychiatrist from the Shridevi Institute of Medical Sciences and Research Hospital in Tumkur, Karnataka. This hospital oversaw the DT program with supervision from its IRB. During the initial visit, each patient received a diagnosis and (if appropriate) an individualized course of treatment. Patients diagnosed with depression received commonly-used off-patent antidepressants. These drugs have mild and well-understood side effects (Cascade et al. 2009). A local NGO provided participants with return transportation to the hospital and made monthly visits to all participants to monitor side effects. Angelucci and Bennett (2022) describe this intervention in more detail and study its effects on depression and socioeconomic outcomes.

For the FD intervention, we provided 600ml of hand sanitizer (one 500ml bottle and one more portable 100ml bottle; Figure A1 shows a picture of the 100ml bottle). This quantity is equivalent to around 300 doses. Surveyors gave a brief hygiene lesson, demonstrated how to use the product, and offered to answer questions about the product prior to distribution. Appendix A.1 provides the script for this interaction.

2.2 Implementation

This investigation took place in 506 localities within three peri-urban sub-districts northwest of Bangalore, Karnataka. Before recruitment, we randomly assigned localities to DT and no-DT arms. We stratified this randomization by sub-district and by terciles of a locality socioeconomic index based on the 2011 Census of India, for a total of nine strata. This approach minimized treatment spillovers across intervention arms.

We recruited 1-2 people per locality to obtain a sample of 1000 participants. Surveyors followed a door-skip pattern within each locality and then randomly chose an available adult to screen for depression symptoms using the PHQ-9 depression severity scale (Kroenke et al. 2001). This instrument has been widely validated to screen for depression and measure the response to depression treatment in India and elsewhere in the world (e.g., Patel et al. 2008, Manea et al. 2012, Indu et al. 2018). To obtain a sample of people with mild or moderate depression symptoms, we recruited subjects with PHQ-9 scores of 9-20.[2]

Starting in January 2017, 40 percent of study participants were offered depression treatment. When we offered the FD intervention approximately four months later, the DT inter-

[2] The PHQ-9 scale ranges from 0-27 and higher values indicate more severe symptoms. 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 had 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. We did not recruit participants with disabilities that prevented them from working, who were currently earning more than Rs. 6000 per month, or whose child care duties required them to remain at home throughout the day. We also excluded pregnant women due the additional risks of pharmacotherapy during pregnancy.

vention was ongoing and 94 percent of the original sample remained in the study. We offered FD to 80 percent of these participants, randomized at the individual level, and everyone in the FD intervention accepted the product. The disproportionate share of people in the FD arms improved statistical power to assess the impact of depression treatment on product use under free distribution.[3]

This study is based on two additional follow-up surveys. We surveyed participants six months after free distribution, when most FD participants had not yet depleted the product. At this point, we elicited self-reported sanitizer use and checked how much of the previously distributed product remained. We visited participants again twelve months after free distribution and confirmed that most FD participants had little or no hand sanitizer remaining. At that point, we elicited product demand. This staggered approach allowed us to measure product use when most people still had the distributed product and demand when most people had depleted the product.[4] Figure 1 illustrates the study timeline.

3 Data

We rely on the PHQ-9 scale to measure depression severity. The PHQ-9 is useful both to screen for depression and as a consideration in depression diagnosis. Higher values of the PHQ-9 are associated with more severe symptoms of depression. We also create an indicator variable for people with a PHQ-9 of at least 10, which is the severity threshold for major depression (Kroenke et al. 2001).

We used the Becker-Degroot-Marschak (BDM 1964) mechanism to elicit participants' willingness to pay for a 100ml bottle of hand sanitizer (depicted in Figure A1). At the time, this product sold for 80 rupees ($1.17) locally, which is less than 1 percent of the average monthly household budget. BDM is an incentive-compatible way to elicit willingness to pay and has been validated in the field (Berry et al. 2020).[5]

[3] Five percent of participants share a locality with another study participant who received the opposite FD assignment. Results do not change if we drop these observations.

[4] Six percent of participants who were present at the time of free distribution attrited by the six-month survey and twelve percent attrited by the twelve-month survey. Appendix A.2 shows that attrition is balanced across intervention arms and implements several robustness tests.

[5] In the BDM game, the respondent states an offer price and then draws a price at random. She must purchase the good for the drawn price if the offer price exceeds the drawn price. She cannot purchase the

We measure product use in two ways. We elicited self-reported daily use for all participants at six months, when most FD participants still had the distributed product.[6] In addition, surveyors measured the quantity remaining in the bottles distributed to FD participants at 6 and 12 months. For people in the FD group with sanitizer remaining, daily use and quantity remaining are negatively correlated, suggesting that frequent personal use corresponds to less quantity remaining. 61 percent of FD participants had no sanitizer remaining twelve months after free distribution. At this time, only 8 percent had more than half of the distributed product remaining.

We also assess knowledge of the intended use of the product and familiarity with the product twelve months after free distribution. Only 9 percent of control participants were familiar with hand sanitizer, which helps to validate the novelty of the product.

Our analysis includes several outcomes that allow us to test for alternative pathways. We assess the role of the budget constraint using data on weekly earnings by the respondent, as well as household income and consumption. With these data, we also calculate the household budget share for health-related consumption, which is the sum of spending on medical care and personal care products.[7] Since hand sanitizer is most useful away from home, we use the locations associated with 24-hour time diary entries to compute time spent outside the home. We measure cognitive performance through Raven's Progressive Matrices and forward and backward digit spans. We also create a bargaining power index that combines the respondent's budget share allocated to the evening meal and measures of participation in employment and savings decisions. We compute the cognitive performance and bargaining power indices using the first principal component.

good if the offer price is less than the drawn price. After verifying that participants understood the game, surveyors elicited the WTP for hand sanitizer. We also elicit WTP before free distribution for a subset of participants. We do not use these data in our analysis since we do not observe the entire sample and since measurement occurred before respondents had completed depression treatment. Estimates of the impact of DT that include these observations are lower but not significantly different from our primary estimates ($p = 0.37$). Focusing on respondents who provided WTP in both surveys, we find that DT increases WTP by 0.95 rupees at the time of free distribution ($p = 0.45$) and increases WTP by 2.62 rupees twelve months later ($p = 0.06$). The pooled effect is 1.79 rupees ($p = 0.07$).

[6] We attempted to measure self-reported use at twelve months but a software issue led to a high number of missing observations, which rendered this variable unusable. Conceptually, self-reported use at twelve months is not very informative because most FD recipients had run out of sanitizer by that time.

[7] Medical care includes doctor fees, medications, and other medical expenses. Personal care products include soap, toothpaste, toothbrushes, cosmetics, umbrellas, beauty salon expenses, hair oil, razor blades, non-prescription sunglasses, and other toiletries.

Table A1 summarizes respondent characteristics and available outcome variables by intervention arm at baseline. These variables are generally balanced, and the variables are not jointly significantly different across arms ($p = 0.50$ for respondent characteristics and $p = 0.47$ for outcomes). The table omits willingness to pay for hand sanitizer, hand sanitizer use, knowledge of the intended use of the product, and familiarity with the product because we do not observe these variables at baseline. One concern is that baseline depression severity is higher in the arm receiving free distribution only (Column 3). To investigate this issue, we estimate the regressions below using entropy weights to impose balance across arms in the first three moments of the PHQ-9 distribution (Hainmueller 2012, Hainmueller and Xu 2013). Our findings are robust to weighting, and weighted and unweighted estimates are generally similar.

4 Identification and Estimation

We estimate the impacts of depression treatment and free distribution through the following equation:

$$Y_{ij} = \alpha \ + \ \beta DT_j \ + \ \gamma FD_{ij} \ + \ X_j'\theta \ + \ \varepsilon_{ij} \tag{1}$$

The subscripts i and j refer to respondents and localities. DT is an indicator for assignment to depression treatment and FD is an indicator for assignment to free distribution. X is a vector of controls for the nine randomization strata. Whenever possible, we add the baseline value of the dependent variable to our set of controls.[8] The parameter of interest is β, which identifies the average intent-to-treat effect of depression treatment under the assumption that the effects of DT and FD are additive. Random assignment ensures that the treatment and control group do not vary systematically. Assigning depression treatment by locality and treating up to two people per locality minimizes concerns about spillover effects.

A second specification that includes the interaction between DT and FD allows us to

[8] An alternative specification selects the right-hand-side covariates by using the Belloni et al. (2014) double-lasso selection method. The results are unchanged and are available upon request.

distinguish between the impact of DT with and without FD.

$$Y_{ij} = \eta \ + \ \delta DT_j \ + \ \theta FD_{ij} \ + \ \lambda(DT_j \times FD_{ij}) \ + \ X_j'\psi \ + \ \varepsilon_{ij} \tag{2}$$

This specification does not require the assumption that the effects of DT and FD are additive. However, the DT coefficient is less precisely estimated in this specification because only 55 participants were offered DT without FD. Here, δ identifies the impact of depression treatment in the absence of free distribution, θ shows the impact of free distribution in the absence of depression treatment, and λ indicates whether free distribution moderates the impact of depression treatment. The sum of the coefficients δ and λ is the impact of depression treatment among FD participants. We estimate the parameters by OLS and clusters standard errors by village in all specifications.

5 Proximate Effects of Depression Treatment and Free Distribution

5.1 Depression Treatment Improves Mental Health

The DT intervention succeeded in reducing depression severity. The left panel of Figure 2 shows that depression treatment shifts the distribution of PHQ-9 scores to the left, consistent with mental health improvements throughout the support. The right panel shows that, as expected, free distribution has no effect on depression severity. In Kolmogorov-Smirnov tests, we reject equality of the distributions in the left panel ($p = 0.004$) but fail to reject equality of the distributions in the right panel ($p = 0.99$). Table A2 provides more detail about the impact on depression severity: DT reduces symptom severity by 0.18 SD after twelve months ($p = 0.02$). With DT compliance of 48 percent, the corresponding average treatment effect on the treated (ATT) is 0.38 SD. This estimate is similar to Singla et al.'s (2017) impact of psychotherapy in developing countries and to the impact of pharmacotherapy in industrialized countries (Gartlehner et al. 2017). The proportion of people with symptoms consistent with major depression (PHQ-9 ≥ 10) decreases by 9 percentage points ($p = 0.01$), a 19 percent reduction. The table also confirms our finding above that free distribution has a small and statistically insignificant effect on depression severity.

Next, we consider the effect of depression treatment on the demand for hand sanitizer and other related outcomes. This discussion presumes that the primary effect of depression treatment is to reduce depression severity. We acknowledge that treatment may have additional effects, such as side effects of the medications. However, only 15 DT compliers report that they experienced side effects. Additional null results in Section 9 also support this interpretation.

5.2 Free Distribution Increases the Use of Hand Sanitizer

Free distribution increased hand sanitizer use. Figure 3 shows the percent of respondents who use hand sanitizer at least daily six months after free distribution. 54 percent of FD participants use hand sanitizer, compared to 18 percent of no-FD participants ($p < 0.001$). Within the FD arm, respondents had used 65 percent of the distributed hand sanitizer at six months and 85 percent at twelve months. Consistent with this pattern, Table A3 and Appendix A.3 show large effects of free distribution on product knowledge and familiarity. These results suggest that free distribution was effective in increasing product use in our sample.

6 Depression Treatment and the Demand for Hand Sanitizer

6.1 Depression Treatment Increases the WTP for Hand Sanitizer

Figure 4 plots the inverse demand for hand sanitizer in the depression treatment and no depression treatment arms without controlling for free distribution.[9] Demand is almost 100 percent and inelastic below 40 rupees. It decreases rapidly at higher prices, and only 23 percent of no-DT participants are willing to pay the retail price of 80 rupees. The average price elasticity of demand is -2, but falls below -4 at prices above 50 rupees. The difference between the DT and no-DT curves is largest in the 55-80 rupees range. Conversely, the FD and no-FD curves are very similar in Figure A3.

[9]Figure A2 reproduces Figure 4 separately for the FD and no-FD arms. These figures closely resemble Figure 4.

Panel A of Table 1 provides average intent-to-treat effects on willingness to pay according to Equation (1). Column 1 shows that depression treatment increases WTP by 3 rupees ($p = 0.02$), a 4.9 percent increase. Extrapolating from the 19 percent reduction in the share of people with symptoms of major depression (Column 4 of Table A2), eliminating major depression in our sample would increase WTP by 26 percent. The table also shows that free distribution does not increase WTP.

The impact of depression treatment on demand increases in both absolute and relative terms as the price rises.[10] Columns 2-8 examine the impact on indicators that WTP exceeds several price thresholds. In Column 2, depression treatment increases demand by 1 percentage point ($p = 0.18$) at a price of 30 rupees (a 1 percent increase), while it increases demand by 9 percentage points ($p = 0.01$) at a price of 80 rupees (a 50 percent increase). We reject the hypothesis that the DT coefficients in columns 2-8 are identical ($p = 0.03$).[11] Therefore, depression treatment changes the slope of the demand curve. Since these are intent-to-treat effects and the depression treatment take-up rate is 48 percent, we expect the average treatment-on-the-treated effects to be substantially larger.[12] Column 8 shows that depression treatment has no effect on demand beyond the retail price of 80 rupees. Overall, these findings suggest that alleviating depression symptoms can have a substantial effect on product demand at close to retail price.

Estimates following Equation (2) appear in Panel B. Results are similar, although estimates are less precise because we do not pool intervention arms. In Column 1, DT increases WTP by 2.7 rupees with free distribution ($p = 0.06$) and increases WTP by 5.6 rupees without free distribution ($p = 0.03$). In Columns 2-8, the impact of DT across the price distribution is similar in the FD and no-FD arms. Estimates of λ are not statistically significant. However, the negative signs in most columns suggest that free distribution may reduce

[10] The small impact of DT at low prices may reflect the nearly universal demand for one unit of the product at these prices in the no-DT arm. For instance, 99 percent of no-DT participants are willing to pay at least 30 rupees, which leaves little scope for DT to increase demand further.

[11] For each coefficient in Columns 5-7, we also reject the hypothesis that the coefficient is equal to Column 2.

[12] 83 percent of people who bid weakly more than the drawn price actually bought the good. The interventions did not affect the likelihood of complying with the requirement of the BDM game to actually purchase the product. Results are robust if we exclude people who did not carry out purchases that they should have made under BDM.

the impact of depression treatment on WTP. Finally, estimates of θ (the impact of FD in the absence of depression treatment) are mostly positive and statistically insignificant. The non-negative estimates of θ suggest that free distribution does not reduce demand through anchoring effects, in contrast to Fischer et al. (2019).[13]

6.2 Depression Treatment Does Not Increase the Use of Hand Sanitizer

Estimates for self-reported daily use of hand sanitizer appear in Column 9 of Table 1. DT has a statistically insignificant effect, overall (Panel A) and by FD (Panel B). While self-reported use is observable regardless of free distribution, it may be subject to recall or experimenter demand bias. For FD participants, the quantity remaining in the distributed bottles is an objective indicator of hand sanitizer use. Table A6 shows that DT has a small and statistically insignificant effect on this outcome, increasing the quantity remaining by 1.8 percentage points after six months ($p = 0.46$) and decreasing the quantity remaining by 0.5 percentage points after twelve months ($p = 0.80$). Figure 5 shows the cumulative densities of quantity remaining by depression treatment. The curves are very similar at both intervals, and Kolmogorov-Smirnov tests fail to reject equality of the DT and no-DT distributions ($p = 0.68$ at six months and $p = 0.99$ at twelve months). This evidence also validates that free distribution recipients had little sanitizer remaining after twelve months.

7 Pathways

Depression may limit the demand for hand sanitizer through multiple channels. To illustrate possible pathways, consider a person who receives utility from a novel health product, h, and a basket of other normal goods, c.[14] Purchasing the novel product entails a non-monetary decision cost, $k \geq 0$, which includes the psychic cost of departing from a routine. Although we model this cost as a constant, k could instead be an increasing function of p, which would

[13]Appendix A.4 investigates subgroup heterogeneity in these impacts, Appendix A.5 shows that results are robust under alternative specifications, and Appendix A.6 shows that the effect of DT on WTP does not vary systematically for people with different amounts of sanitizer remaining. Dizon-Ross and Jayachandran (2022) note that controlling for the WTP of an unrelated good may improve precision of WTP regressions. Including the WTP for biscuits as a covariate in Table 1 does not affect our estimates.

[14]Free distribution has enabled people to form beliefs about the product's expected net benefit.

align with evidence that performance is impaired when stakes are high (Ariely et al. 2009). The consumer faces the following constrained optimization problem.

$$\max_{h,c} \ U(h,c,k) \ = \ u(h,c) \ - \ \mathbb{1}(h>0)\cdot k$$

$$\text{subject to:}$$

$$p_h h \ + \ p_c c \ \leq \ y$$

At an interior solution, (h^*, c^*), the consumer equates the marginal rate of substitution to the marginal rate of transformation, so that $\frac{u_h(h^*,c^*)}{u_c(h^*,c^*)} = \frac{p_h}{p_c}$. However the consumer may also reach a corner solution, $(0, \frac{y}{p_c})$, in which she does not adopt the product if $u(0, \frac{y}{p_c}) > u(h^*, c^*) - k$.

We consider several pathways through which depression and depression treatment may affect the demand for good h.

Decision costs. Making decisions entails cognitive, psychic, and other costs. Over time, people develop heuristics that reduce the cost of familiar choices. Since people lack these heuristics for novel choices, the cost of making novel choices is likely higher (Heiner 1983, Gigerenzer and Gaissmaier 2011). Indecisiveness, a common depression symptom, may reduce demand by amplifying decision costs (Leykin and DeRubeis 2010, Leykin et al. 2011, Beck and Alford 2009). In the model, depression exacerbates indecisiveness, which increases k and makes a corner solution in which $h = 0$ more likely. However, k does not affect h^* on the intensive margin because k is absent from the first order condition. Since k is no longer relevant once the consumer owns the product, decision costs do not affect product use.[15] In this case, depression treatment may increase product demand, moving away from a corner solution, but not product use conditional on ownership. Panel A of Figure 6 illustrates this case.

Learning. Experiential learning is an important determinant of technology adoption (Foster and Rosenzweig 1995, Dupas 2014b). Free distribution may increase the marginal utility of hand sanitizer by allowing recipients to learn about the benefits of the product. Depression could disrupt learning by, e.g., impairing concentration and cognition, and thereby

[15] For hand sanitizer, using the product has lower stakes than purchasing the product. A link between the stakes of a decision and the decision cost may rationalize the lack of a decision cost associated with product use (Ariely et al. 2009).

blunt the positive effect of free distribution on WTP (Kuzis et al. 1997, Moritz et al. 2002). Panel B of Figure 6 illustrates the potential effect of depression treatment on demand via this pathway.[16,17]

Anhedonia and Pessimism. Anhedonia and pessimism are two core symptoms of depression (Malhi and Mann 2018). Anhedonia reduces the pleasure derived from current and anticipated positive events. Pessimism causes people to underestimate the *expected* benefit of an action. Either symptom could decrease the marginal utility of hand sanitizer as well as the marginal utility of other goods. Since both the numerator and the denominator decrease, the effect on the MRS between hand sanitizer and other goods is ambiguous. Panel B of Figure 6 illustrates the case in which anhedonia and pessimism lead people with depression to disfavor hand sanitizer, and thus substitute toward other goods. As before, depression treatment increases h^*.

Risk and time preferences. Research suggests that depression may make people less risk averse and patient (Angelucci and Bennett 2022, Bhat et al. 2022). Depression may decrease both demand and use of hand sanitizer by decreasing the expected value of health-related prevention. Panel B of Figure 6 also illustrates this pathway. Since these pathways have similar predictions, we proceed to refer to anhedonia, pessimism, risk tolerance, and impatience as "preference pathways."

Based on the discussion above, we can test these pathways by estimating the effects of our interventions on product use (U) and WTP (W). Table 2 summarizes the predictions of each pathway. The key parameters are the overall impact of DT (β), the impact of DT among no-FD participants (δ), the impact of DT among FD participants ($\delta + \lambda$), and the interaction between DT and FD (λ).

- Under the decision costs pathway, depression treatment increases demand by reducing the fixed cost of purchasing the good, so that $\beta^W > 0$, $\delta^W > 0$, and $\delta^W + \lambda^W > 0$. Depression treatment has no effect on product use if decision cost associated with hand

[16]Learning could also *reduce* the demand for a new technology (e.g., Adhvaryu 2014). A negative effect is more plausible if the good has negative characteristics that consumers do not initially recognize. For instance, deworming medications may cause stomach pain and chlorination tablets give drinking water an unpleasant taste. This feature does not seem relevant for hand sanitizer.

[17]Social learning, another determinant of technology adoption, is unlikely in our setting since only 1 or 2 people per village receive hand sanitizer.

sanitizer use is negligible, so that $\beta^U = 0$, $\delta^U = 0$, and $\delta^U + \lambda^U = 0$.

- For the learning pathway, free distribution enables people to learn about the benefits of the product. Depression treatment may increase the marginal utility of the product by enabling people to learn about these benefits more easily. Therefore, under the learning pathway, $\lambda^U > 0$ and $\lambda^W > 0$.

- Under the preferences pathway, the effects of depression treatment on product use and WTP must have the same sign: people who place more value on the product both use the product more frequently and are willing to pay more for it.[18] Since people must own the product in order to use it, we focus on the effects for the FD group: $\delta^U + \lambda^U > 0$ and $\delta^W + \lambda^W > 0$. We also predict that $\beta^U > 0$ and $\beta^W > 0$ because most study participants receive free distribution.[19]

We can test these hypotheses by considering the estimates in Columns 1 and 9 of Table 1. The evidence is consistent with the decision costs pathway. Under this pathway, DT increases WTP but does not increase product use. Estimates for β, δ, and $\delta + \lambda$ are positive and statistically significant for WTP but small and statistically insignificant for daily use. Results for quantity of distributed hand sanitizer remaining in Figure 5 and Table A6 reinforce the null effect of depression treatment on product use.[20]

Conversely, the evidence in Columns 1 and 9 of Table 1 is not consistent with the other pathways. In contrast to our prediction under the learning pathway, λ estimates are negative

[18] We rule out the possibility that valuing the good may be associated with hoarding it rather than using it. First, consumer theory predicts that people may hoard assets and consumption goods that they expect will be scarce in the future (Baddeley 2020). Hand sanitizer does not meet this criterion. Secondly, while many hoarders experience depression, most people with depression do not engage in hoarding (Frost et al. 2000).

[19] The predictions that $\delta^U > 0$ and $\delta^W > 0$ are theoretically correct but are not useful to test because most no-FD participants do not own the product.

[20] Other mechanisms might lead to an effect of DT on product demand but no effect on product use. Pessimism might lead depressed people to underestimate their potential use of the product before (but not after) purchasing it. Another possibility is that people may have binary perceptions of product quality ("low-quality" and "high-quality") and have zero demand for low-quality products. Pessimism about product quality may discourage depressed people from buying the product without affecting the utility of the product among people who do buy it. A limitation of these alternatives is that they require pessimism to operate only on particular parameters without affecting others. For instance, it is unclear why pessimism decreases expected product use but not expected utility of the product. Separately identifying these potential alternatives is beyond the scope of the paper. The finding that depression reduces WTP but not use has policy implications (discussed in Section 10) that hold regardless of the pathways that lead to these results.

and statistically insignificant, which suggests that DT does not enhance the impact of FD on product demand or use. We also fail to find evidence to support the preferences pathway, which requires that $\delta + \lambda$ (the effect of DT conditional on FD) should have the same sign for WTP and use. While the impact on WTP is positive and statistically significant, the impact on daily use is negative and statistically insignificant. We can also reject the hypothesis that the percentage effect on daily use is as large as the percentage effect on WTP ($p = 0.05$).

8 Decision Costs: Additional Evidence

Three additional findings support the decision costs pathway. First, depression may not affect the demand for *familiar* products through the decision costs pathway, since these products are likely to have low decision costs. To investigate, we examine the impact of depression treatment on the WTP for a packet of biscuits (cookies), a familiar product with a price of 30 rupees ($0.46). Before eliciting the WTP for hand sanitizer, we used the same BDM procedure to elicit WTP for biscuits. Depression treatment does not have a significant effect on demand for this product ($p = 0.13$) and we reject the hypothesis that the impact of DT on hand sanitizer demand and biscuit demand are equal ($p = 0.04$).[21]

Secondly, we can rule out that the effect of depression treatment on WTP for hand sanitizer reflects an increase in demand for health-related consumption more generally. As part of a broader consumption module, we measure the household budget share for medical care and personal care products. Depression treatment does not increase the budget share of these expenditures: the intervention reduces the share of health-related spending from 11.7 percent to 11.0 percent ($p = 0.27$). The lack of a positive and significant effect further suggests that DT does not increase WTP through a preferences pathway.

Finally, we expect that owning and using hand sanitizer should increase familiarity with the product and reduce decision costs for subsequent purchases. In this case, the effect of DT on demand should be larger for no-FD participants, who did not previously receive the product for free, so that $\lambda < 0$. In addition, free distribution should increase WTP regardless of DT, so that $\theta > 0$. Column 1 of Table 1 suggests that this pattern may be present. While

[21]If we standardize the prices of biscuits and hand sanitizer, the impact of DT for hand sanitizer is 46 percent larger but the difference is no longer statistically significant ($p = 0.40$).

neither estimate is statistically significant, the λ estimate is negative and the θ estimate positive.

If depression reduces WTP by increasing decision costs, it is useful to understand how this effect varies with product price. A comparison of the DT and no-DT demand curves in Figure 4 shows that demand is both lower and more elastic for the no-DT arms, which have higher decision costs under our interpretation of the underlying mechanisms Table 1 shows that this slope difference is statistically significant. This evidence suggests that decision costs increase with prices: if decisions costs were fixed, demand would be lower in the no-DT group for all prices. This finding may be relevant for policy, as we discuss below.

9 Other Explanations

Other channels could lead to an effect of depression treatment on the demand for hand sanitizer. First, depression treatment may raise purchasing power by increasing labor supply and productivity. Secondly, depression treatment could increase demand for the product by making people become more active, which is relevant because hand sanitizer is especially useful for people who need to clean their hands while they are away from home. Thirdly, depression treatment could improve cognition, leading people to place more value on the product. Finally, depression treatment might increase bargaining power (Baranov et al. 2020), which could increase WTP if study participants prefer hand sanitizer more than other household decision-makers.

Table 3 shows estimates for earnings, time spent outside the home, and indices of cognitive performance and intrahousehold bargaining power. Depression treatment does not increase any of these outcomes, which suggests that these channels are unlikely to explain the positive effect on WTP.[22] The null effect of DT on product use is also inconsistent with an effect through these pathways.

Finally, we presume in the discussion above that depression treatment primarily works by improving mental health, rather than through other independent channels. The DT intervention involved a psychiatric diagnosis and several consultations with a psychiatrist.

[22]We also find that depression treatment does not increase household income or consumption. Estimates are available from the authors.

These components could independently affect time use (e.g. through self-isolation or self-care), intra-household bargaining power, or the salience of health and prevention. Null estimates for bargaining power and time use in Table 3 suggest that these pathways are not critical. In addition, the lack of effects of DT on the health-related budget share or on awareness of hand sanitizer (in Table A3) suggest that the intervention did not primarily operate by changing the salience of health and prevention. While we cannot rule out all alternative explanations, these findings support our interpretation that depression treatment primarily worked by improving mental health.

10 Policy Implications

Our findings help explain features of the demand for preventative health products in developing countries. Depression appears to limit the demand for hand sanitizer in our setting. Since depression is common among poor people (Ridley et al. 2020), this result suggests that depression may contribute to low demand for prevention and for novel technologies more broadly, a frequent phenomenon in low-income countries. We also find that depression decouples product demand and use. This pattern may help to explain the low correlation between product price and use in studies by Cohen and Dupas (2010), Dupas (2014a), Tarozzi et al. (2014), and others: by amplifying decision costs, depression may lead people to have low willingness to pay for products that they would use under free distribution.

These findings also contribute to the debate about how to design effective policies to increase product adoption. Free distribution may be preferable to cost sharing in high-depression settings, since charging a positive price could screen out many depressed people who would use the product if they owned it. By contrast, free distribution may lead to high use and limited wastage in cases in which depression hinders willingness to pay but not use. For products like hand sanitizer, point-of-use distribution (e.g., by providing sanitizer stations near latrines) may maximize reach while also limiting wastage.

More generally, interventions that lower decision costs may foster technology adoption in high-depression settings. In applicable situations, the use of smart defaults could be a promising way to encourage adoption. For example, if depression leads to inaction, policies that automatically enroll people unless they opt out may disproportionately increase adoption among people with depression (Bhat et al. 2022). Our results also suggest that decision costs may be increasing in prices. This potential link suggests that depressed people may be especially responsive to price subsidies, which also reduce decision costs. Our trial is not designed to study these approaches. However, there is evidence consistent with the conjecture that lowering decision costs fosters product adoption (Arulsamy and Delaney 2022, Dupas et al. 2020).

11 Conclusions

A well-known public health puzzle in developing countries is that the adoption of preventative health products is low and demand highly elastic even when these products are affordable and have large health benefits. Studies have identified learning, information, financial constraints, and preferences as possible causes for this phenomenon (Dupas 2011). We provide evidence for an additional explanation: depression may reduce the demand for novel preventative health products.

Working with a sample of 1000 depressed low-income adults, we show that treating depression improves mental health and increases the demand for hand sanitizer. Our estimates indicate that treating major depression increases willingness to pay by 26 percent. The impact on demand is highest at close to retail price, which suggests that depression may be most detrimental to take-up under zero or modest subsidies. Despite increasing demand, depression treatment does not affect product use, which is high after free distribution. While a variety of explanations are possible, the most plausible explanation is that indecisiveness, which is a common depression symptom, increases the decision costs of the purchase.

Since depression is often endemic in high-poverty settings (Ridley et al. 2020), these findings may help to explain the low demand for preventative health products and the low correlation between WTP and product use (Cohen and Dupas 2010, Dupas 2014a, Tarozzi et al. 2014, Dupas and Miguel 2017). They strengthen the argument for free distribution over cost-sharing in high-depression settings, especially for products with highly elastic demand. Finally, if decision costs are an important pathway through which depression reduces demand, interventions that minimize such costs (e.g., by bringing the product to users or implementing smart defaults) may be especially effective for people with depression.

Table 1: Treatment Effects on the Hand Sanitizer Willingness to Pay and Daily Use

(1) $Y_{ij} = \alpha + \beta DT_j + \gamma FD_{ij} + X_j'\theta + \varepsilon_{ij}$

(2) $Y_{ij} = \eta + \delta DT_j + \theta FD_{ij} + \lambda(DT_j \times FD_{ij}) + X_j'\psi + \varepsilon_{ij}$

		$\mathbb{1}(WTP \geq X)$							Daily Use
	WTP	$X = 30$	$X = 40$	$X = 50$	$X = 60$	$X = 70$	$X = 80$	$X = 85$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A: Specification (1)									
β	3.27***	0.011	0.031**	0.012	0.073**	0.083**	0.097***	0.022	-0.053
	(1.24)	(0.0078)	(0.014)	(0.024)	(0.035)	(0.035)	(0.033)	(0.026)	(0.042)
γ	-0.18	-0.0080	-0.0025	-0.017	0.014	-0.025	0.0010	0.022	0.25***
	(1.44)	(0.0079)	(0.017)	(0.027)	(0.042)	(0.045)	(0.040)	(0.030)	(0.065)
B: Specification (2)									
δ	5.56**	0.011	0.045	0.077*	0.16**	0.16*	0.14*	-0.013	0.082
	(2.59)	(0.011)	(0.029)	(0.046)	(0.074)	(0.082)	(0.075)	(0.051)	(0.12)
θ	1.02	-0.0083	0.0052	0.017	0.058	0.014	0.024	0.0039	0.32***
	(1.93)	(0.013)	(0.026)	(0.038)	(0.054)	(0.060)	(0.048)	(0.041)	(0.091)
λ	-2.87	0.00083	-0.018	-0.081	-0.11	-0.094	-0.054	0.043	-0.16
	(2.96)	(0.014)	(0.034)	(0.054)	(0.084)	(0.091)	(0.083)	(0.060)	(0.13)
$\delta + \lambda$	2.69*	0.011	0.027*	-0.004	0.052	0.065*	0.087**	0.030	-0.07
	(1.41)	(0.009)	(0.016)	(0.027)	(0.039)	(0.039)	(0.037)	(0.030)	(0.05)
Months since free distribution	12	12	12	12	12	12	12	12	6
Control mean	60.7	0.99	0.93	0.85	0.54	0.37	0.22	0.12	0.22
Observations	825	825	825	825	825	825	825	825	821

Note: The table reports AIT effects. Village-clustered standard errors appear in parentheses. Column 1 shows willingness to pay for a 100ml bottle of hand sanitizer, which was elicited through the Becker-Degroot-Marschak mechanism. Columns 2-8 shows indicators that the willingness to pay is greater or equal than X rupees, for $X \in \{30, 40, 50, 60, 70, 80, 85\}$. The local retail price of this product is 80 rupees. Column 9 shows self-reported daily use. WTP outcomes are measured twelve months after free distribution and daily use is measured six months after free distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Coefficient Signs Under Alternative Pathways

(1) $Y_{ij}^p = \alpha^p + \beta^p DT_j + \gamma^p FD_{ij} + X_j' \theta^p + \varepsilon_{ij}^p, \ \ p \in \{U, W\}$

(2) $Y_{ij}^p = \eta^p + \delta^p DT_j + \theta^p FD_{ij} + \lambda^p (DT_j \times FD_{ij}) + X_j' \psi^p + \varepsilon_{ij}^p$

	Pathways		
	Decision Costs	Learning	Preferences
	(1)	(2)	(3)
β^U	0		+
δ^U	0		+
λ^U		+	
$\delta^U + \lambda^U$	0		+
β^W	+		+
δ^W	+		+
λ^W		+	
$\delta^W + \lambda^W$	+		+

Note: The table shows predicted signs for β, δ, λ, and $\delta + \lambda$. $p \in \{U, W\}$ represent the outcome variables: use and willingness to pay. β is the impact of depression treatment across both free distribution and no free distribution arms. δ is the impact of depression treatment without free distribution, λ is the differential impact of depression treatment under free distribution, and $\delta + \lambda$ is the impact of depression treatment under free distribution. We derive these predictions under the assumption that each pathway is the only operable channel. Predictions are contingent upon a positive effect of depression treatment on WTP. We exclude scenarios through which depression treatment might decrease WTP, although we acknowledge that a negative effect is possible through several channels.

Table 3: Effects on Earnings, Time Use, Cognitive Performance, and Bargaining Power

(1) $Y_{ij} = \alpha + \beta DT_j + \gamma FD_{ij} + X_j'\theta + \varepsilon_{ij}$

(2) $Y_{ij} = \eta + \delta DT_j + \theta FD_{ij} + \lambda(DT_j \times FD_{ij}) + X_j'\psi^p + \varepsilon_{ij}$

	Earnings	Time Outside The Home	Cognitive Performance	Bargaining Power
	(1)	(2)	(3)	(4)
A: Specification (1)				
β	-0.14*	-0.040	-0.16**	0.00070
	(0.080)	(0.077)	(0.069)	(0.075)
γ	0.090	0.061	0.015	0.028
	(0.096)	(0.084)	(0.085)	(0.097)
B: Specification (2)				
δ	-0.18	-0.043	0.063	0.12
	(0.17)	(0.14)	(0.15)	(0.17)
θ	0.070	0.060	0.13	0.089
	(0.13)	(0.12)	(0.11)	(0.14)
λ	0.048	0.0027	-0.27	-0.15
	(0.19)	(0.17)	(0.17)	(0.19)
$\delta + \lambda$	-0.13	-0.039	-0.21***	-0.028
	(0.09)	(0.090)	(0.078)	(0.084)
Months since free distribution	12	12	12	12
Control mean	0	0	0	0
Observations	825	825	825	824

Note: The table shows estimates for four potential pathways. Panel A follows Specification (1) and Panel B follows Specification (2). All outcomes are standardized. Earnings is measured over one week and is winsorized at 5 percent. Time outside the home is the amount of time spent outside the respondent's house or yard according to time diaries. Cognitive performance is an index that combines eight Ravens Progressive Matrix puzzles and forward and backward digit spans. Bargaining power is an index that combines the respondent's budget share allocated to the evening meal and measures of participation in employment and savings decisions. We compute all indices using the first principal component. All outcomes are measured twelve months after free distribution, which coincides with the WTP elicitation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

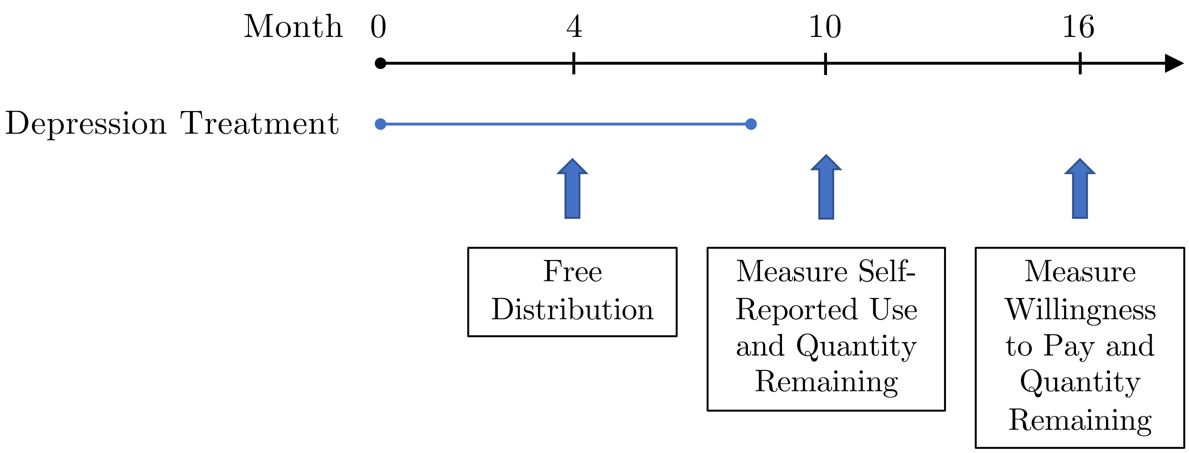


Figure 1: Study Timeline

Note: The figure shows the timing of the interventions and survey measurements. Depression treatment began in Month 0 and lasted for up to eight months. Free distribution occurred during Month 4, while depression treatment was ongoing. We measured self-reported use in Month 10 (six months after free distribution). For FD participants, we measured the quantity of distributed hand sanitizer remaining in Month 10 and Month 16 (twelve months after free distribution). We measured willingness to pay in Month 16.

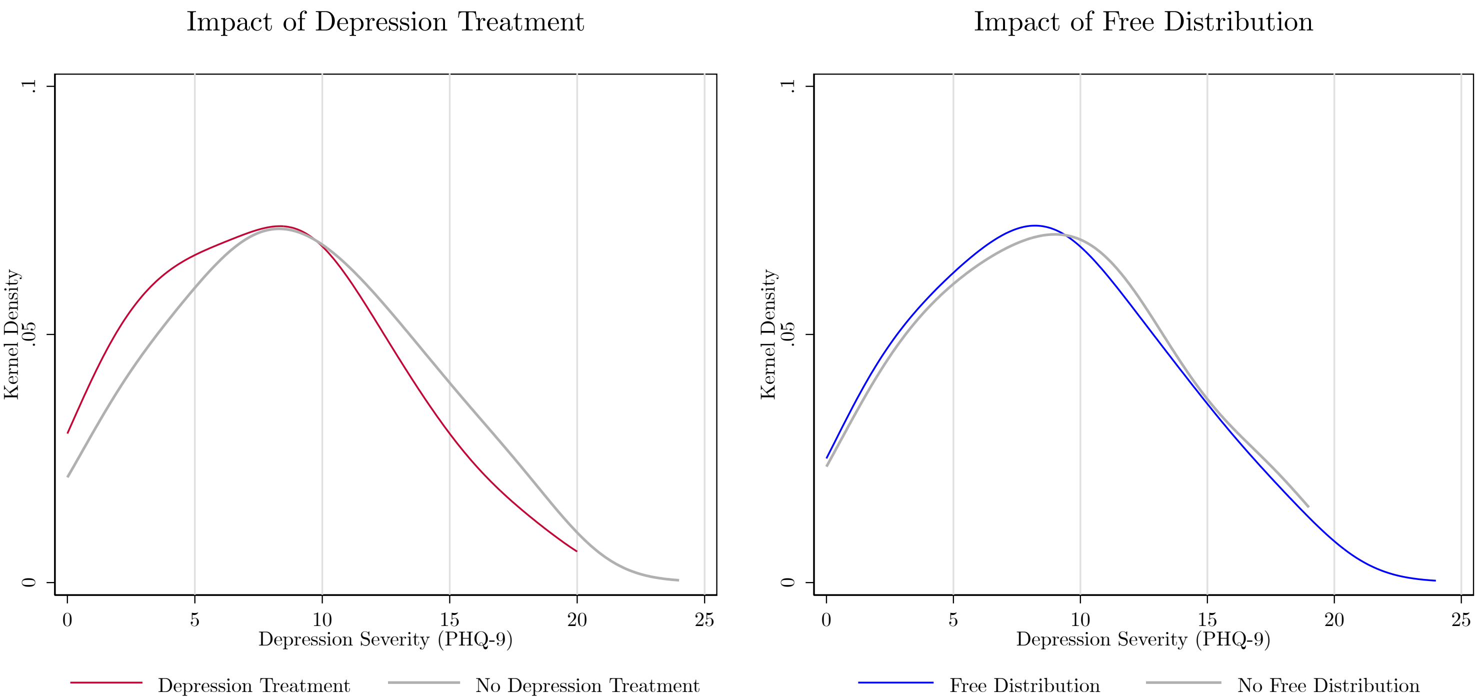


Figure 2: Impact of Depression Treatment and Free Distribution of Hand Sanitizer on Depression Severity

Note: The figure shows densities of the PHQ-9 Depression Severity Scale during the follow-up period. We pool the six month and twelve month survey rounds. The left panel compares the arms that received depression treatment and did not receive depression treatment, irrespective of free distribution. The right panel compares the arms that received free distribution and did not receive free distribution, irrespective of depression treatment. In Kolmogorov-Smirnov tests, we reject equality of the distributions in the left panel ($p = 0.001$) but we fail to reject equality of the distributions in the right panel ($p = 0.91$).

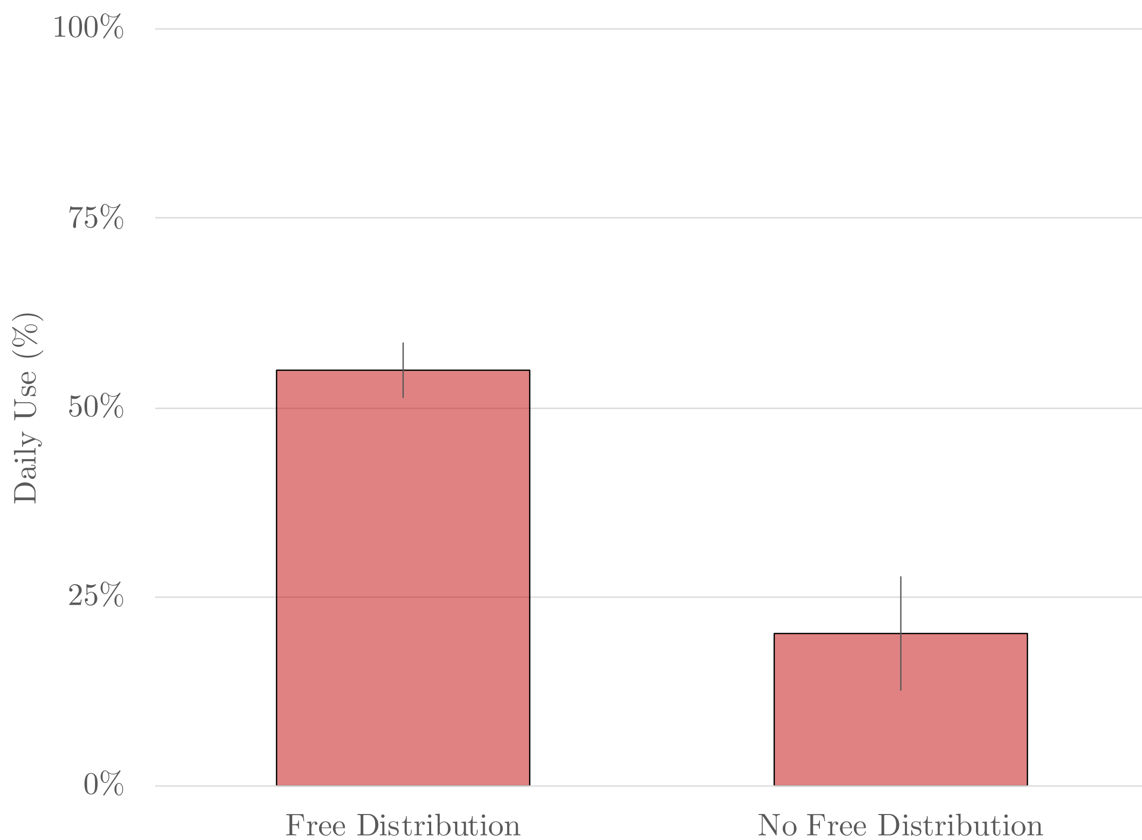


Figure 3: Impact of Free Distribution on Daily Use of Hand Sanitizer

Note: the figure shows the percent of respondents who use hand sanitizer at least daily six months after free distribution. Error bars show 90 percent confidence intervals. We reject equality of the means ($p < 0.001$).

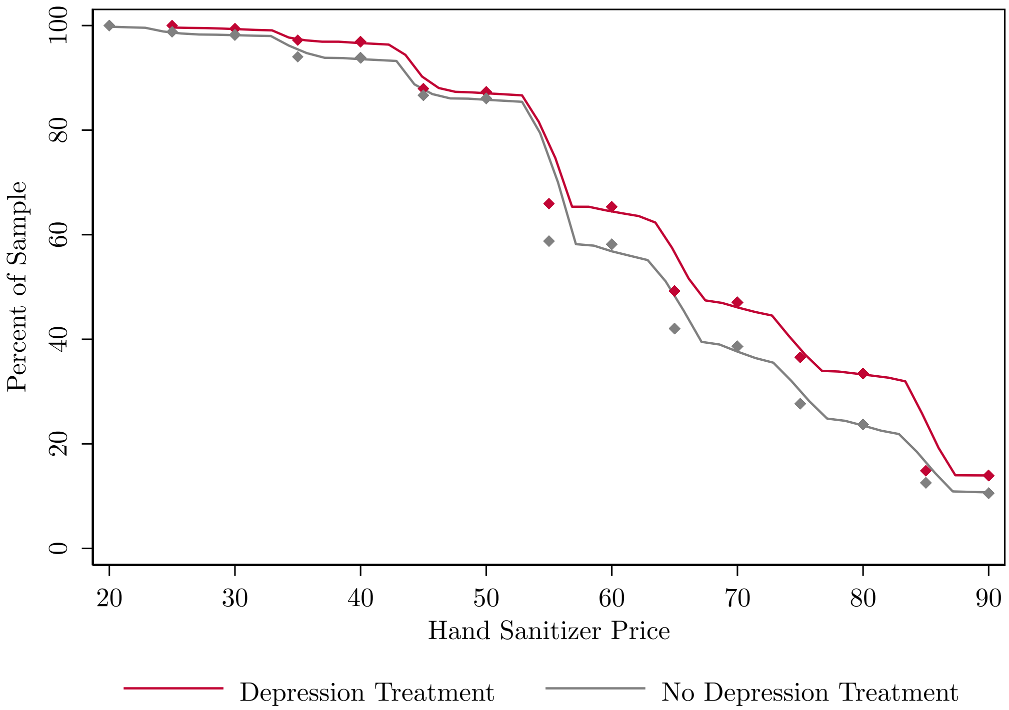


Figure 4: The Demand for Hand Sanitizer for the Depression Treatment and the No Depression Treatment Arms

Note: the figure shows the demand for a 100 ml bottle of hand sanitizer for the Depression Treatment and No Depression Treatment arms. Diamonds indicate the mean demand by intervention arm at each price. The curve is based on willingness to pay, which we elicited using the Becker-Degroot-Marschak mechanism. The local retail price was 80 rupees at the time of the experiment in 2017 ($1.17 at the 2017 exchange rate).

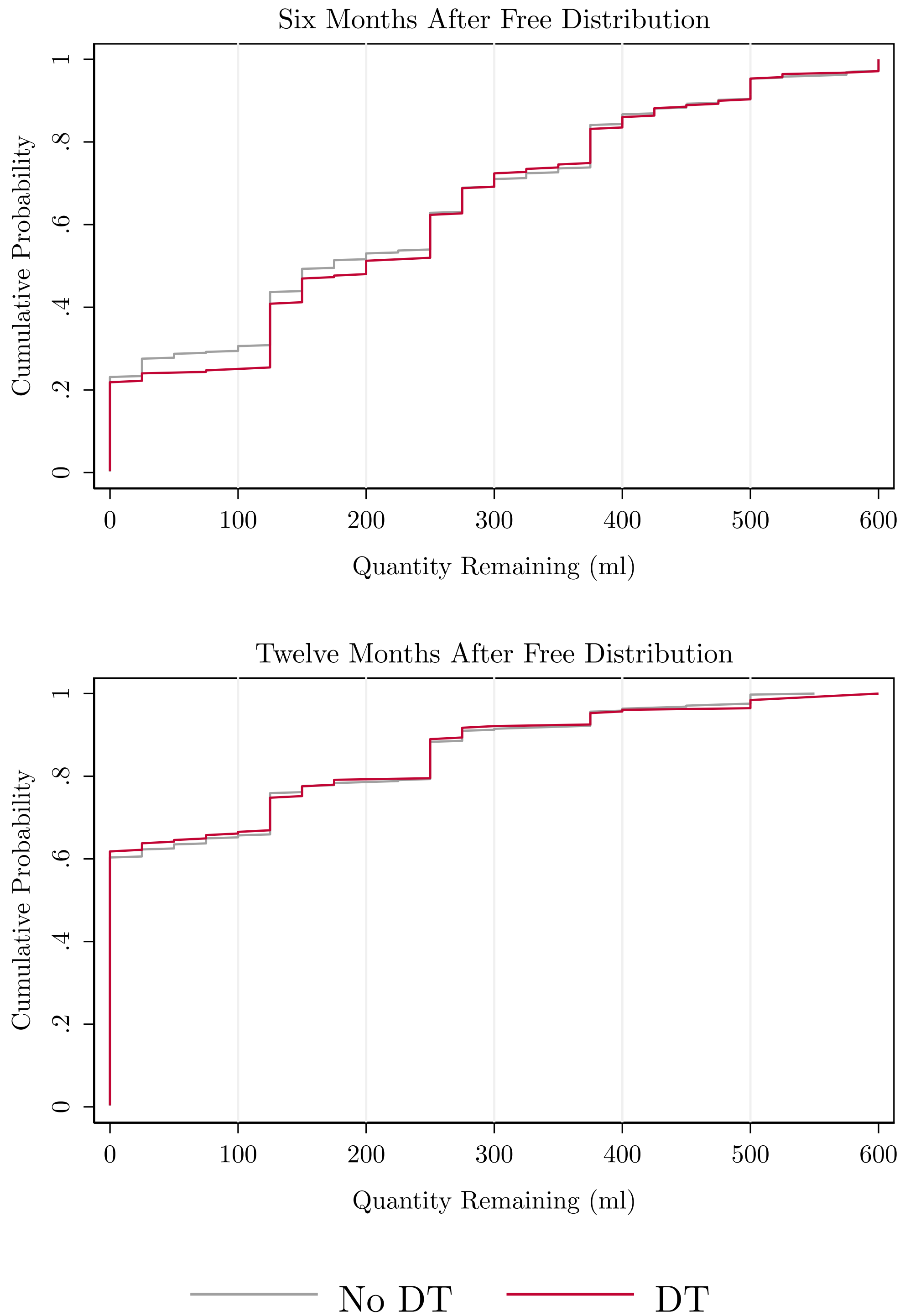
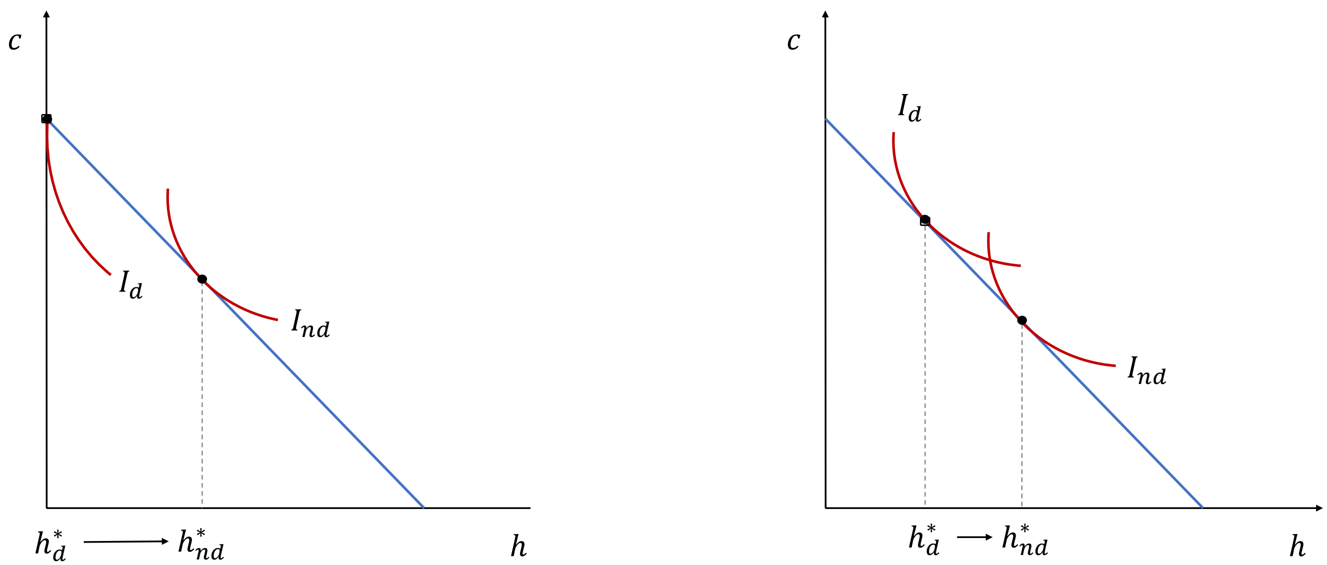


Figure 5: Quantity of Sanitizer Remaining Six and Twelve Months after Free Distribution

Note: participants in the FD arms were given 600 ml of hand sanitizer for free. The figure shows the cumulative densities of the quantity of sanitizer remaining after six months and after twelve months. The figure distinguishes between the arms that received depression treatment ("DT") and the arms that did not ("No DT"). We fail to reject the equality of the DT and no-DT distributions in both panels: the Kolmogorov-Smirnov p-values are 0.84 at six months and 0.99 at twelve months.



(A) Decision Costs

(B) Learning and Preferences

Figure 6: Pathways Through Which Depression Treatment May Increase Demand

Note: the figure shows pathways through which depression treatment may increase the adoption of a new health product. In each panel, h is the new product and c represents all other consumption. The subscripts d and nd indicate the states of being depressed and not depressed. In Panel (A), the person with depression is in a corner solution in which $h = 0$ because of a high decision cost. By reducing this cost, depression treatment may increase h without affecting the marginal rate of substitution between h and c. In Panel (B), depression treatment changes preferences or enables learning, which increases the marginal utility of h.

A Appendix

A.1 Hand Sanitizer Information Script

Finally I'd like to talk to you about the importance of keeping your hands clean. Germs are small, invisible life forms that are all around us. Some germs can make you or your children sick with illnesses like diarrhea, cough, pneumonia, ear ache, and eye infections. Some of these illnesses can be very serious and even deadly. Infants and young children are in extra danger since their bodies aren't yet strong enough to fight these illnesses. Diarrhea and pneumonia are the leading causes of death for children under five. Germs can get on your hands, clothes, and body when you use the toilet, change a diaper, or care for animals, or just touch something dirty. The skin is a barrier that keeps the germs out of your body. However people often touch their eyes, nose, and mouth without even realizing it. Once germs get inside your body, they can make you sick. You can also pass germs to other people, and they may get sick as well. You can protect yourself from germs by keeping your hands clean. Be sure to clean your hands:

- *After you use the toilet*
- *After you handle animals or work in the fields*
- *After you change a diaper*
- *After you touch someone else who is sick*
- *After you touch anything dirty*
- *Before eating or preparing food*
- *Before touching someone else, especially a small child.*

Using soap and water is the best way to wash your hands. However, soap isn't always convenient. Hand sanitizer kills almost all of the germs on your hands. Just squirt a little bit onto your hands, rub your hands together, and let your hands air dry. You don't need water. Using hand sanitizer is a good way to stay clean when you can't wash your hands.

[Surveyor demonstrates the product on himself and the respondent.]

Hand sanitizer is safe to use on your hands, but don't put it anywhere else, including your mouth or eyes. Keep it away from small children. It's safe to use, but it may sting a little if you have a cut on your hands. Do you have any questions?

A.2 Analysis of Attrition and Missing Data

This subsection provides more detail about attrition, missing data, and the selection of the estimation sample. We initially recruited 1000 adults with depression through door-to-door screening. We immediately began offering depression treatment for participants in the DT arms. Free distribution occurred four months later among a random subset of the 939 people who remained in the study at that point.

Our analysis relies on two follow-up surveys that occurred six months and twelve months after free distribution. Of the participants who were present at the time of free distribution, 5.5 percent were lost to follow-up at six months and 12.1 percent were lost to follow-up at twelve months. The lower panel of Table A1 shows the attrition in both rounds by intervention arm. We fail to reject balance in attrition across arms ($p = 0.43$ after six months and $p = 0.46$ after twelve months).

Next, we investigate the possibility of selective attrition. We implement a lasso procedure to select covariates that could be associated with attrition from among a large list of baseline respondent characteristics.[23] The procedure does not select any covariates as predictors of attrition, suggesting that selective attrition is unlikely in our setting. Finally, we construct the "propensity to attrit" according to these varaibles and use Hainmueller (2012) entropy weights to balance predicted attrition across intervention arms. We expect this procedure to have a minimal effect on our estimates, since attrition is already balanced without weighting. Estimates (available from the authors) confirm that results are robust under this weighting approach. We use all available data for each variable in the analysis. Sample sizes vary slightly across regressions because of a limited number of missing observations for particular variables.

A.3 Knowledge of Intended Use and Familiarity with Hand Sanitizer

Twelve months after free distribution, we measured knowledge of the product by asking about the intended uses of hand sanitizer. We create an indicator for participants who identified "cleaning hands" as an intended use. Given the name of the product, even people without direct experience might infer its intended purpose. At that time, surveyors also showed all respondents a 100ml bottle of hand sanitizer and asked whether respondents were familiar with the product. We create an indicator for participants who showed familiarity.

Table A3 shows estimates of the treatment effects on knowledge of the intended use and familiarity from Equations 1 and 2. Only 37 percent of control participants correctly identified the intended use of hand sanitizer and only 13 percent were familiar with the product. These patterns reinforce that hand sanitizer was a novel product in this context and that demand for hand sanitizer outside of our intervention was low. Results show that free distribution had a large effect on product awareness: according to the γ estimates in Panel B, FD increased knowledge of the intended uses of hand sanitizer by 59 percentage points (159 percent, $p < 0.001$) and increased familiarity with the product by 77 percentage points (592 percent, $p < 0.001$). Estimates for β, δ, and λ are not statistically significant,

[23] For the lasso regression, we allow the estimator to select from the following list of baseline covariates: strata indicators, round indicators, gender, marital status, education, scheduled caste/tribe, literacy, household size, PHQ-9 score and components, PHQ-9 $<$ 10 indicator, PHQ-9 $<$ 5 indicator, GAD-7 (anxiety) score and components, activities of daily living index and components, time use (all work, paid work, unpaid work, sleep, leisure, and job search hours), per capita household non-durable consumption and expenditures (total, food, non-food, clothes for children, medical), sanitation/hygiene index and components, older child human capital index and components, young child health index and components, per capita net savings and components, durable goods index and components, risk intolerance index and components, negative shock index and components, cognition index and components, subjective wellbeing index and components, participation in household decision and components.

meaning that DT did not directly affect these outcomes or moderate the impact of FD. The insignificant λ estimates provide additional evidence against the learning pathway.

A.4 Heterogeneous Treatment Effects

This appendix explores whether the impacts of DT and FD on willingness to pay and daily use vary according to the baseline characteristics of respondents or households. We consider heterogeneity by the age, gender, marital status, household head status, education, and earnings of respondents, as well as the income, consumption, size, and composition (presence of small children) of households. We divide the sample according to these characteristics and split at the median for continuous variables (age, education, household income, household consumption, and household size). For willingness to pay, Figure A4 shows subgroup heterogeneity in the effect of DT and Figure A5 shows subgroup heterogeneity in the effect of FD. The effect of DT is larger for men, married people, and people with below-median household income. The effect of FD is larger for people with large households. We do not find statistically significant differences by age, household head status, education, earnings, household consumption, or the presence of young children. For daily use, Figure A6 shows subgroup heterogeneity in the effect of DT and Figure A7 shows subgroup heterogeneity in the effect of FD. The effect of DT on daily use is not significantly different across any subgroups. The effect of FD on daily use is larger for small households.

In addition, we use seemingly unrelated regressions (SUR) to test whether these heterogeneous effects across subgroups are jointly significant. For willingness to pay, heterogeneity in impacts is not jointly significant for DT ($p = 0.66$) and is jointly significant for FD ($p = 0.06$). For daily use, heterogeneity in impacts is not jointly significant for either DT or FD ($p = 0.96$ for DT and $p = 0.22$ for FD).

We also test and reject the hypothesis that DT has heterogeneous impacts on PHQ-9: respondents whose households contain young children have significantly larger impacts of DT, but other dimensions of heterogeneity are not statistically significant (estimates are available upon request). This finding does not support the hypothesis that heterogeneity in the impact of DT on WTP could be due to heterogeneity in the impact of DT on depression severity.

A.5 The Role of Livelihoods Assistance

A subset of study participants were cross-randomized to receive a livelihoods assistance (LA) intervention as part of the larger study (Angelucci and Bennett 2022). LA is a light-touch intervention incorporating two NGO-moderated group meetings to discuss work-related issues and a handful of one-on-one meetings with NGO staff to help participants identify and pursue income-generating activities. Strategies were tailored to the circumstances of participants, and included job search assistance, small loans, and training. 68 percent of LA respondents attended at least one group or individual meeting. However, LA had no effect on time use, employment, or earnings. The disproportionate share of women in our sample may have weakened the labor market effects of LA. While the intervention had a minimal effect on depression severity, it amplified the benefit of pharmacotherapy when the treatments were offered jointly.

Since LA alone had a negligible effect on depression severity or socioeconomic outcomes, it is unlikely that LA had an independent effect on WTP for hand sanitizer. As a robustness test, Table A4 reproduces Table 1 (Panel A) with three alternative specifications. In Panel A, we add an indicator variable for LA to Equation 1 in order to control for any additive effect of the LA intervention on WTP and product use. Panel B limits the sample to participants in the LA arms and Panel C limits the sample to participants not in the LA arms. A comparison with Table 1 shows that the key coefficient estimates are similar: DT increases the willingness to pay for hand sanitizer by about 3 rupees across all specifications. Similarly, we find increases in the demand for hand sanitizer at prices of 40-80 rupees in all specifications. Fewer estimates in Panels B and C are statistically significant because dividing the sample reduces statistical power. We find a negative and significant effect of DT on daily use in Panel B ($p = 0.06$). Column 1 shows that FD has a statistically insignificant effect on WTP in all panels. However, two point estimates in Panel B are negative and significant.

Next, we use SUR to test whether estimates differ significantly across these three regressions. P-values for these tests appear at the bottom of the table. Estimates do not vary significantly (with one exception for γ in Column 4 and β in Column 5). We also use this method to test whether impacts on WTP and daily use are jointly significantly different from zero. In Column 1, we reject the hypothesis that the β estimates are jointly equal to zero ($p = 0.03$) and in Column 9, we fail to reject the hypothesis that the β estimates are jointly equal to zero ($p = 0.28$). These patterns support the validity of pooling across LA arms in our main analysis.

A.6 Heterogeneity According to Quantity Remaining

Free distribution could potentially suppress product demand if recipients had not yet exhausted their distributed supplies (Fischer et al. 2019). This issue is unlikely to influence our results since most FD participants had exhausted the distributed hand sanitizer by the time of the WTP elicitation. As a robustness test, Table A5 examines heterogeneity in the impact on WTP according to the quantity of hand sanitizer that the respondent still possessed at twelve months. While the estimates are not statistically significant in Columns 1 and 2 (the smallest samples), point estimates are similar across samples and we cannot reject equality of the coefficients in the table ($p = 0.53$). Although the quantity remaining is endogenous, the similarity of these estimates suggests that the presence of some remaining distributed sanitizer is not a major consideration in practice.

Table A1: Baseline Characteristics of the Estimation Sample by Intervention Arm

	DT + FD	DT Only	FD Only	Control	P-Value
	(1)	(2)	(3)	(4)	(5)
A: Respondent Characteristics					
Age	35.3	35.6	35.4	35.4	0.76
Female	0.83	0.85	0.89	0.85	0.10*
Married	0.78	0.80	0.78	0.74	0.77
Schooling (years)	4.8	5.6	4.9	5.0	0.66
Scheduled caste/tribe	0.56	0.49	0.53	0.44	0.28
Literacy (1-3)	1.9	2.0	1.9	1.9	0.78
Household size	4.1	4.4	4.1	4.1	0.34
Joint p-value	–	–	–	–	0.50
B: Outcome Variables					
PHQ-9 depression scale (0-27)	13.5	14.4	14.3	13.7	0.08*
Major depression (PHQ-9 $\geq$ 10)	0.85	0.93	0.88	0.84	0.12
Earnings (std.)	0.19	0.07	0.02	0	0.41
Health-related budget share	0.12	0.13	0.12	0.12	0.84
Time outside the home (std.)	-0.12	-0.09	-0.15	0	0.64
Bargaining power (std.)	0.09	-0.16	0	0	0.26
Cognitive performance (std.)	0.04	0.05	0.06	0	0.79
Joint p-value	–	–	–	–	0.40
Attrition after six months	0.04	0.04	0.07	0.06	0.43
Attrition after twelve months	0.13	0.08	0.12	0.14	0.46
Observations	293	75	465	106	–

Note: The table reports baseline means by intervention arm for respondent characteristics and available outcome variables. The sample consists of 939 respondents who remained in the study at the time of free distribution. We do not observe willingness to pay or hand sanitizer use at baseline. DT indicates depression treatment and FD indicates free distribution. P-values in Column 5, which are based on regressions with village-clustered standard errors, test whether the four arms are jointly significantly different. Joint p-values at the bottom of each panel are based on multinomial logistic regressions of the four intervention arms on all of the variables in each panel. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Treatment Effects on Depression Severity

(1) $Y_{ij} = \alpha \ + \ \beta DT_j \ + \ \gamma FD_{ij} \ + \ X_j'\theta \ + \ \varepsilon_{ij}$

(2) $Y_{ij} = \eta \ + \ \delta DT_j \ + \ \theta FD_{ij} \ + \ \lambda(DT_j \times FD_{ij}) \ + \ X_j'\psi \ + \ \varepsilon_{ij}$

	Depression Severity PHQ-9 (std.)		Major Depression $\mathbb{1}$(PHQ-9 $\geq$ 10)	
	(1)	(2)	(3)	(4)
A: Specification (1)				
β	-0.22***	-0.18**	-0.066*	-0.087**
	(0.077)	(0.071)	(0.037)	(0.036)
γ	-0.054	-0.066	-0.019	-0.050
	(0.089)	(0.086)	(0.045)	(0.043)
B: Specification (2)				
δ	-0.29*	-0.18	-0.079	-0.013
	(0.16)	(0.15)	(0.080)	(0.074)
θ	-0.088	-0.063	-0.026	-0.011
	(0.12)	(0.12)	(0.060)	(0.059)
λ	0.082	-0.0070	0.016	-0.092
	(0.18)	(0.17)	(0.091)	(0.085)
$\delta + \lambda$	-0.20**	-0.18**	-0.06	-0.11***
	(0.09)	(0.08)	(0.04)	(0.04)
Months since free distribution	6	12	6	12
Control mean	0	0	0.45	0.46
Observations	887	825	887	825

Note: The table reports AIT effects following Equations (1) and (2). Village-clustered standard errors appear in parentheses. Columns 1-2 show impacts on standardized PHQ-9 scores. Columns 3-4 show impacts on the probability that the PHQ-9 score is at least 10, which corresponds approximately to major depressive disorder. Columns 1 and 3 show results six months after free distribution and Columns 2 and 4 show results twelve months after free distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Treatment Effects on Hand Sanitizer Knowledge and Familiarity

(1) $Y_{ij} = \alpha \ + \ \beta DT_j \ + \ \gamma FD_{ij} \ + \ X_j'\theta \ + \ \varepsilon_{ij}$

(2) $Y_{ij} = \eta \ + \ \delta DT_j \ + \ \theta FD_{ij} \ + \ \lambda(DT_j \times FD_{ij}) \ + \ X_j'\psi \ + \ \varepsilon_{ij}$

	Knowledge of Intended Use	Familiarity
	(1)	(2)
A: Specification (1)		
β	-0.015	0.013
	(0.025)	(0.024)
γ	0.54***	0.77***
	(0.044)	(0.032)
B: Specification (2)		
δ	0.086	0.030
	(0.089)	(0.061)
θ	0.59***	0.77***
	(0.053)	(0.040)
λ	-0.13	-0.022
	(0.092)	(0.066)
$\delta + \lambda$	-0.041*	0.008
	(0.022)	(0.025)
Months since free distribution	12	12
Control mean	0.37	0.13
Observations	825	825

Note: The table reports AIT effects following Equations (1) and (2). Village-clustered standard errors appear in parentheses. Column 1 shows an indicator that the respondent correctly identifies "to clean hands" as the intended use of hand sanitizer. Column 2 shows an indicator for self-reported familiarity with the product. Both outcomes are measures twelve months after free distribution. $\delta + \lambda$ indicates the impact of DT within the free distribution arms. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Treatment Effects on the Willingness to Pay for Hand Sanitizer by Livelihoods Assistance Arm

$Y_{ij} = \alpha + \beta DT_j + \gamma FD_{ij} + X_j'\theta + \varepsilon_{ij}$

		$\mathbb{1}(WTP \geq X)$							Daily Use
	WTP	$X = 30$	$X = 40$	$X = 50$	$X = 60$	$X = 70$	$X = 80$	$X = 85$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A: Control for Livelihoods Assistance									
β	3.53***	0.012	0.034**	0.019	0.076**	0.088**	0.10***	0.028	-0.040
	(1.24)	(0.0082)	(0.014)	(0.023)	(0.035)	(0.035)	(0.033)	(0.026)	(0.043)
γ	-0.15	-0.0079	-0.0021	-0.016	0.014	-0.025	0.0016	0.023	0.25***
	(1.45)	(0.0079)	(0.017)	(0.028)	(0.042)	(0.045)	(0.040)	(0.030)	(0.066)
Control mean	60.7	0.99	0.93	0.86	0.54	0.37	0.22	0.12	0.22
Observations	825	825	825	825	825	825	825	825	821
B: Livelihoods Assistance Arms Only									
β	4.66**	0.015	0.029	-0.0012	0.18***	0.11**	0.13***	0.015	-0.13*
	(1.91)	(0.015)	(0.027)	(0.039)	(0.053)	(0.053)	(0.050)	(0.035)	(0.067)
γ	-2.27	-0.013*	-0.029	-0.096**	-0.033	-0.082	-0.016	0.037	0.092
	(2.16)	(0.0076)	(0.025)	(0.041)	(0.067)	(0.068)	(0.059)	(0.037)	(0.11)
Control mean	58.5	1.0	0.91	0.83	0.52	0.35	0.13	0.04	0.30
Observations	329	329	329	329	329	329	329	329	325
C: No Livelihoods Assistance Arms Only									
β	2.60	0.0095	0.038**	0.029	-0.0036	0.068	0.080*	0.038	0.011
	(1.63)	(0.0092)	(0.016)	(0.028)	(0.047)	(0.047)	(0.044)	(0.036)	(0.056)
γ	1.11	-0.0052	0.013	0.023	0.060	0.0072	0.016	0.0034	0.33***
	(1.92)	(0.011)	(0.023)	(0.036)	(0.055)	(0.061)	(0.052)	(0.043)	(0.081)
Control mean	61.5	0.99	0.94	0.85	0.54	0.38	0.25	0.15	0.21
Observations	496	496	496	496	496	496	496	496	496
β differs across panels (p-value)	0.67	0.92	0.93	0.70	0.03	0.81	0.74	0.90	0.25
γ differs across panels (p-value)	0.47	0.84	0.44	0.05	0.43	0.58	0.91	0.58	0.58

Note: The table follows Equation 1 and reports AIT effects. Panel A includes an indicator for the Livelihoods Intervention (LA) arms as a covariate, Panel B is limited to respondents in the LA arms, and Panel C is limited to respondents not in the LA arms. Village-clustered standard errors appear in parentheses. Column 1 shows willingness to pay for a 100ml bottle of hand sanitizer, which was elicited through the Becker-Degroot-Marschak mechanism. Columns 2-8 show the impact on an indicator that the willingness to pay is greater or equal than X rupees, for $X \in \{30, 40, 50, 60, 70, 80, 85\}$. The local retail price of this product is 80 rupees. Column 9 shows self-reported daily use. WTP outcomes are measured twelve months after free distribution and daily use is measured six months after free distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Impact of DT on WTP by Quantity of Distributed Hand Sanitizer Remaining Among FD Participants

$(Y_{ij} = \rho + \pi DT_j + X_j'\tau + \varepsilon_{ij}) \mid FD_{ij} = 1$

	WTP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
π	1.89	2.37	3.01*	3.01**	2.86**	2.49*	2.63*
	(1.84)	(1.78)	(1.58)	(1.49)	(1.44)	(1.43)	(1.42)
Months since Free Distribution	12	12	12	12	12	12	12
Quantity remaining (ml)	0ml	$\leq$ 100ml	$\leq$ 200ml	$\leq$ 300ml	$\leq$ 400ml	$\leq$ 500ml	Any
Quantity remaining (%)	0	$\leq$ 17%	$\leq$ 33%	$\leq$ 50%	$\leq$ 67%	$\leq$ 83%	Any
Observations	405	439	524	610	640	660	665

Note: The table shows the impact of depression treatment on the willingness to pay for a 100ml bottle of hand sanitizer, which was elicited through the Becker-Degroot-Marschak mechanism. The local retail price of this product is 80 rupees. Village-clustered standard errors appear in parentheses. The sample is limited to the free distribution arms. Columns 1-6 limit the sample to respondents with $\leq X$ milliliters of distributed hand sanitizer remaining, for $X \in \{0, 100, 200, 300, 400, 500\}$, and Column 7 shows the estimate for the full FD sample. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Impact of DT on Quantity of Sanitizer Remaining Among FD Participants

$(Y_{ij} = \rho + \pi DT_j + X_j'\tau + \varepsilon_{ij}) \mid FD_{ij} = 1$

	Sanitizer Remaining (%)	
	(1)	(2)
π	0.018	-0.0050
	(0.024)	(0.020)
Control mean	0.35	0.15
Observations	707	665

Note: The table reports the impact of depression treatment on the percent of distributed hand sanitizer remaining among FD participants. All regressions control for strata indicators. Column 1 reports results six months after free distribution and Column 2 reports results twelve months after free distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Hand Sanitizer Bottle

Note: The figure illustrates the product that respondents purchased through the Becker-Degroot-Marschak mechanism. Surveyors elicited the willingness to pay for a 100ml bottle of Himalaya brand liquid hand sanitizer.

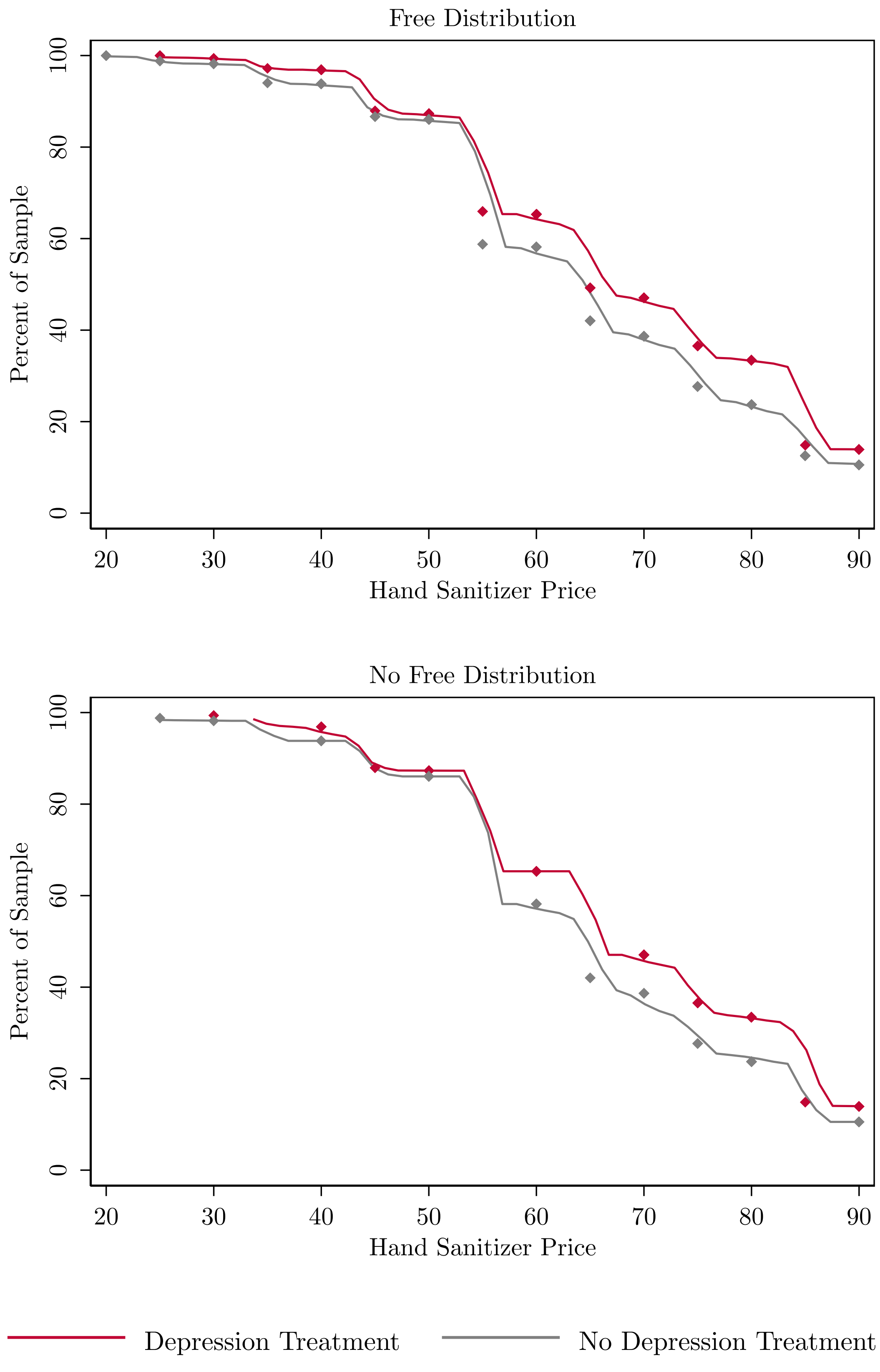


Figure A2: The Impact of Depression Treatment on the Demand for Hand Sanitizer Within the Free Distribution and No Free Distribution Arms

Note: the figure shows the demand for a 100 ml bottle of hand sanitizer by depression treatment. The top panel shows results for the arms that received free distribution and the bottom panel shows results for the arms that did not receive free distribution. Diamonds indicate the mean demand by intervention arm at each price. Curves are based on willingness to pay, which we elicited using the Becker-Degroot-Marschak mechanism. The local retail price is 80 rupees.

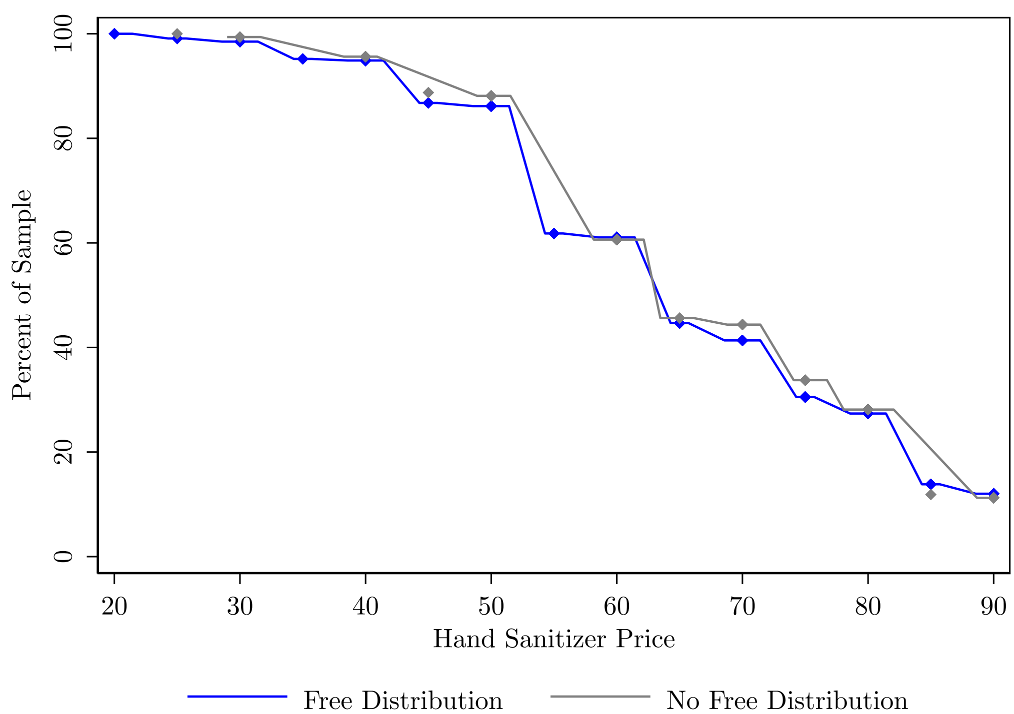


Figure A3: The Demand for Hand Sanitizer for the Free Distribution and No Free Distribution Groups

Note: The figure shows the demand for a 100 ml bottle of hand sanitizer for the Free Distribution and No Free Distribution arms. Diamonds indicate the mean demand by intervention arm at each price. The curve is based on willingness to pay, which we elicited using the Becker-Degroot-Marschak mechanism.

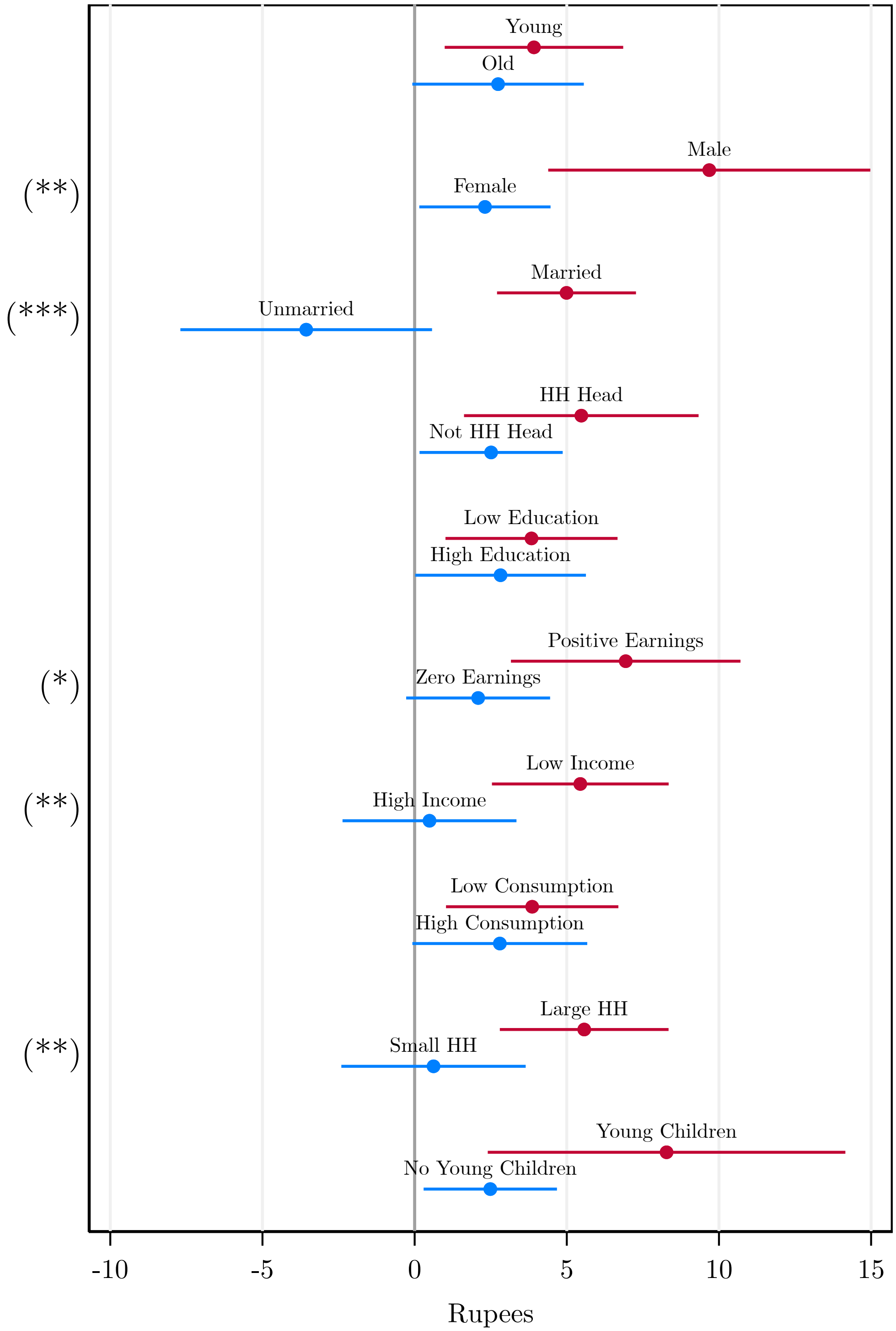


Figure A4: Subgroup Heterogeneity in the Impact of Depression Treatment on WTP

Note: the figure shows subgroup heterogeneity in the impact of depression treatment on willingness to pay according to age, gender, marital status, status as the household head, education, earnings, household income, household consumption, household size, and the presence of young children. Estimates follow Equation (1). Age, education, household income, household consumption, and household size are divided at the median. All subgroups are defined using baseline values. Error bars indicate 90 percent confidence intervals. Stars indicate statistically significant differences in the impact of DT across subgroups: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

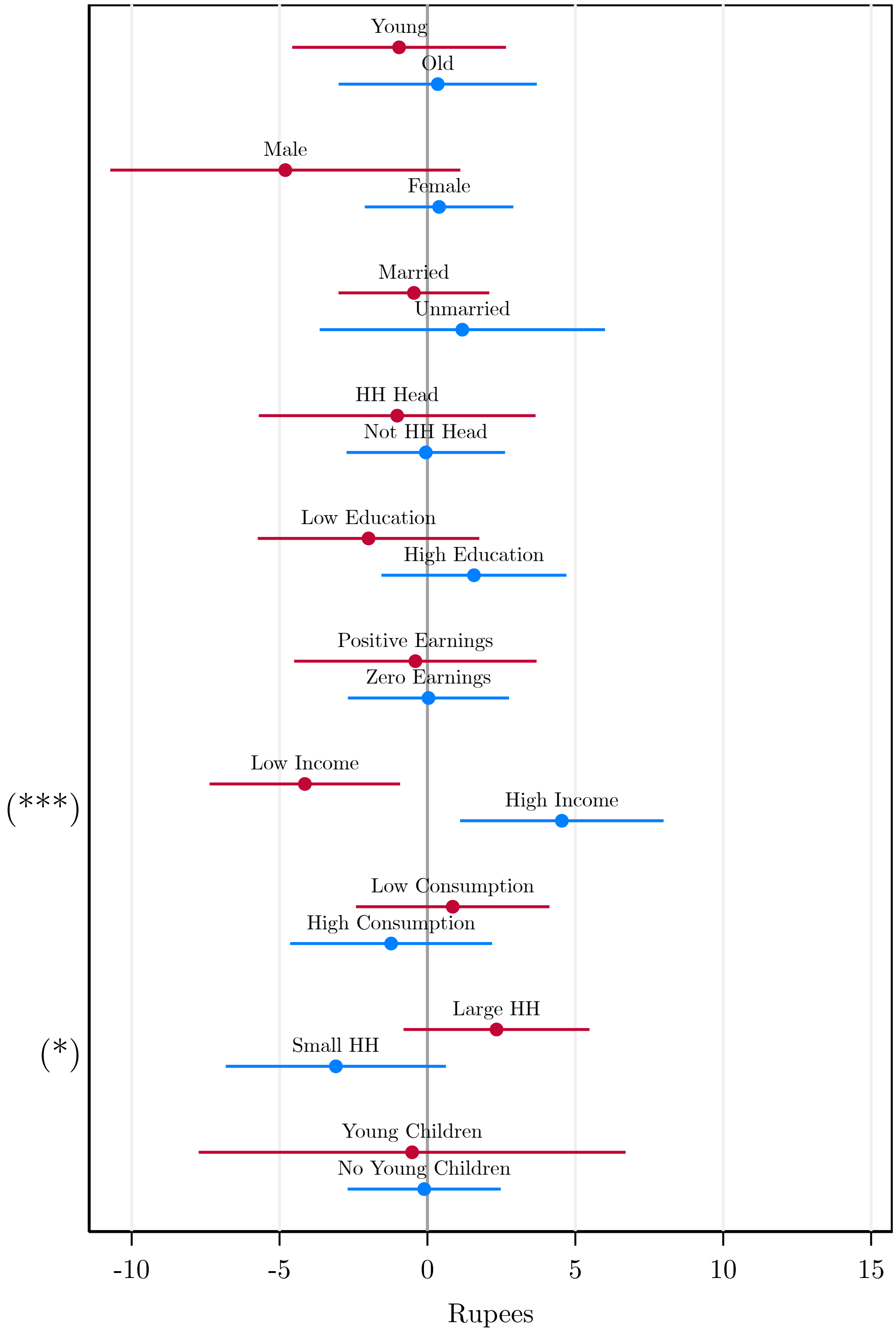


Figure A5: Subgroup Heterogeneity in the Impact of Free Distribution on WTP

Note: the figure shows subgroup heterogeneity in the impact of free distribution on willingness to pay according to age, gender, marital status, status as the household head, education, earnings, household income, household consumption, household size, and the presence of young children. Estimates follow Equation (1). Age, education, household income, household consumption, and household size are divided at the median. All subgroups are defined using baseline values. Error bars indicate 90 percent confidence intervals. Stars indicate statistically significant differences in the impact of FD across subgroups: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

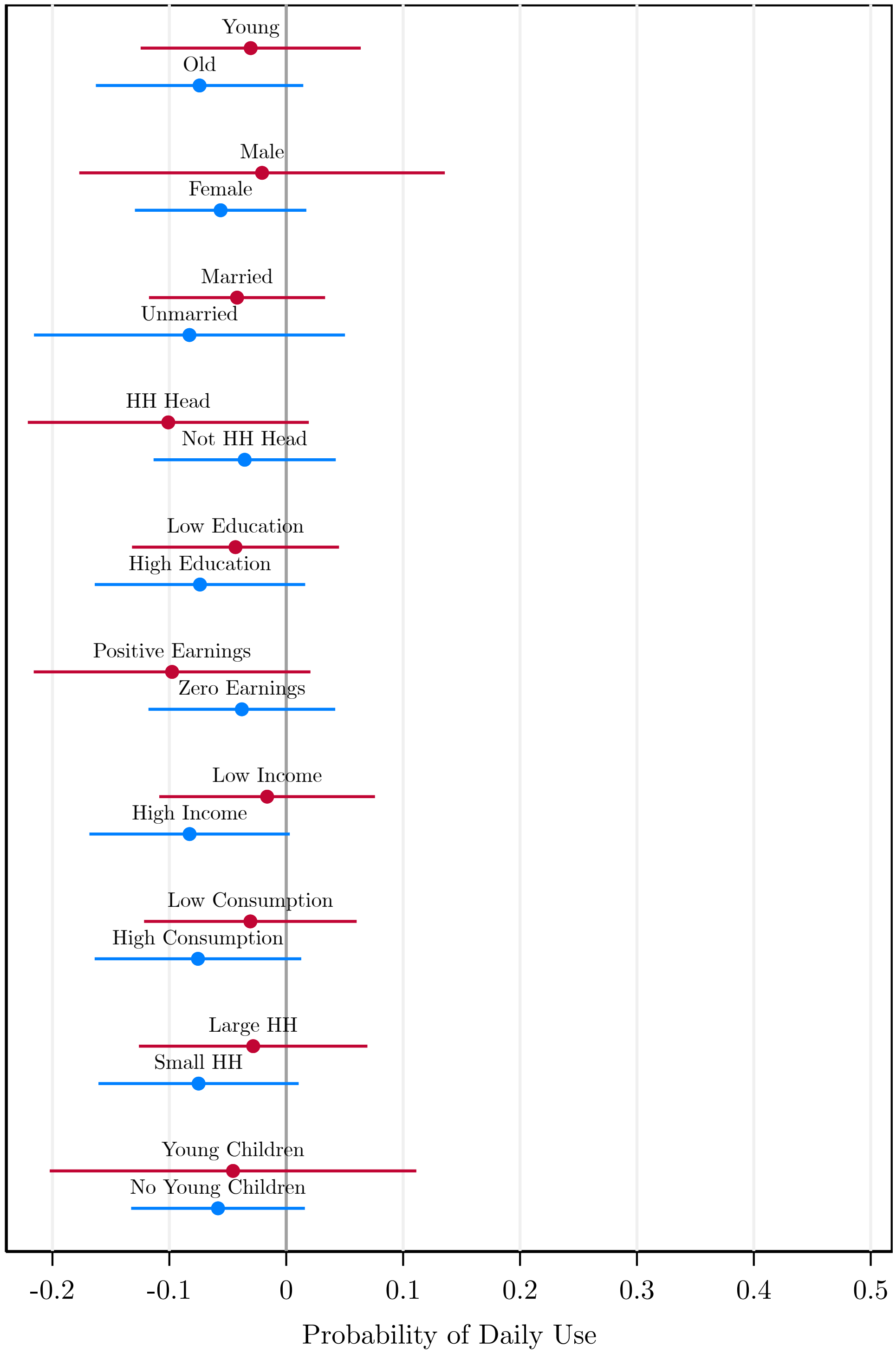


Figure A6: Heterogeneity in the Impact of Depression Treatment on Daily Use

Note: the figure shows subgroup heterogeneity in the impact of depression treatment on willingness to pay according to age, gender, marital status, status as the household head, education, earnings, household income, household consumption, household size, and the presence of young children. Estimates follow Equation (1). Age, education, household income, household consumption, and household size are divided at the median. All subgroups are defined using baseline values. Error bars indicate 90 percent confidence intervals. Stars indicate statistically significant differences in the impact of DT across subgroups: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

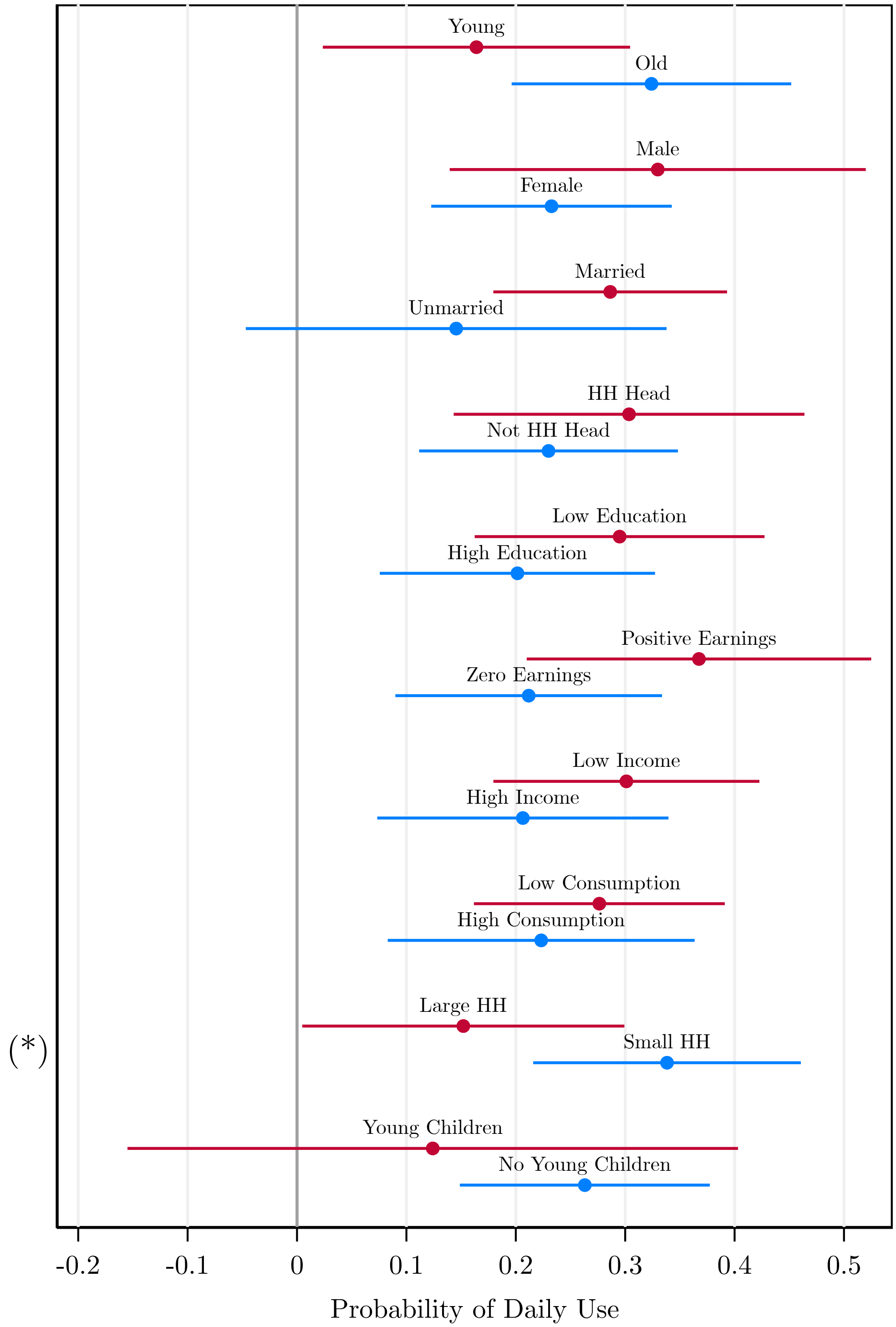


Figure A7: Heterogeneity in the Impact of Free Distribution on Daily Use

Note: the figure shows subgroup heterogeneity in the impact of free distribution on self-reported daily use according to age, gender, marital status, status as the household head, education, earnings, household income, household consumption, household size, and the presence of young children. Estimates follow Equation (1). Age, education, household income, household consumption, and household size are divided at the median. All subgroups are defined using baseline values. Error bars indicate 90 percent confidence intervals. Stars indicate statistically significant differences in the impact of FD across subgroups: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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