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

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Abstract

We investigate the link between depression and the demand for a novel health product, hand sanitizer, in India. We cross-randomize pharmacotherapy and free distribution of the product, and measure impacts on willingness to pay and product use. Depression treatment improves mental health and increases willingness to pay, implying that having major depression reduces willingness to pay by 26 percent. It does not change product use, which is high after free distribution regardless of depression treatment. We rule out effects through the budget constraint, preferences, time use, and experiential learning. Results are consistent with an effect of depression on decision costs.

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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, 24 percent of adults in our low-income study area have at least some depression symptoms. Rates of depression are even higher in specific sub-populations. The prevalence of depression is around 50 percent among elderly women in China, India, and Mexico (Banerjee et al. 2023); it is around 40 percent among ultrapoor women in the Democratic Republic of Congo (Angelucci et al. 2022).

Depression may influence the demand for health products through several pathways. For example, it may raise the decision costs of adoption and reduce the marginal utility of these products by increasing indecisiveness, anhedonia, and pessimism. It may interfere with learning about the benefits of unfamiliar products by affecting cognition. In addition, it may reduce the value of prevention by changing risk and time preferences or lower purchasing power by reducing labor supply and productivity.

We study the relationship between depression and the demand for a preventative health

[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.

product, liquid hand sanitizer. Hand sanitizer is a useful alternative to soap in settings where infectious diseases are common and people have 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 conducted a field experiment in Karnataka, India, in which we treated people for depression. 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), as well as product use. This design allows us to measure how depression treatment affects both the willingness to pay for a novel preventative health product and the use of the product under free distribution.

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.

This study has two main findings. First, 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. Secondly, 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.

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 does not necessarily cause widespread wastage because depression decouples demand from use. Because it leads to high use regardless of depression treatment, free distribution may be an effective way to foster technology adoption in psychologically distressed populations. For hand sanitizer, free distribution at the point of use, such as through sanitizer stations near latrines, may be a cost-saving approach.

We investigate potential pathways that could contribute to the effect of depression treatment on demand. We do not find evidence that changes in experiential learning, preferences, income, time use, cognition, or intrahousehold bargaining explain our findings. We reject these pathways because they all entail increases in both WTP and use, which is not the pattern we observe. In addition, the effect of depression treatment on WTP is not higher in the free distribution group, which is inconsistent with experiential learning. DT does not increase the demand for health-related consumption in general, which is inconsistent with a preferences pathway. The intervention does not affect income, time use, or intrahousehold bargaining, which weighs against each of these pathways. Finally, we find that DT decreases cognitive performance, which is unlikely to explain the pattern of higher WTP and no change in use.

Instead, the finding that depression treatment increases WTP without changing product use is consistent with a decision costs pathway. The choice to buy a novel product like hand sanitizer entails decision costs. By making a person more indecisive, depression may magnify these costs and thereby reduce WTP without affecting use conditional on ownership.

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 (Bhat et al. 2022). 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 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 also contribute to the study of the psychology of poverty (e.g., Mani et al. 2013, Mullainathan and Shafir 2013, Haushofer and Fehr 2014, Haushofer and Shapiro 2016) and of the links between depression and decision-making (Baranov et al. 2020, Bhat et al. 2022). Depression, which is more common among poor people, may be a channel through which poverty affects decision-making. This study also provides new evidence of a link between mental and physical health (Ohrnberger et al. 2017). A large body of research documents associations between mental and physical health, with a focus on non-communicable diseases. We contribute by providing evidence of a causal effect on a novel dimension of health behavior.

2 Study Design and Implementation

2.1 Treatments

We partnered with Grameena Abudaya Seva Samsthe (GASS), a local NGO that assists people with physical and mental disabilities. GASS facilitates psychiatric care by organizing walk-in clinics and driving people to health centers. It also offers livelihoods assistance by connecting workers to prospective employers and providing small start-up loans.

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. The most frequently prescribed anti-depressants were Selective Serotonin Reuptake Inhibitors (SSRIs), which have mild and well-understood side effects (Cascade et al. 2009) and are effective for treatment of unipolar adult major depression disorder (Gartlehner et al. 2017, Cipriani et al. 2018). A local NGO provided participants with return transportation to psychiatric appointments and made monthly visits to all participants to monitor side effects. 48 percent of participants attended at least one psychiatric visit. Angelucci and Bennett (2022) describe this intervention in more detail and study its effects on depression and socioeconomic outcomes but do not consider the FD intervention.[2] Appendix A.1 discusses ethical aspects of the DT intervention.

For the FD intervention, we provided 600ml of hand sanitizer (one 500ml bottle and one more portable 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.2 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.

We recruited 1-2 people per locality and screened 6446 people 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

[2] Some study participants were cross-randomized to receive a livelihoods assistance (LA) intervention as part of the larger study. LA incorporated 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. LA had no effect on time use, employment, earnings or depression severity but it amplified the benefit of pharmacotherapy on depression when the treatments were offered jointly. We return to this issue below.

of people with mild or moderate depression symptoms, we recruited subjects with PHQ-9 scores of 9-20.[3]

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 intervention was ongoing and 94 percent of the original sample remained in the study. We offered FD to 80 percent of these participants and randomized at the individual level. Everyone in the FD intervention accepted the product. The disproportionate share of people in the FD arms improves statistical power to assess the impact of depression treatment on product use under free distribution.[4]

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 measured quantity remaining of the distributed product and self-reported use. Twelve months after free distribution, we measured quantity remaining again, and we observed that most FD participants had depleted the freely distributed supplies. We also elicited willingness to pay. This staggered approach allowed us to measure product use when most people still had the distributed product and to measure demand when most people had depleted the product.[5] 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 create an indicator

[3]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.

[4]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.

[5]Six percent of participants present when free distribution occurred had attrited six months later, and twelve percent one year later. Appendix A.3 shows that attrition is balanced across intervention arms and implements several robustness tests.

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. Figure A.1 shows a picture of the 100ml bottle. 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). Appendix A.4 provides the script of the willingness to pay elicitation.

We measure product use through the quantity of hand sanitizer remaining in the bottles distributed to FD participants. We observe this outcome six months and twelve months after free distribution. At twelve months, only 8 percent of FD respondents had more than half of the distributed product remaining. As a robustness check, we also elicit self-reported daily use for all participants at six months.[6] For FD group members with hand sanitizer remaining, daily use and quantity remaining are negatively correlated, suggesting that frequent personal use corresponds to lower quantity remaining. We also assess product knowledge and familiarity at twelve months. Only 9 percent of control participants were familiar with hand sanitizer, which confirms 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

[6]Since self-reported use may be subject to recall or experimenter demand bias, we do not consider it a primary outcome in this analysis. We attempted to measure self-reported use at twelve months but software issues led to a high number of missing observations, which rendered this variable unusable. 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.

employment and savings decisions. We compute the cognitive performance and bargaining power indices using the first principal component.

Table 1 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 $p = 0.40$ for outcomes). Baseline depression severity is highest in the arm receiving depression treatment only (Column 2). 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 described in Section 2.2. 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 cluster standard errors by locality in all specifications.

5 Proximate Effects of Depression Treatment and Free Distribution

Table 2 shows treatment effects on depression severity according to Equations (1) and (2). Columns 1 and 2 show estimates for an indicator that the PHQ-9 score is at least 10, which is the threshold consistent with major depression. Columns 3 and 4 show estimates for the standardized PHQ-9 score. Six months after free distribution, the DT intervention reduced the probability of major depression by 6.6 percentage points (95% CI: -13.9 to 0.6) and reduced PHQ-9 scores by 0.22 standard deviations (SD; 95% CI: -0.37 to -0.07). Twelve months after free distribution, the DT intervention reduced the probability of major depression by 8.7 percentage points (95% CI: -15.8 to -1.6). This estimate represents a 19 percent reduction from the control group mean. The DT intervention also reduced PHQ-9 scores by 0.18 SD (95% CI: -0.32 to -0.04). These effect sizes align with other studies in the literature (Singla et al. 2017, Gartlehner et al. 2017). The statistically insignificant λ estimates in Panel B indicate that the impact of DT on depression severity is similar across the FD and no-FD arms. In addition, small and insignificant γ and θ estimates show that, as expected, free distribution did not have a significant effect on depression severity.

Our subsequent discussion presumes that depression treatment primarily works by improving mental health, rather than through other independent channels. Treatment potentially has other effects, such as side effects of the medications. However, only 15 DT compliers report that they experienced side effects. Section 7.2 offers additional support for this interpretation.

Free distribution had 100 percent uptake, as all participants accepted the offered product. Free distribution also led to widespread use: at six months, FD participants had used 65 percent of the distributed hand sanitizer and 23 percent of participants had fully depleted the product. At this time, 54 percent of FD participants indicated that they used hand sanitizer at least daily, compared to 18 percent of no-FD participants ($p < 0.001$). By the time of the WTP elicitation at twelve months, FD participants had used 85 percent of the distributed hand sanitizer and 61 percent of participants had fully depleted the product. Only 8 percent of respondents had more than half of the distributed product remaining. We conclude that free distribution increased the use of hand sanitizer. Consistent with this pattern, we also find large effects of free distribution on product knowledge and familiarity. Table A.3 and Appendix A.6 provide further details.

6 Depression Treatment and the Demand for Hand Sanitizer

6.1 Depression Treatment Increases the WTP for Hand Sanitizer

Figure 2 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 is 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 curve is very similar to the no-FD curve in Figure A.3.

Panel A of Table 3 provides average intent-to-treat effects on willingness to pay according to Equation (1). Column 1 shows that depression treatment increases WTP by 3.27 rupees

[9]Figure A.2 reproduces Figure 2 separately for the FD and no-FD arms. These figures closely resemble Figure 2.

(95% CI: 0.83 to 5.71), a 4.9 percent increase. Extrapolating from the 19 percent reduction in the share of people with symptoms of major depression, 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 2-7 examine the impact on indicators that WTP exceeds several price thresholds. In Column 2, depression treatment increases demand by 1 percentage point (95% CI: -0.4 to 2.7) at a price of 30 rupees (a 1 percent increase), while it increases demand by 10 percentage points (95% CI: 3.2 to 16.3) at a price of 80 rupees (a 50 percent increase). We reject the equality of the DT coefficients in Columns 2-7 ($p = 0.04$), meaning that depression treatment changes the slope of the demand curve.[11] 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. 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 of δ and $\delta + \lambda$ are less precise because we do not pool intervention arms. In Columns 2-7, 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 the impact of depression treatment on WTP. Finally, estimates of θ are mostly positive and statistically insignificant, suggesting that FD does not reduce demand through anchoring effects, unlike in Fischer et al. (2019).[12]

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

[12] Table A.1 and shows that results are robust to using entropy weights to impose balance across arms in baseline depression severity. Appendix A.5 shows that results are robust to accounting for the LA intervention. 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 3 does not affect our estimates.

6.2 Depression Treatment Does Not Increase the Use of Hand Sanitizer

Table 4 shows the impact of DT on the quantity of distributed hand sanitizer remaining within the FD arms. The effect of DT is 10.7 ml (95% CI: -18.1 to 39.6) or 1.8 percent (95% CI: -3.0 to 6.6) after six months and -3.0 ml (95% CI: -26.3 to 20.3) or -0.5 percent (95% CI: -4.3 to 3.4) after twelve months. To investigate further, Figure 3 plots the cumulative densities of the quantity remaining for the DT and no-DT arms after six months and twelve months. The distributions are very similar in both rounds, and Kolmogorov-Smirnov tests fail to reject equality ($p = 0.84$ at six months and $p = 0.99$ at twelve months).[13] As a robustness test, Table A.3 shows estimates of Equations (1) and (2) for self-reported daily use, knowledge of the intended use of the product, and familiarity with the product. These results (discussed further in Appendix A.6) are consistent with the quantity remaining estimates. This evidence also confirms that free distribution recipients had little hand sanitizer left by the time of the WTP elicitation. Appendix A.7 investigates subgroup heterogeneity for WTP and product use and Appendix A.8 shows that the effect of DT on WTP does not vary systematically across people with different amounts of hand sanitizer remaining.

7 Evidence Regarding Potential Pathways

7.1 Pathways

We consider several pathways through which depression and depression treatment may affect product demand.

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 to be higher (Heiner 1983, Gigerenzer and Gaissmaier 2011). Consider the choices of a consumer with income y over a novel health good, h, and another normal good, c. The consumer incurs a

[13] Table A.2 and Figure A.4 show that these results are robust to using entropy weights to impose balance in baseline PHQ-9 scores.

decision cost, $k \geq 0$, if she purchases a positive quantity of the health good:

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

$$\text{subject to:}$$

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

We let the decision cost be a function of p. A positive relationship between the price and the decision cost aligns with evidence that high stakes impair performance (Ariely et al. 2009). An increase in k reduces the demand for the health good by increasing the potential for a corner solution in which $h^* = 0$. However, the decision cost associated with purchasing the product does not affect product use conditional on ownership.[14] Indecisiveness, which is a common depression symptom, may amplify decision costs (Leykin and DeRubeis 2010, Leykin et al. 2011, Beck and Alford 2009). As a result, depression may reduce the demand for the health product without affecting use conditional on ownership.

Experiential Learning. Experiential learning about the value of a novel product is an important pathway to 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, thus increasing both WTP and use. By impairing concentration or cognition, depression could disrupt learning and thereby blunt the positive effect of free distribution on WTP and use (Kuzis et al. 1997, Moritz et al. 2002).[15]

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

[14] In some cases, choosing whether to use a product may entail additional decision costs. To use some goods, the consumer must bear an additional cost (e.g., follow complex instructions or experience unpleasant side effects), which may require the consumer to weigh the pros and cons of using a product she already owns. For hand sanitizer, the marginal cost of using the product after purchasing it is minimal. Therefore, the decision costs associated with use are negligible.

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

as the marginal utility of other goods). If these symptoms lead depressed people to disfavor hand sanitizer, then depression should suppress both WTP and product use.

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 through these channels by decreasing the expected value of health-related prevention. Since anhedonia, pessimism, and risk and time preferences have similar predictions, we proceed to refer to these channels collectively as "preferences pathways."

7.2 Evidence

Our estimates for WTP and product use allow us to test these predictions. Under the decision costs pathway, depression treatment increases WTP but does not affect product use. Conversely, under the preferences and experiential learning pathways, depression treatment increases both WTP and product use. Column 1 of Table 3 shows that DT increases WTP both overall (β) and for the FD and no-FD subgroups (δ and $\delta+\lambda$). However, Table 4 shows that DT does not affect product use. This pattern is consistent with the decision costs pathway and is inconsistent with the preferences and experiential learning pathways.[16,17]

Under our interpretation that decision costs are an underlying mechanism, the finding in Figure 1 that DT makes demand significantly less elastic suggests that decision costs may increase with product price. If decision costs were price-invariant, depression would lead to lower demand in the no-DT arms for all prices. This finding may be relevant for policy, as

[16] 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.

[17] 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 $\lambda < 0$. Free distribution should also increase WTP regardless of DT, so that $\theta > 0$. This pattern may be present: while neither estimate in Column 1 of Table 3 is statistically significant, the λ estimate is negative and the θ estimate positive.

we discuss in Section 8.[18]

Table 5 provides several additional findings that help to rule out alternative explanations. Under the preferences pathways, depression treatment may increase the demand for health-related consumption more generally. However, Column 1 shows that DT does not increase the share of health-related expenditures within the household budget. Depression treatment could enhance purchasing power by increasing earnings or household income. Column 2 shows that earnings do not increase.[19] Depression treatment could increase product demand by making people become more active, which might mechanically increase the usefulness of the product. In Column 3, we find no statistically significant changes in time spent outside the home, which is inconsistent with this pathway. Next, depression treatment could improve cognition, leading people to place more value on the product. However, Column 4 shows that impact on cognition is actually negative.[20] Finally, depression treatment could increase bargaining power (Baranov et al. 2020), which would increase WTP if study participants value hand sanitizer more highly than other household decision-makers. Column 5 shows no economically or statistically significant impacts on this outcome. Therefore, these channels are unlikely to explain the positive effect on WTP. The null effect of DT on product use is also inconsistent with an effect through these pathways.

Finally, this discussion presumes 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. These components could independently affect time use (e.g., through self-isolation or self-care), intra-

[18]We expect decision costs to be lower for *familiar* products because the buyer can more easily evaluate the benefits of these goods. Therefore, depression may have a weaker effect on the demand for familiar products through the decision costs pathway. 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$). If we standardize the prices of biscuits and hand sanitizer, the impact of DT for hand sanitizer is 46 percent larger but the difference is no longer statistically significant ($p = 0.40$).

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

[20]It is unlikely that *lower* cognition increases WTP. Cognitive performance is positively correlated with WTP within the no-DT arms ($\rho = 0.15$), which is consistent with a literature that links cognition to health investment (e.g. Conti et al. 2010). Moreover, a cognition channel would affect both WTP and product use in the same direction, which is not the pattern we observe.

household bargaining power, or the salience of health and prevention. Null estimates for bargaining power and time use in Table 5 suggest that these non-depression channels 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 A.3) suggests 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.

8 Policy Implications

These findings help to explain why demand for preventative health products in developing countries is low. 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. We also find that depression decouples WTP from product use. This pattern may explain the low correlation between product price and use in studies by Cohen and Dupas (2010), Dupas (2014a), Tarozzi et al. (2014), and others.

These findings also contribute to the debate about how to design effective policies to increase product adoption. Free distribution may be an effective policy in high-depression settings: charging a positive price could screen out many depressed people who would use a product that they owned. By contrast, free distribution may lead to high use and limited wastage. For products like hand sanitizer, point-of-use distribution (e.g., by providing sanitizer stations near latrines) may maximize reach and limit wastage.

More generally, interventions that lower decision costs may foster technology adoption in high-depression settings. Decision costs are a likely barrier to the uptake of a range of programs, such as welfare programs and health insurance (Banerjee et al. 2021, Finkelstein et al. 2019, Finkelstein and Notowidigdo 2019). The use of smart defaults could be a promising way to encourage adoption in psychologically depressed communities. For example, if depression leads to inaction, policies that automatically enroll people may disproportionately increase adoption among people with depression (Bhat et al. 2022).

Our results also suggest that decision costs may be increasing in prices. Under this potential link, depressed people may be especially responsive to adequate price subsidies, which also reduce decision costs. For example, in our study, subsidies of at least 50% may also be effective. 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).

9 Conclusions

A well-known public health puzzle in developing countries is that the adoption of preventative health products is low and demand is 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, which is common in low-income settings, 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.

Since depression is often endemic in high-poverty settings (Ridley et al. 2020), these findings may help 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) commonly observed in studies in low and middle-income countries. Our results strengthen the argument for free distribution over cost-sharing in high-depression settings, especially for products with highly elastic demand.

Although depression could affect WTP through several possible pathways, we do not find evidence that depression affects product demand by changing risk and time preferences, anhedonia, pessimism, experiential learning, earnings, time use, cognitive performance, or bargaining power. The most plausible explanation is that indecisiveness, which is a common depression symptom, increases the decision costs of the purchase. If decision costs are an important pathway through which depression reduces demand, interventions that minimize these costs (e.g., by bringing the product to users or implementing smart defaults) may be especially effective for people with depression.

Table 1: 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					
Major depression (PHQ-9 $\geq$ 10)	0.85	0.93	0.88	0.84	0.12
PHQ-9 depression scale (0-27)	13.5	14.4	14.3	13.7	0.08
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 quantity remaining of hand sanitizer 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.

Table 2: Treatment Effects on Depression Severity

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

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

	Major Depression $\mathbb{1}$(PHQ-9 $\geq$ 10)		Depression Severity PHQ-9 (std.)	
	(1)	(2)	(3)	(4)
A: Specification (1)				
β	-0.066*	-0.087**	-0.22***	-0.18**
	(0.037)	(0.036)	(0.077)	(0.071)
γ	-0.019	-0.050	-0.054	-0.066
	(0.045)	(0.043)	(0.089)	(0.086)
B: Specification (2)				
δ	-0.079	-0.013	-0.29*	-0.18
	(0.080)	(0.074)	(0.16)	(0.15)
θ	-0.026	-0.011	-0.088	-0.063
	(0.060)	(0.059)	(0.12)	(0.12)
λ	0.016	-0.092	0.082	-0.0070
	(0.091)	(0.085)	(0.18)	(0.17)
$\delta + \lambda$	-0.06	-0.11***	-0.20**	-0.18**
	(0.04)	(0.04)	(0.09)	(0.08)
Months since free distribution	6	12	6	12
Control mean	0.45	0.46	0	0
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 the probability that the PHQ-9 score is at least 10, which corresponds approximately to major depressive disorder. Columns 3-4 show impacts on standardized PHQ-9 scores. 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 3: Treatment Effects on Willingness to Pay for Hand Sanitizer

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

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

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

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 2-7 shows indicators that the willingness to pay is greater or equal than X rupees, for $X \in \{30, 40, 50, 60, 70, 80\}$. The local retail price of this product is 80 rupees. WTP outcomes are measured twelve months after free distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Treatment Effects on Quantity of Hand Sanitizer Remaining

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

	Milliliters		Percent	
	(1)	(2)	(3)	(4)
π	10.7	-3.03	0.018	-0.005
	(14.7)	(11.9)	(0.024)	(0.020)
Months since free distribution	6	12	6	12
Control mean	210	89	0.35	0.15
Observations	707	665	707	665

Note: The table reports AIT estimates of the effect of DT on the quantity of distributed hand sanitizer remaining among FD participants. Columns 1 and 3 show results six months after free distribution and Columns 2 and 4 show results twelve months after free distribution. Columns 1-2 show estimates in milliliters and Columns 3-4 express estimates as a percent of the originally distributed quantity (600ml). Village-clustered standard errors appear in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Treatment Effects Related to Several Potential Pathways

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

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

	Health Budget Share	Earnings	Time Outside The Home	Cognitive Performance	Bargaining Power
	(1)	(2)	(3)	(4)	(5)
A: Specification (1)					
β	-0.007	-74.3*	-1.37	-0.16**	0.0007
	(0.0065)	(42.9)	(2.59)	(0.069)	(0.075)
γ	-0.007	48.4	2.07	0.015	0.028
	(0.0085)	(51.5)	(2.85)	(0.085)	(0.097)
B: Specification (2)					
δ	0.016	-95.1	-1.44	0.063	0.12
	(0.016)	(89.5)	(4.67)	(0.15)	(0.17)
θ	0.006	37.5	2.03	0.13	0.089
	(0.011)	(70.6)	(4.05)	(0.11)	(0.14)
λ	-0.029*	26.1	0.092	-0.27	-0.15
	(0.018)	(102.4)	(5.67)	(0.17)	(0.19)
$\delta + \lambda$	-0.013	-69.0	-1.35	-0.21***	-0.028
	(0.007)	(48.9)	(3.06)	(0.078)	(0.084)
Months since free distribution	12	12	12	12	12
Control mean	0.12	362	21.7	0	0
Observations	825	825	825	825	824

Note: The table shows estimates for five potential pathways. Panel A follows Specification (1) and Panel B follows Specification (2). Health budget share is the share of household budget for health-related consumption. Earnings is measured in rupees per week and is winsorized at 5 percent. Time outside the home is the number of hours per week 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 the cognitive peformance index and the bargaining power index using the first principal component and standardize these variables using the control group mean. All outcomes are measured twelve months after free distribution, which coincides with the WTP elicitation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

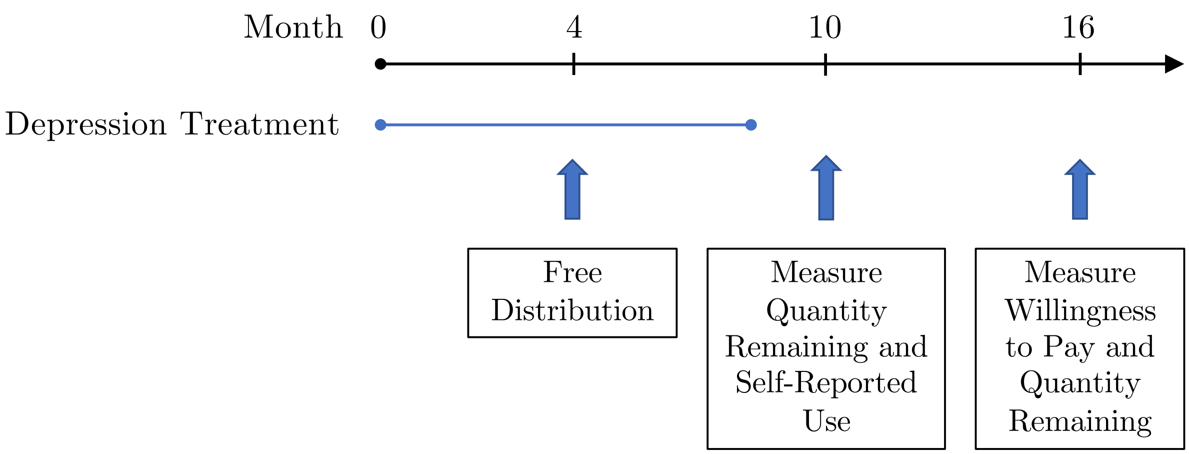

Figure 1: Study Timeline

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. For FD participants, we measured the quantity of distributed hand sanitizer remaining in Month 10 and Month 16. We measured willingness to pay in Month 16. We measured self-reported use in Month 10.

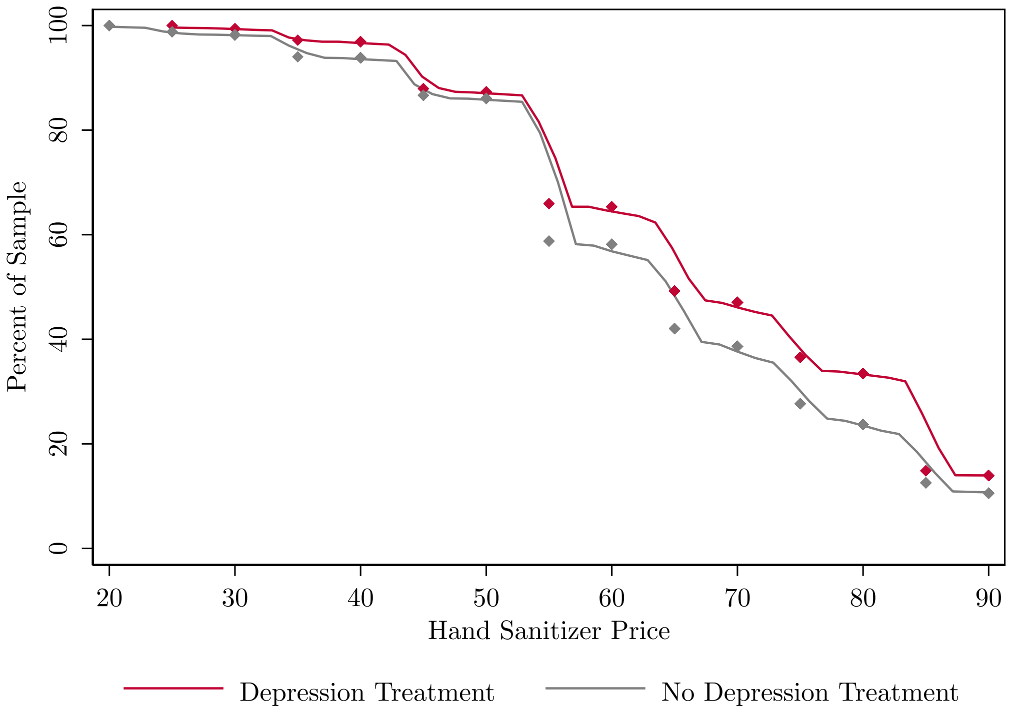

Figure 2: The Demand for Hand Sanitizer for the Depression Treatment and the No Depression Treatment Arms

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).

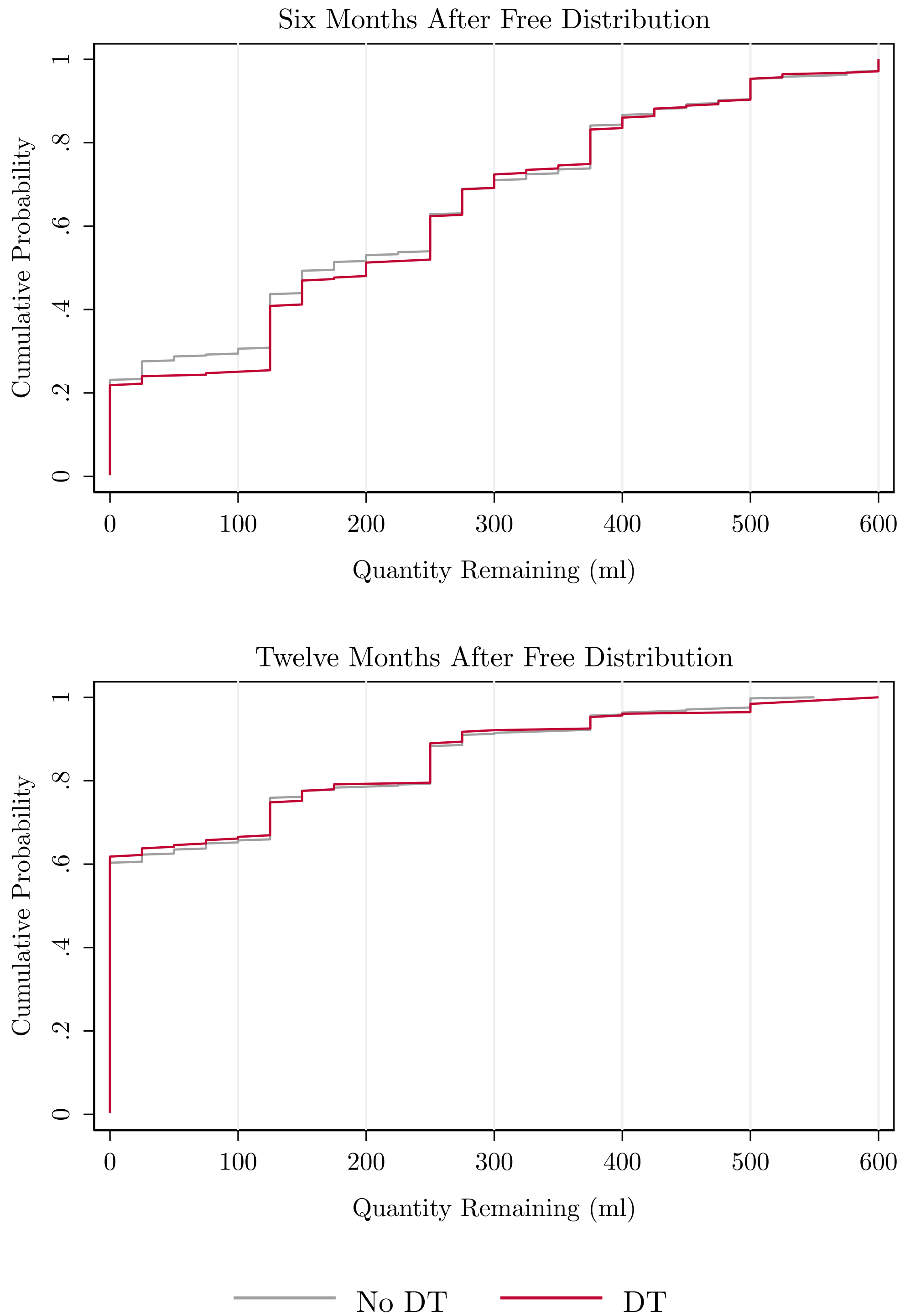

Figure 3: Quantity of Sanitizer Remaining Six and Twelve Months after Free Distribution

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 Appendix

A.1 Ethics and IRB Oversight

This appendix describes the ethical considerations for this study. The Institutional Ethical Committee of the Shridevi Institute of Medical Sciences and Research Hospital in Tumkur, Karnataka provided primary oversight of the pharmacotherapy intervention. We also received IRB approval from the Institute for Financial Management and Research (IFMR), which led the data collection, and the University of Chicago, the University of Michigan, the University of Southern California, the University of Texas at Austin.

The DT intervention facilitated the provision of a service that was otherwise available in the community. For example, each subdivision operates a public hospital with weekly psychiatric office hours for drop-in treatment. SSRIs are also available for free through these consultations.

We developed practices to ensure the safety and protection of study participants. We solicited written informed consent before participating in the initial screening to identify people with depression symptoms who were eligible for the study. Moreover, we sought consent again before participants joined the study and completed the baseline survey. Lastly, when seeking consent for screening or intervention participation, we informed subjects of the availability of free health care from the local hospital during the weekly clinics.

We developed a protocol to monitor the wellbeing of all study participants throughout the study. Subjects with PHQ-9 scores greater than 20, indicating severe depression, were ineligible to join the study. Anyone with a PHQ-9 score of 21 or more was referred for immediate treatment for free at Shridevi Hospital. In practice, 19 people had a PHQ-9 score greater than 20 during screening. All study participants received monthly staff visits. Our protocol required anyone whose symptoms worsened into severe depression to be referred for immediate treatment for free at Shridevi Hospital.

A psychiatrist established a customized course of treatment for each DT participant. The research team did not play a role in determining courses of treatment. Participants with depression received off-patent SSRIs such as escitalopram, fluoxetine, paroxetine, or setraline. These FDA-approved medications have been widely used since 1988 to treat depression (Hillhouse and Porter 2015). Side effects for these drugs include nausea, nervousness, dizziness, reduced sexual desire, drowsiness, insomnia, weight gain or loss, headache, dry mouth, vomiting, and diarrhea. Reduced sexual desire, weight gain, and sleep disturbance are the most common side effects. Side effects are generally mild and changing drugs or adjusting the dosage can generally minimize them (Ferguson 2001). In practice, 12 percent of DT compliers ($n = 15$) reported experiencing any side effects after the intervention.

A.2 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.3 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 1 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.[21] 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.4 Willingness to Pay: Elicitation Script and Other Considerations

This appendix describes our implementation of the Becker-Degroot-Marschak (BDM, 1964) elicitation of willingness to pay. In the exercise, 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 good if the offer price is less than the drawn price. Surveyors began by practicing the game with a package of biscuits (cookies) with a retail price of Rs. 30. After verifying that participants understood the game, surveyors elicited the WTP for hand sanitizer. The script of this elicitation follows:

I will need your full attention for this activity. I would like to play a game to understand how much you value this bottle of hand sanitizer. We may have played this game with you before, but let me explain it again.

[Surveyor shows bottle.]

In this game, I will offer to sell you this 100 ml bottle of hand sanitizer. You won't have to buy the product if you don't want to, and you will not have to spend any more than you wish. The MRP of this bottle is Rs. 80, but you can choose whatever price you want in this game. To pick a price, think about how valuable this product is for you and how much money you can afford to spend. For example, if this product is not very valuable to you, you could bid Rs. 5 or even less. If the product is very valuable to you, you could bid Rs. 80 or more. You might bid more than Rs. 80 if you don't want to go to the trouble of finding the product at a shop. However if you can only afford to spend Rs. 50 today, you may wish to bid Rs. 50 even if you think the product is worth more. There is no right or wrong answer, and different people may give different bids.

[21] 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.

Here's how the game works:

1. *I will ask you the highest price that you would be willing to pay for this bottle, which is your bid.*
2. *This bag holds many cards. Each card has a different price written on it. Surveyor shows bag and cards. I will ask you to select a card from the bag.*
3. *If the price from the bag is less than your bid, you will buy the bottle for the price on the card. If you draw a price of zero from the bag, you will get the item for free.*
4. *If the price from the bag is more than your bid, you will not be able to buy the bottle.*

Here are some things to remember:

- *You will only have one chance to play for the bottle of hand sanitizer.*
- *You cannot change your bid after you draw from the bag.*
- *If your bid is higher than the price on the card, you will need to buy and pay for the bottle immediately. Say the price that you are actually willing to pay right now.*
- *Think carefully about how much the bottle is worth to you. Once you think of a value, ask yourself, "is the bottle really worth a little more or a little less?"*
- *The best strategy is to say the highest price you are willing to pay for the bottle. If you answer truthfully, you are guaranteed to get the bottle at the price you want to pay or less.*
- *Even if you played this game before and received free hand sanitizer, this time you may have to pay, depending on how you bid.*

Do you have any questions?

[Play a practice round with a packet of biscuits.]

Let's practice on this packet of biscuits. These biscuits are available at local shops for Rs.30, but in this game you can offer to buy them for whatever price you want. One person said he would pay Rs. 40 because he loves biscuits and wants to have them right now. Another woman said that she would only pay Rs. 2 because she doesn't like them. Think carefully about how much the biscuits are worth you.

[Respondent states bid X.]

Please take a moment to check if you have Rs. X to pay for the biscuits.

[Surveyor waits while respondent checks.]

This is just a practice round, but in the real game, you will be required to pay for the product if you bid more than the price that draw from the bag.

This bag contains cards with many different prices on them. Please take a card from the bag.

[The surveyor and respondent look at the price on the card.]

A. If the price on the card is higher than the bid: You drew a price that was higher than your bid. What happens now?

[Surveyor and respondent discuss the rules of the game: the respondent does not purchase the biscuits.]

B. If the price on the card is lower than the bid: You drew a price that was lower than your bid. What happens now?

[Surveyor and respondent discuss the rules of the game: the respondent purchases the biscuits for the price on the card.]

This was a trial run. Do you have any questions about the game?

[Take time to answer questions.]

[Play for real with the bottle of hand sanitizer.]

Now we will play for real with this bottle of hand sanitizer. Hand sanitizer cleans the germs on your hands when you can't use soap and water. Using it will help keep you and your family healthy. The MRP of this bottle is Rs. 80 but in this game you can offer to buy it for whatever price you want. To pick a price, think about how valuable this product is for you and how much money you can afford to spend. For example, if this product is not very valuable to you, you could bid Rs. 10 or even less. If the product is very valuable to you, you could bid Rs. 80 or more. You might bid more than Rs. 80 if you don't want to go to the trouble of finding the product at a shop. However if you can only afford to spend Rs. 50 today, you may wish to bid Rs. 50 even if you think the product is worth more. There is no right or wrong answer, and different people may give different bids. Once you think of a number, ask yourself, "is this bottle really worth a little more or a little less?"

[Respondent states bid X.]

Please take a moment to make sure you have Rs. X with you to pay for the bottle. Surveyor waits while the respondent checks. You will be required to buy the bottle if you bid more than the price on the card.

[Respondent draws a price from the bag.]

A. Since your bid was higher than the price on the card, you will receive the hand sanitizer and pay Rs. [AMOUNT ON CARD]

B. Since your bid was lower than the price on the card, you will not receive the hand sanitizer and will not pay anything.

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.

We also elicited 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 0.97 rupees at the time of free distribution (95% CI: -1.51 to 3.46) and increases WTP by 2.60 rupees twelve months later (95% CI: -0.18 to 5.38). The pooled effect is 1.79 rupees (95% CI: -0.14 to 3.72).

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 no 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 A.4 reproduces Table 3 (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. Next, 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 3 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. 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 the exception of γ in Column 4 and β in Column 5). We also use this method to test whether the impact on WTP is jointly significantly different from zero across the three approaches. In Column 1, we reject the hypothesis that the β estimates are jointly equal to zero ($p = 0.03$). β estimates in Columns 3, 5, 6, and 7 are also jointly statistically significant. These patterns support the validity of pooling across LA arms in our main analysis.

A.6 Impacts on Self-Reported Use, Knowledge of Intended Use, and Familiarity with Hand Sanitizer

Six months after free distribution, when most FD participants had not yet depleted the freely distributed supplies of hand sanitizer, we elicited from respondents whether they used hand sanitizer at least daily. 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 A.3 shows estimates of the treatment effects on these outcomes following Equations (1) and (2). 22 percent of control participants indicated that they used the product daily after six months. However, only 37 percent of control participants correctly identified the intended use of hand sanitizer and only 13 percent were familiar with the product after twelve months. 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. They also suggest that the daily use variable may be over-reported, since, e.g., more control-group people appear to use the product daily than be familiar with it. Results show that free distribution had a large effect product use and awareness: according to the γ estimates in Panel B, FD increased the probability of daily use by 32 percentage points (145 percent; 95% CI: 14 to 50), the knowledge of the intended uses of hand sanitizer by 59 percentage points (159 percent; 95% CI: 49 to 70), and familiarity with the product by 77 percentage points (592 percent; 95% CI: 70 to 85). Estimates for β, δ, and λ are not statistically significant, 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.7 Heterogeneous Treatment Effects on WTP and Product Use

This appendix explores whether treatment effects vary according to the baseline characteristics of respondents or households. We consider heterogeneity by the depression severity (PHQ-9), 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 (PHQ-9, age, education, household income, household consumption, and household size). Figures A.5 and A.6 show subgroup heterogeneity in the effects of DT and FD on willingness to pay. 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 depression severity, age, household head status, education, earnings, household consumption, or the presence of young children. Figure A.7 shows subgroup heterogeneity in the effect of DT on the quantity of hand sanitizer remaining among FD participants. This figure pools the six-month and twelve-month rounds for concision. Round-specific estimates appear similar and are available from the authors. The figure shows that all subgroup-specific estimates and cross-subgroup comparisons are statistically insignificant. 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 ($p = 0.35$) and is jointly significant for FD ($p = 0.01$). For quantity remaining, heterogeneity in the impact of DT is not jointly significant ($p = 0.87$).

In principle, heterogeneous impacts of DT on WTP or product use could arise through heterogeneous impacts of DT on depression severity. However, we do not find evidence of heterogeneous effects on depression severity that align with the patterns above. With the exception of households with young children (who have significantly larger impacts), all dimensions of heterogeneity are not statistically significant (estimates 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.8 Heterogeneous Treatment Effects on WTP by 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 A.5 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 A.1: Treatment Effects on Willingness to Pay for Hand Sanitizer Using Entropy Weights for Baseline PHQ-9 Scores

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

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

		$\mathbb{1}(WTP \geq X)$					
	WTP	$X = 30$	$X = 40$	$X = 50$	$X = 60$	$X = 70$	$X = 80$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Specification (1)							
β	3.90***	0.014	0.034**	0.024	0.094***	0.093**	0.11***
	(1.30)	(0.0097)	(0.016)	(0.025)	(0.036)	(0.036)	(0.034)
γ	-0.60	-0.012	-0.0037	-0.022	-0.0090	-0.041	-0.0015
	(1.54)	(0.0077)	(0.018)	(0.029)	(0.045)	(0.047)	(0.042)
B: Specification (2)							
δ	5.86**	0.010	0.056	0.096*	0.15*	0.15*	0.15**
	(2.74)	(0.0096)	(0.034)	(0.051)	(0.079)	(0.086)	(0.074)
θ	0.67	-0.014	0.011	0.025	0.028	-0.0029	0.024
	(2.12)	(0.013)	(0.032)	(0.045)	(0.062)	(0.064)	(0.047)
λ	-2.42	0.0049	-0.027	-0.089	-0.071	-0.072	-0.049
	(3.12)	(0.014)	(0.039)	(0.060)	(0.089)	(0.095)	(0.083)
$\delta + \lambda$	3.44**	0.015	0.029	0.0063	0.081**	0.079**	0.099***
	(1.48)	(0.011)	(0.018)	(0.029)	(0.041)	(0.040)	(0.038)
Months since free distribution	12	12	12	12	12	12	12
Control mean	60.3	0.99	0.92	0.82	0.54	0.37	0.21
Observations	825	825	825	825	825	825	825

Note: The table reports AIT effects. Village-clustered standard errors appear in parentheses. Regressions use entropy weights to impose balance in baseline depression severity (PHQ-9 scores) across intervention arms (Hainmueller 2012, Hainmueller and Xu 2013). Column 1 shows willingness to pay for a 100ml bottle of hand sanitizer, which was elicited through the Becker-Degroot-Marschak mechanism. Columns 2-7 shows indicators that the willingness to pay is greater or equal than X rupees, for $X \in \{30, 40, 50, 60, 70, 80\}$. The local retail price of this product is 80 rupees. WTP outcomes are measured twelve months after free distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Treatment Effects on Quantity of Hand Sanitizer Remaining Using Entropy Weights for Baseline PHQ-9 Scores

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

	Milliliters		Percent	
	(1)	(2)	(3)	(4)
π	15.6	-2.25	0.026	-0.004
	(15.0)	(12.0)	(0.025)	(0.020)
Months since free distribution	6	12	6	12
Control mean	208	88	0.35	0.15
Observations	707	665	707	665

Note: The table reports AIT estimates of the effect of DT on the quantity of distributed hand sanitizer remaining among FD participants. Columns 1 and 3 show results six months after free distribution and Columns 2 and 4 show results twelve months after free distribution. Columns 1-2 show estimates in milliliters and Columns 3-4 express estimates as a percent of the originally distributed quantity (600ml). Village-clustered standard errors appear in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Treatment Effects on Hand Sanitizer Daily Use, Knowledge, and Familiarity

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

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

	Daily Use	Knowledge of Intended Use	Familiarity
	(1)	(2)	(3)
A: Specification (1)			
β	-0.053	-0.015	0.013
	(0.042)	(0.025)	(0.024)
γ	0.25***	0.54***	0.77***
	(0.065)	(0.044)	(0.032)
B: Specification (2)			
δ	0.082	0.086	0.030
	(0.12)	(0.089)	(0.061)
θ	0.32***	0.59***	0.77***
	(0.091)	(0.053)	(0.040)
λ	-0.16	-0.13	-0.022
	(0.13)	(0.092)	(0.066)
$\delta + \lambda$	-0.074	-0.041*	0.008
	(0.046)	(0.022)	(0.025)
Months since free distribution	6	12	12
Control mean	0.22	0.37	0.13
Observations	821	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 A.4: Treatment Effects on the Willingness to Pay for Hand Sanitizer by Livelihoods Assistance Arm

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

	WTP	$\mathbb{1}(WTP \geq X)$					
		$X = 30$	$X = 40$	$X = 50$	$X = 60$	$X = 70$	$X = 80$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Control for Livelihoods Assistance							
β	3.53***	0.012	0.034**	0.019	0.076**	0.088**	0.10***
	(1.24)	(0.0082)	(0.014)	(0.023)	(0.035)	(0.035)	(0.033)
γ	-0.15	-0.0079	-0.0021	-0.016	0.014	-0.025	0.0016
	(1.45)	(0.0079)	(0.017)	(0.028)	(0.042)	(0.045)	(0.040)
Control mean	60.7	0.99	0.93	0.86	0.54	0.37	0.22
Observations	825	825	825	825	825	825	825
B: Livelihoods Assistance Arms Only							
β	4.66**	0.015	0.029	-0.0012	0.18***	0.11**	0.13***
	(1.91)	(0.015)	(0.027)	(0.039)	(0.053)	(0.053)	(0.050)
γ	-2.27	-0.013*	-0.029	-0.096**	-0.033	-0.082	-0.016
	(2.16)	(0.0076)	(0.025)	(0.041)	(0.067)	(0.068)	(0.059)
Control mean	58.5	1.0	0.91	0.83	0.52	0.35	0.13
Observations	329	329	329	329	329	329	329
C: No Livelihoods Assistance Arms Only							
β	2.60	0.0095	0.038**	0.029	-0.0036	0.068	0.080*
	(1.63)	(0.0092)	(0.016)	(0.028)	(0.047)	(0.047)	(0.044)
γ	1.11	-0.0052	0.013	0.023	0.060	0.0072	0.016
	(1.92)	(0.011)	(0.023)	(0.036)	(0.055)	(0.061)	(0.052)
Control mean	61.5	0.99	0.94	0.85	0.54	0.38	0.25
Observations	496	496	496	496	496	496	496
β differs across panels (p-value)	0.67	0.93	0.93	0.70	0.03	0.81	0.74
γ differs across panels (p-value)	0.47	0.84	0.44	0.06	0.43	0.58	0.91

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 2-7 show the impact on an indicator that the willingness to pay is greater or equal than X rupees, for $X \in \{30, 40, 50, 60, 70, 80\}$. The local retail price of this product is 80 rupees. WTP outcomes are measured twelve months after free distribution. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: 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.

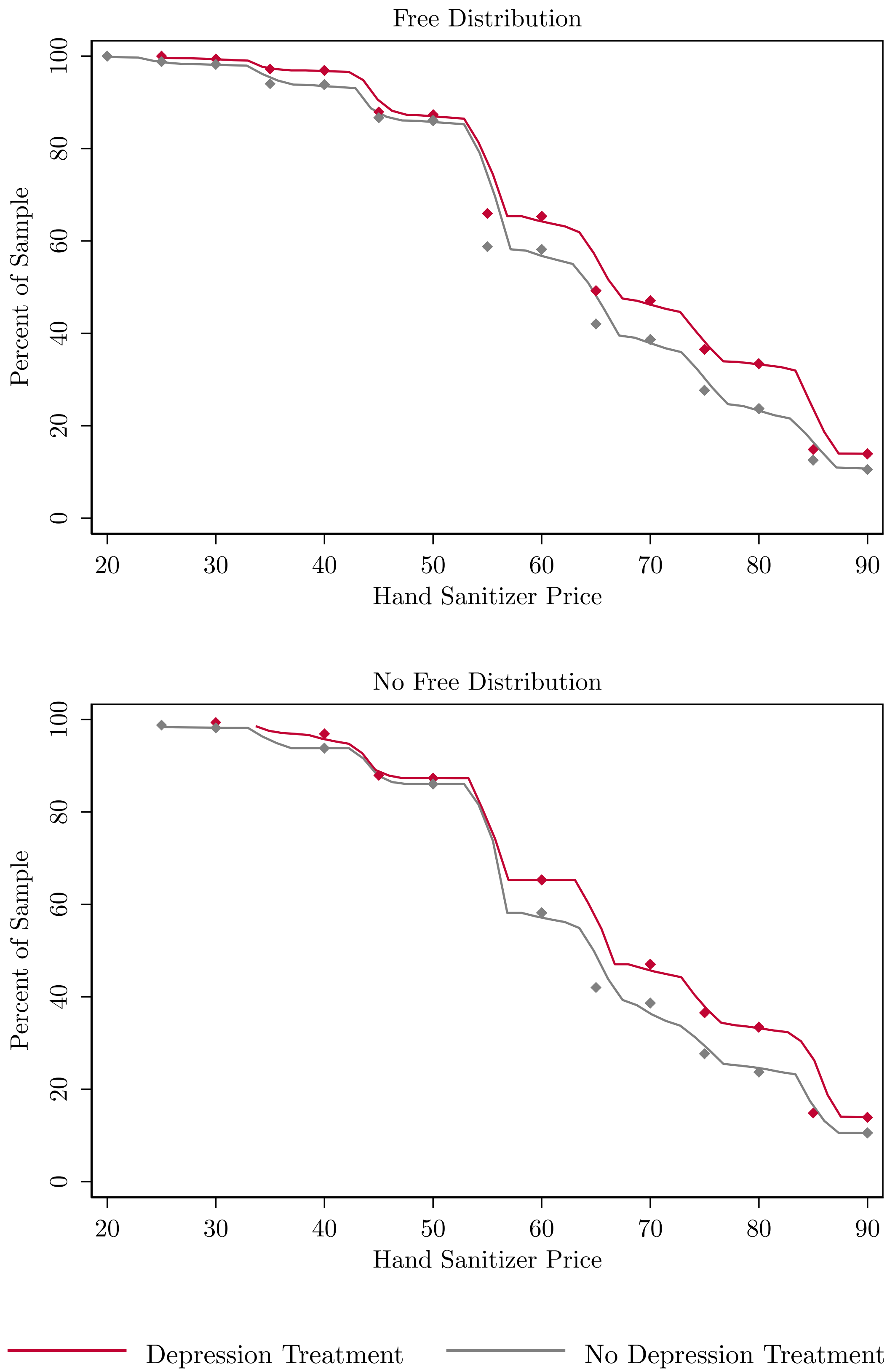

Figure A.2: The Impact of Depression Treatment on the Demand for Hand Sanitizer Within the Free Distribution and No Free Distribution Arms

Note: the figure shows the demand for a 100 ml bottle of hand sanitizer by depression treatment arm. 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.

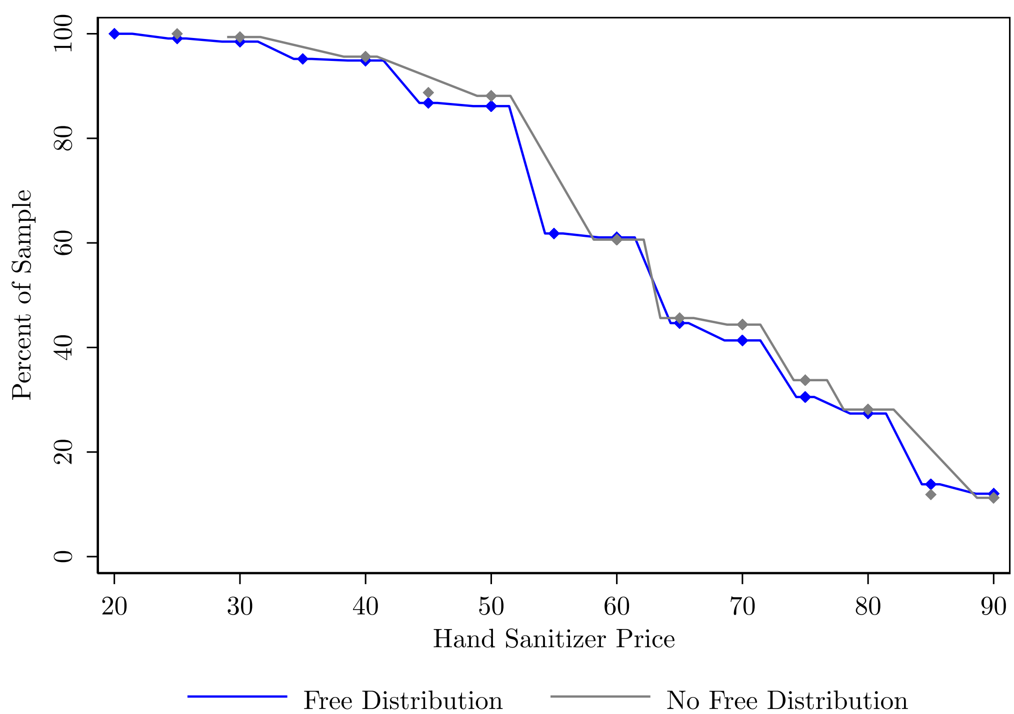

Figure A.3: The Demand for Hand Sanitizer for the Free Distribution and No Free Distribution Groups

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. The local retail price is 80 rupees.

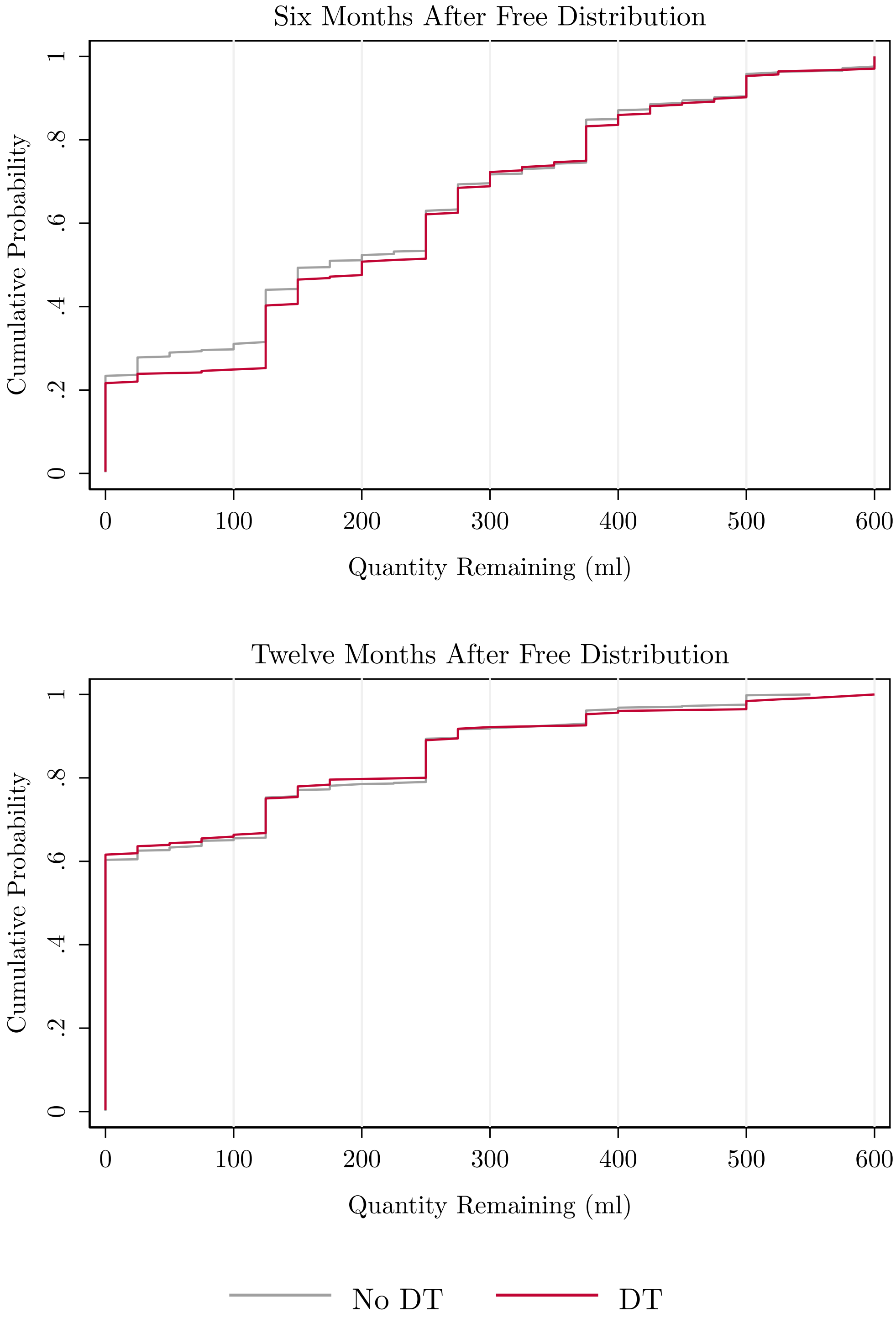

Figure A.4: Quantity of Sanitizer Remaining Six and Twelve Months after Free Distribution Using Entropy Weights for Baseline PHQ-9 Scores

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. Plots are weighted using entropy weights to impose balance in baseline depression severity (PHQ-9 scores) across intervention arms (Hainmueller 2012, Hainmueller and Xu 2013). 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 0.68 at six months and 0.99 at twelve months. AIT estimates are based on equation $Q_{ij} = \kappa + \pi DT_j + X_j'\theta + \varepsilon_{ij}$, in which Q_i is person i's quantity of the product remaining in milliliters, DT_j is an indicator for assignment to depression treatment in locality j, and X_j is a vector of controls for the nine randomization strata, as described in Section 2.2. The parameter σ is the standard error of π. We estimate the parameters of this equation by OLS within the $FD_j = 1$ subgroup, cluster standard errors by locality, and incorporate entropy weights to balance by baseline PHQ-9 score.

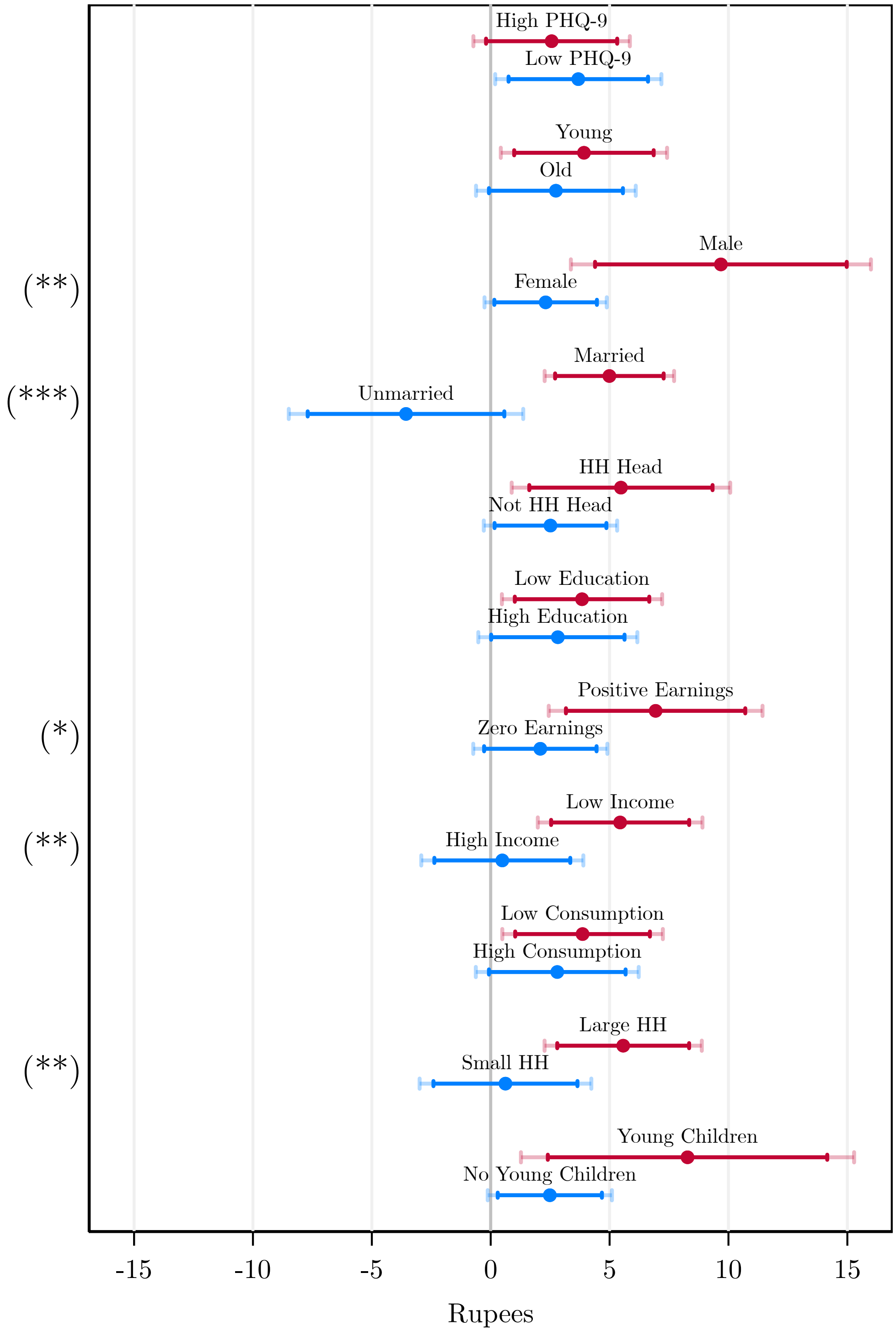

Figure A.5: Subgroup Heterogeneity in the Impact of Depression Treatment on WTP

Note: the figure shows subgroup heterogeneity in the impact of depression treatment on willingness to pay according to baseline depression severity (PHQ-9 score), 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). Depression severity, age, education, household income, household consumption, and household size are divided at the median. All subgroups are defined using baseline values. Light error bars indicate 95 percent confidence intervals and dark error bars indicate 90 percent confidence intervals based on locality-clustered standard errors. Stars indicate statistically significant differences in the impact of DT across subgroups: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

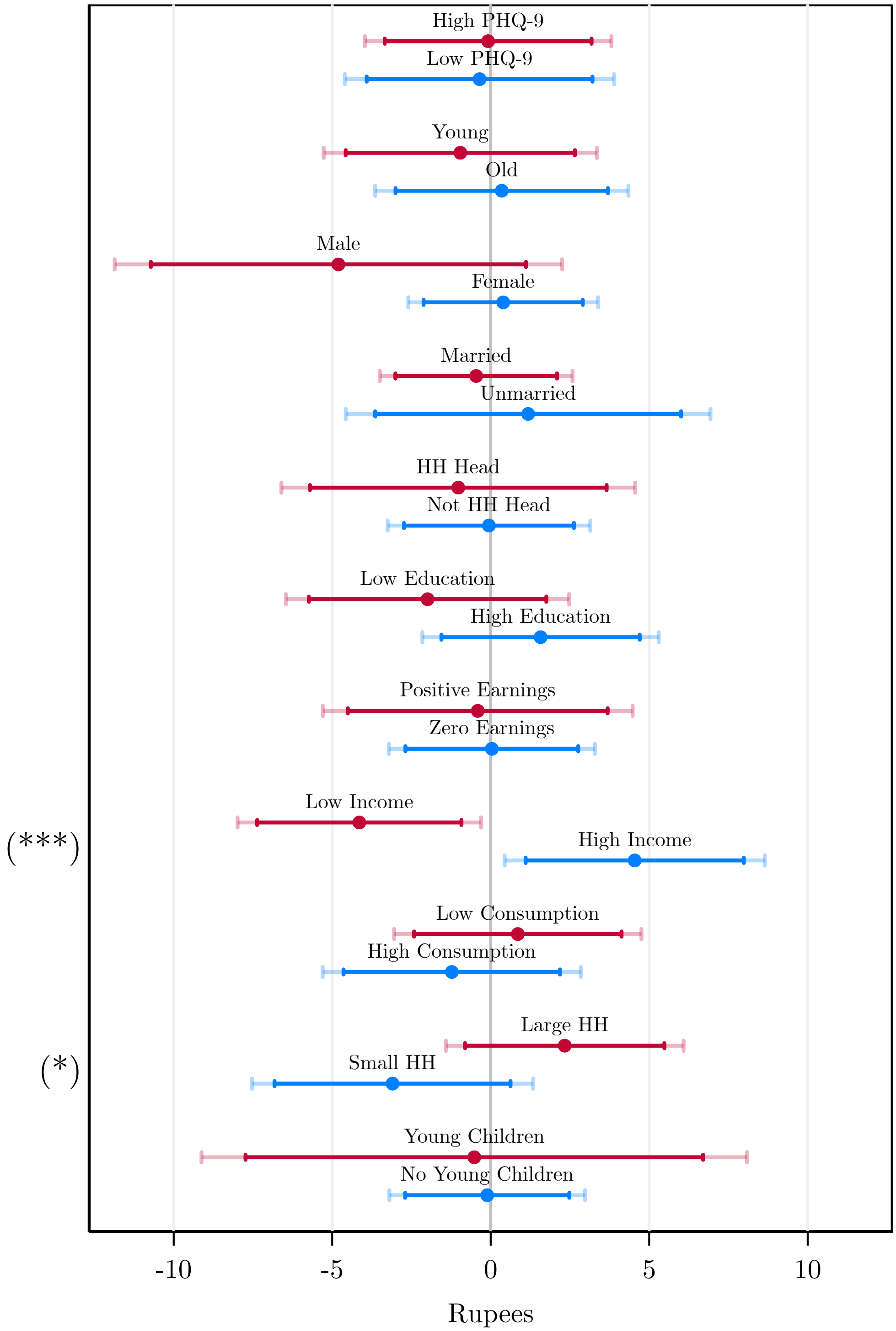

Figure A.6: Subgroup Heterogeneity in the Impact of Free Distribution on WTP

Note: the figure shows subgroup heterogeneity in the impact of free distribution on willingness to pay according to baseline depression severity (PHQ-9 score), 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. Light error bars indicate 95 percent confidence intervals and dark error bars indicate 90 percent confidence intervals based on locality-clustered standard errors. Stars indicate statistically significant differences in the impact of FD across subgroups: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

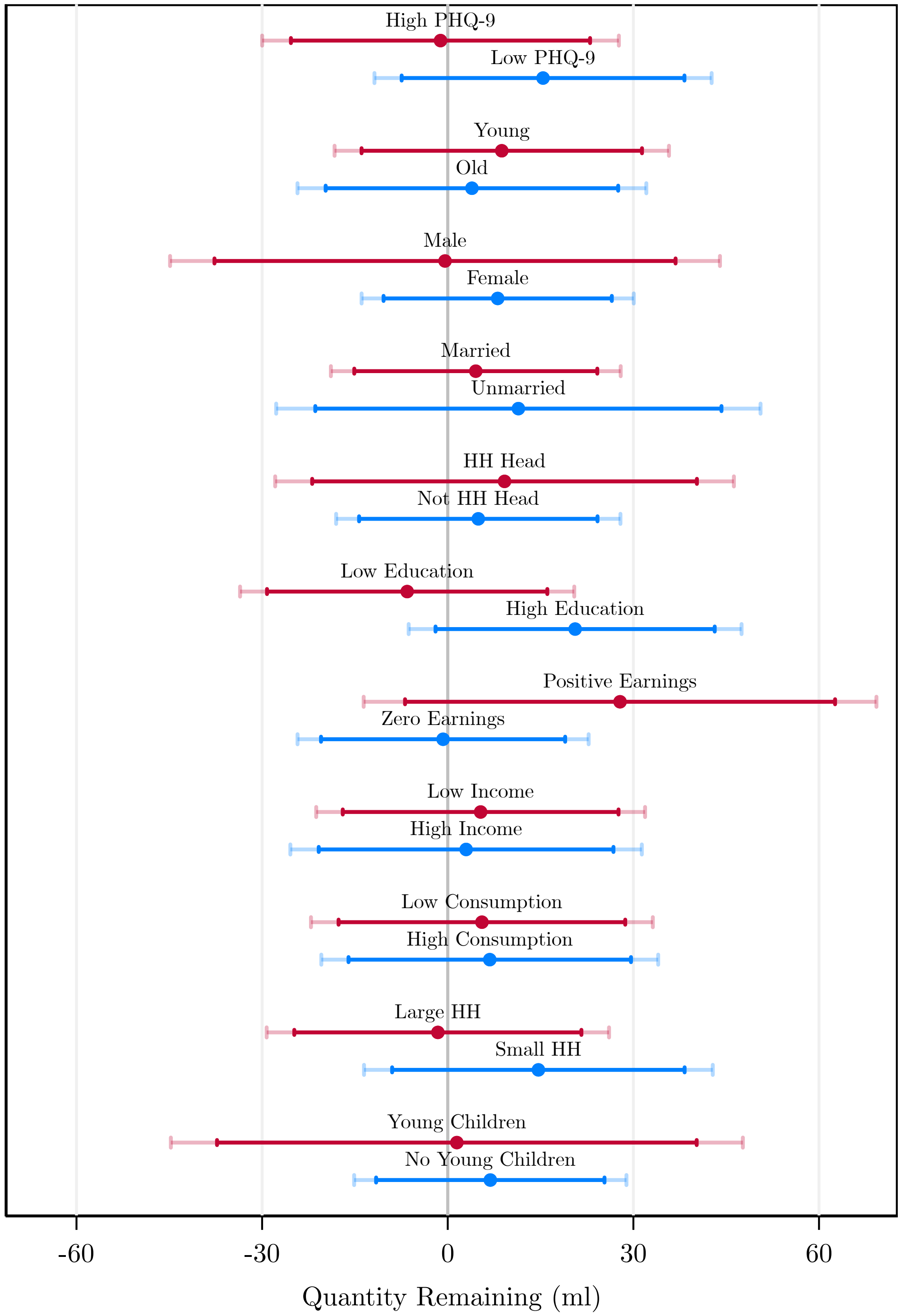

Figure A.7: Heterogeneity in the Impact of Depression Treatment on the Quantity Remaining of Hand Sanitizer Under Free Distribution

Note: the figure shows subgroup heterogeneity in the impact of depression treatment on the quantity of freely distributed hand sanitizer remaining according to baseline depression severity (PHQ-9), age, gender, marital status, status as the household head, education, earnings, household income, household consumption, household size, and the presence of young children. Estimates are based on the equation $Q_{ijt} = \kappa + \pi DT_j + X_j'\theta + \delta_t + \varepsilon_{ijt}$, in which Q_{ijt} is person i's quantity of the product remaining in Round t in milliliters, DT_j is an indicator for assignment to depression treatment in locality j, δ_t is a survey round indicator, and X_j is a vector of controls for the nine randomization strata, as described in Section 2.2. Estimates pool the six-month and twelve-month follow-up rounds. Depression severity, age, education, household income, household consumption, and household size are divided at the median. All subgroups are defined using baseline values. Light error bars indicate 95 percent confidence intervals and dark error bars indicate 90 percent confidence intervals based on locality-clustered standard errors. None of the differences across in the impact of DT across subgroups is statistically significant at the 10 percent level.

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