Testing Customized Behavioral Contracts in a Public Sector Setting: Experimental Evidence from Pakistan

Preliminary and Incomplete. Do Not Cite. *

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October 3, 2023

Abstract

The question of how to incentivize behavioral change has been fundamental for social scientists. While most incentives tend to be one-size-fits-all policies, we test individually tailored contracts using structurally estimated time-preference parameters. We use a within-subject design to estimate time preferences of community health workers based on their allocation of effort over time. Using the estimates, we offer individually tailored contracts for Leontief (smooth) and maximizing policy objectives. We compare the treatment contracts to random contracts for the same health workers. We find that the contracts function as theorized one and six months after eliciting preferences. While the maximizing contract leads to more tasks being accomplished, the Leontief contract leads to more equalized work across the two dates. Further, both contracts lead to desired public service delivery in the field when conducting household health surveys as measured by the number of forms completed, the distance traveled, and the time between surveys.

JEL classification: D1, D3, D90

Keywords: structural estimation, out-of-sample prediction, discounting, present bias

*We are grateful to Rashid Mahmood Langrial (former commissioner of Lahore), Dr. Ain-ul-Momina (University of the Punjab), and Mst. Noor-ul-Ain (deputy secretary of Health Department-Development Wing) for championing the project. We are thankful for financial support from the International Growth Center. We are grateful to research consultants (RCONS) at the Center for Economic Research Pakistan for excellent logistic support. We are especially indebted to Charles Sprenger (Caltech), Christine Binzel (FAU), Muhammad Yasir Khan (Pittsburgh) and participants at the Advances in Field Experiments for many conversations about this project. Shanila Parveen and Ahson Riaz provided excellent research assistance. The research is approved by the Institutional Review Board at Lahore University of Management Sciences. The study is registered in the AEA RCT Registry as AEARCTR-0010065.

1 Introduction

The question of how to incentivize behavioral change has been fundamental for social scientists. The incentives include monetary incentives, nonmonetary incentives, and monitoring in a variety of domains.[1] However, the effects of incentive policies substantially depend on baseline behavior, or type, because they are one-size-fits-all. These policies are typical in the public sector, as governments are legally constrained from offering pay-for-performance contracts. This paper uses structural time-preference parameters to create individually tailored, nonmonetary contracts for public sector health workers. Thus, it aims to use information about the type of every individual to personalize incentives and optimize potential change in the short to medium run.

We use time-preference parameters to create contracts because many important economic decisions about consumption, investment, or savings are intertemporal. These models have been shown to explain human behavior well, with differences in experimental measures of time preferences correlating with and causing differences in a number of behaviors such as take-up of commitment devices as well as borrowing, exercise, and health behaviors (Chabris et al. 2008; Meier and Sprenger 2013; Ashraf et al. 2006; Bortolotti et al. 2021; Castillo et al. 2011). This research suggests that we could leverage individual information on time preferences to tailor unique policies for each person. By using such tailoring policies, we can potentially increase the effectiveness of incentives to shape real-world behavior without offering monetary or nonmonetary incentives. Finally, the use of time-preference parameters is important because they are fundamental (or sometimes *deep*) parameters governing human behavior. Thus, we expect them to be stable, and through our experiment, we provide novel evidence that the time-preference parameters have medium-term out-of-sample predictability.

We conduct a field experiment with public sector health workers in Pakistan to test such individually tailored contracts. In close collaboration with the Department of Health in Punjab, we run a large, year-long health campaign and collect household-level data on disease prevalence. These data are usually nonexistent, which hampers the ability of health author-

[1] Examples include education (e.g., Barrera-Osorio et al. (2011)), savings (Gertler et al. 2019), and preventive health (Jones et al. 2019).

ities to react to emergencies.[2] The public sector workers in our experiment are (exclusively female) Community Health Workers (CHWs), who are essential frontline health workers and provide door-to-door health services. CHWs are employed in most developing countries and some developed countries to provide basic medication and supplements, provide health advice to women, and conduct disease surveillance and sometimes vaccinations. Our field experiment aims to improve public service delivery using individually tailored contracts rather than one-size-fits-all policies.

In the experiment, we investigate the effects of the individually tailored contracts on allocation of work over time and household health visits over a two-week health campaign. Consider a policy maker who knows the time-preference parameters of individuals, such as their discount factor (δ) and their present-bias parameter (β), and wishes to attain a policy objective. In our theoretical setup, the policy maker has only one policy tool: manipulating the task rate at the individual level, R_i, which it can choose to maximize an objective function subject to a CHW's offer curve. With this setup, we test two extreme types of contracts or policy maker targets. The first policy preference is a maximizing preference, in which the policy maker desires the maximum effort over the span of all CHW workdays. The maximizing contract is a nonlinear function of β, δ, and γ. The second policy preference is a Leontief preference, in which the policy maker desires an even amount of effort on each day. The Leontief contract is a linear function of β and δ. These are two extreme contracts that show a trade-off between quantity and quality. A policy maker can generate a high number of household health surveys but at some cost to quality, or they can achieve higher quality through more equalized work over time but at a cost in overall output. Finally, we create two random contracts by drawing from two uniform distributions that mimic the treatment contracts. When our treatment is the maximizing contract, every other contract—Leontief and the two random contracts—is part of our control group, and vice versa when the Leontief contract is the treatment contract.

To test the contracts, we first elicit preferences for intertemporal allocation of effort (following Andreoni and Sprenger (2012a)), then estimate time-preference parameters for

[2] The idea for this campaign came out of discussions during the COVID-19 crisis, when the department realized that it lacked the data to make quick decisions about health emergencies related to communicable and noncommunicable diseases.

every CHW, and finally create and test individually tailored contracts for all 420 CHWs. We collect data and elicit preferences from the CHWs on the first day of the experiment (Day 0). We ask every CHW to divide a total number of household health visits, m, between two dates that are one week apart, Day 7 and Day 14. The Day 7 allocation is v_1, and the Day 14 v_2. Thus, the intertemporal task-allocation budget is set as follows: $v_1 + Rv_2 = m$. The total number of household surveys she has to divide between the two days is one experimentally varied variable. We ask her to come in again on Day 7, when we ask her to make the same decision again before conducting household surveys chosen for that day. The elicitation is done for multiple numbers of total tasks, m=15, 18...53, 57, and multiple task rates, R = 0.4, 0.5...1.7, 1.8. A task rate acts as an interest rate between the present and the future. As the CHWs make many decisions—on Day 0 and Day 7, and for multiple m's and R's—we probabilistically choose one of the many decisions to be implemented ("the decision-that-counts"). A CHW earns a fixed bonus of \$12.50 for completing her randomly chosen decision over the two-week drive, and 0 otherwise.

Using these allocation decisions, we structurally estimate the time-preference parameters, such as the discount rate δ, the present bias β, and the effort-cost parameter, γ. The structural estimates are used to design individual Leontief and maximizing contracts for every CHW. The contracts are derived by a policy maker who maximizes a set objective (achieve the maximum number of households surveyed or equalize households surveyed across both days) under the constraint of the CHW's offer curve. This gives us an optimal task rate, R, as a function of some time-preference parameters. This allows us to create individually tailored contracts. We conduct two exercises with these contracts. First, we test the out-of-sample predictability of the time-preference parameters for the two chosen policy objectives (two contracts). Does the contract lead to the theorized allocation decisions one month and six months after eliciting preferences? Second, we randomly choose one type of contract for each CHW and have her act on a randomly chosen allocation decision in the field, thus testing the effectiveness of the contract for public service delivery. We compare the treatment contract against the remaining three contracts. The task that the CHWs accomplish is a household health visit whereby they conduct disease surveillance for the Department of Health.

We find two main results when we compare our treatment contract to the control group, which comprises the other treatment contract and two random contracts. The maximizing contract is a nonlinear function of β, δ, and γ and is compared to all linear contracts (Leontief and both random contracts). Both contracts function as theorized. Compared to the control group of the Leontief and random contracts, the maximizing contract leads to more tasks being allocated as measured by the log of total tasks chosen over the two weeks. The contract has a positive and statistically significant effect with a coefficient of 0.345 (compared to a control mean of 3.302) in both rounds, which is around a 10 percent increase over the control group. For the aforementioned outcome variable, we see a distributional shift to the right, meaning a shift to more work in total. This is important because our contracts are individually tailored and thus should have an effect across individuals.

Similarly, compared to the control group of maximizing and random contracts, the Leontief contract leads to more equalized work across the two dates as measured by a distance variable (the absolute value of Week 1 task allocations over Week 2 task allocations minus one, which measures how different the allocations are from each other, with zero meaning no difference). This contract has a negative and statistically significant effect with a reported coefficient of -0.383 over the control mean of 1.018, which is around a 35 percent reduction compared to the control group. We see a distributional shift here too. For the aforementioned outcome variable, looking at the distribution of the same absolute-distance variable, we see a leftward shift toward zero across the board.

These results are true both one and six months after eliciting preferences. This clearly shows that the time-preference parameters we estimated do not just have an effect in the medium term but have an effect of similar magnitude, thus showing us that the parameters are stable and usable as a policy tool in the medium term. This matters because when considering using such parameters as policy tools, people are often concerned that the parameters are unstable and thus bad predictors of behavior.

Second, both contracts lead to desired public service delivery in the field when conducting household health surveys. We measure delivery in three ways: the number of forms completed (household surveys), the distance traveled, and the time taken between surveys. We find that the maximizing contract results in 20 percent more forms submitted, 162 meters more distance covered in densely populated areas, and around a quarter-minute reduction in time taken between surveyed households (compared to a control mean of 3 minutes). Similarly, for Leontief contracts, we find that they lead to 16.80 percent fewer forms submitted, 203 less meters covered, but 1.5 more minutes spent between houses. Thus, they lead to higher quality. We find these performance effects one and six months after elicitation, thus showing medium-term effects. All the results are robust to alternative measures of outcomes, measures of treatment, control groups, and outliers.

The above comparison shines a light on the quantity-quality trade-off that a policy maker has to make. We test extreme contracts with a total focus on quantity or quality, and we see opposite effects as expected. Thus, the policy maker has to choose the appropriate policy goal and use the correct contract to achieve their target.

Our results are important for three reasons. First, they show the substantial benefits of tailored contracts, which generate significantly smoother or greater service provision. This demonstrates the value of structural estimates of time preferences, as they predict behavior in the short to medium term and can be predictably used as policy tools. The utility of such contracts in other spheres, such as firms, is vast. The treatment contracts are not just better than other tailored contracts but better than random contracts and random manipulation not based on structural estimates. Second, we study effort-allocation behavior in the field in a developing country to identify time preferences, which is rare.[3] This evidence is important given the ongoing debate about eliciting present-biased preferences with potentially fungible monetary payments (Sprenger 2015). Like Augenblick et al. (2015), our study shows that for nonmonetary choices, present bias may well have empirical support. Finally, the results also illuminate a largely unexplored avenue by which governments can provide services efficiently. Beyond the standard policy levers, such as detecting shirking and increasing pay, our data indicate that temporal incentives may also be instrumental for improving worker productivity.

This paper makes three contributions. First, our within-subject design with elicitation of preferences through effort allocation—both a week in advance of the task performance and immediately beforehand—makes the estimates much cleaner than those in previous work

[3] Other examples of present bias or dynamic inconsistency in field choices include Sadoff et al. (2015) for food choices, Sayman and Öncüler (2009) for cafe-reward choices, and Duflo et al. (2011) for fertilizer purchase decisions.

(Andreoni et al. 2022). We achieve this through generating large variation in the total number of tasks and task rates. This is particularly hard to achieve in the field, compared to the lab, but essential from a policy perspective. Previous work has either used between-subject designs or found it difficult to estimate the effort-cost parameter because of low variation in task rates and number of tasks. Second, we do not just analyze short-term effects but test whether the time-preference parameters are stable and can predict behavior in the medium term. There is a debate about the temporal stability of intertemporal behavior and the estimated parameters. We contribute to this debate by showing that contracts designed using time-preference parameters lead to persistent behavior one month later and six months later. This is important from a policy perspective because if a policy maker offers such individually tailored contracts, they want the contracts to affect behavior for a long period and not have to elicit preferences regularly. Finally, we test multiple contracts and clearly show the value of individually tailored policies for intertemporal choice in a field setting. Previous work has shown the effectiveness of the Leontief contract but has encountered experiment-design issues that we explained above. Thus, we provide more evidence by showing the effectiveness of two extreme contracts and more comparison contracts.

The paper proceeds as follows. Section 2 presents our experimental design, Section 3 the theory of contracts, Section 4 the sample details and structural estimates, Section 5 the results regarding allocation decisions, Section 6 the results for performance, and Section 7 the conclusion.

2 Experimental Design

2.1 Sample Selection

For the experiment we collaborated with the Punjab Department of Health to design an information-collection campaign—involving multiple rounds of household-level data collection about the prevalence of different communicable and noncommunicable diseases in Lahore District—that would be used to design and implement preventive health policies.

After discussions with senior officials of the Department of Health, we decided to select our sample from the universe of CHWs in Lahore following two criteria: (i) the prospective participant had her own smartphone, and (ii) she was a capable user of WhatsApp. This allows us to carefully monitor the work of the CHWs and understand the effect of contracts on public service delivery.

With these two selection criteria in place, we winnowed the sample of participants. We selected 6 towns in Lahore, the capital city of Pakistan's most populous province—Punjab (Lahore has around 3,000 active CHWs working in 11 administrative towns). We shortlisted 500 CHWs in these towns based on the selection criteria. In the first screening round (in March 2022), CHWs' supervisors gave us lists of CHWs who fulfilled the selection criteria. In this round, we excluded 50 CHWs primarily because of the second criterion. In the second round, we randomly invited 60 CHWs for an in-person testing exercise and conducted smartphone-literacy tests. Based on this test, we excluded 10 more CHWs. The purpose of these screening rounds was to ensure that our selected sample could use the technology necessary for us to conduct the experiment in ideal conditions and monitor their activity.

2.2 Design

We conducted the experiment in two phases of two rounds each. First, we explained to the CHWs the overall setup of the experiment. In both rounds of the first phase, we elicited allocation decisions for two dates that were one week apart and then used these decisions to structurally estimate the time-preference parameters, such as the discount rate δ, present bias β, and effort cost γ. In the first round, we only experimentally varied the task rate between the two days of work (R) and kept the total number of tasks constant at m=30, while in the second round, we varied both the total number of tasks and the task rate.

In the second phase, using the elicited allocations from both rounds in the first phase, we estimated the aforementioned structural parameters. We used these individual estimates to design two types of treatment contracts, Leontief and maximizing (explained in Section 3), and two random contracts. We conducted two exercises with these contracts. First, we tested the out-of-sample predictability of the contracts (explained in Section 3) for the chosen objective; that is, we tested whether the contracts change intertemporal allocations. Second, we randomly chose one of the two types of contract as a treatment for each CHW to implement in the field while conducting household surveys, and we tested the effect of the contract on public service delivery. We explain this in detail below.

Phase I, Round I: On Day 0, we called in the CHWs to collect demographic data and elicit preferences after carefully explaining the experimental protocols. The CHWs divided m=30 tasks (household health surveys) between two dates that were one week apart, Day 7 (allocation v_1) and Day 14 (allocation v_2). The CHWs made these decisions at multiple task rates, essentially interest rates between the present and future, which were experimentally varied: R = 0.4, 0.5...1.7, 1.8. For each task allocated to Day 14, the number of tasks allocated to Day 7 was reduced by R. These were advance choices—made one week before the task was to be attempted. On Day 7, all CHWs made the same choices again, but for that very day (before they had to complete the tasks for that day) and the next week. These were the immediate choices—made on the same day the task had to be attempted. As multiple choices were made, in advance and immediately, and at multiple task rates, we chose one choice probabilistically for each CHW to implement. This is the decision-that-counts and was implemented on Day 7 and then again on Day 14. This design was based on Andreoni and Sprenger (2012a).[4] In Figure **??**, we show one example of the decision sets we used to elicit these preferences. This exercise took place in September 2022.

To avoid corner solutions at 0 or m households in allocation decisions, we set a minimum of 5 and maximum of 27 households in the decision sets we offered. The goal of setting a minimum was to ensure that CHWs worked on both dates and made a choice about how to allocate tasks between them.

When CHWs made decisions on Day 7, we did not remind them of the Day 0 allocations. Importantly, on Day 0, CHWs were making decisions involving two future work dates (one and two weeks later), whereas on Day 7, they were making decisions for the same day and the week after.

From every CHW we elicited 15 advance and 15 immediate decisions over two weeks, and 1 of their 30 decisions was assigned to them as the decision-that-counts.

Phase I, Round II: We followed the same setup as Phase I, Round I, except that all allocation decisions were made for $\{(R, m)\} = \{(0.5, 15), (0.5, 18), (0.5, 21), (0.75, 24), (0.75, 27),$

[4]It has been used by Augenblick et al. (2015) and Chaudhry and Hussain (2022).

$(0.75, 30)...(1.5, 51), (1.5, 54), (1.5, 57)\}$. The difference in this round was the experimentally induced variation in m in addition to the variation in R. Every other step remained the same. This exercise took place in October 2022.

Phase II, Round I: We used the intertemporal allocation decisions from both rounds of Phase I to structurally estimate each CHW's discount factor δ, present bias β, and intertemporal effort cost γ. Then, we used these values to create individually tailored contracts (as a function of the policy tool R_i) and again elicited allocation decisions as in the first phase. On Day 0, we asked CHWs to allocate m=30 tasks over two dates that were one week apart (Day 7 and Day 14) for four individually tailored task rates. The values of the task rates determined the four contracts (explained in Section 3): Leontief, maximizing, and two random contracts. These choices allow us to understand whether the contracts affect allocations as theorized. Once the allocations were made, we randomly chose one of the eight contracts for each CHW for implementation on Day 7 and Day 14. In both immediate and advance conditions, the randomly chosen contract was their treatment contract, with the other three contracts being control contracts. One-fourth of our sample of CHWs received one contract each. We monitored the CHWs' performance to evaluate the effectiveness of the contract. This exercise took place in November 2022.

The CHWs' work was incentivized with a fixed bonus of \$12.50 for full completion of their randomly chosen decision over the two-week period, and 0 otherwise. This bonus is equivalent to around 12 percent of their monthly salary (the total time they required for our experiment was only three days).

At the time we elicited preferences, the CHWs were not aware that the choices could be used to tailor individual contracts. They were made aware that they would have to make choices multiple times, but they could not alter their behavior in Phase I to influence their potential interest rate in Phase II.

Phase II, Round II: We repeated the same setup as Phase II, Round I to evaluate medium-term effectiveness, as this exercise took place in June 2023 and used structural parameters estimated on the basis of decisions in September and October 2022.

Task: The CHWs had to conduct a household health survey—a typical part of their routine work. We designed this task in close collaboration with the Department of Health

Panel A:	Drive 1	
1st Round Decision Set		
No. of HH visits on 1st Saturday	No. of HH visits on 2nd Saturday	✓
5	50	
6	48	
7	46	
8	44	
9	42	
10	40	
11	38	
12	36	
13	34	
14	32	
15	30	
16	28	
17	26	
18	24	
19	22	
20	20	
21	18	
22	16	
23	14	
24	12	
25	10	
26	8	
27	6	

Panel B:	Drive 1	
2nd Round Decision Set		
No. of HH visits on 1st Saturday	No. of HH visits on 2nd Saturday	✓
5	28	
6	27	
7	26	
8	25	
9	24	
10	23	
11	22	
12	21	
13	20	
14	19	
15	18	
16	17	
17	16	
18	15	
19	14	
20	13	
21	12	
22	11	
23	10	
24	9	
25	8	
26	7	
27	6	

Figure 1: Elicitation of preferences

Notes: In Panel A, $m = 30$ and $R = 0.5$ in Round 1, and in Panel B, $m = 33$ and $R = 1$ in Round 2.

as part of a larger campaign to collect household-level data on disease prevalence. This initiative came out of discussions with the department during the COVID-19 pandemic, when the department realized that it was always in reactive mode and did not have household-level information to react to health emergencies. We designed this campaign with them and conducted multiple experiments to understand the workers' intertemporal behavior.

These household visits were the tasks being allocated over the two dates (allocations v_1 and v_2). The CHWs had to visit a house within their area of work—their officially assigned catchment area—and conduct a survey with the female household member. The experiment incentivized the collection of these important household-level data, which allowed the department to plan its future health campaigns. The work was to be done in one day between 9 a.m. and 5 p.m. Pakistan Standard Time (the official workday). The CHWs had to fill out a form and deposit this form at a health center at the end of the workday (the same center where they received training and where they picked up the forms). The forms were different for each round.

The survey took a maximum of 10 minutes, which was verified prior to the experiment. The questions had yes-or-no answers about disease prevalence, and thus the survey context itself could not be tested for quality, but it required around this much time to be conducted well. We use time spent as a proxy for quality.

Monitoring: We asked the CHWs to share their GPS location while performing their tasks after every five households. At the end, we had a third-party auditor verify all the surveys of a randomly chosen 15 percent of the CHWs in our sample. The auditor went to each reported household and verified whether the survey had taken place on the specific dates.

3 Intertemporal Contracts

Under the set of structural assumptions we explained above, each CHW's allocation in an intertemporal contract identifies her discount factor (δ) and present-bias parameter (β). We consider a policy maker who knows such preferences and wishes to attain a specific policy objective. In our setup, the policy maker can manipulate the task rate at the individual level, R_i, to maximize an objective function subject to the CHW's offer curve. We formalize the problem as maximizing policy preferences, $P(v_{1,i}(R_i), v_{2,i}(R_i))$, subject to the CHW's offer curve:

$$\max_{R} \; P(v_{1i}^*(R), v_{2i}^*(R))$$

s.t.

$$(v_{1i}^*(R), v_{2i}^*(R)) \; = \; \min_{\{v_{1i}, v_{2i}\}} C(v_{1i}, v_{2i})$$

s.t.

$$v_{1i} + v_{2i} \; R = m$$

The solution to the maximization problem maps the policy preferences onto an interest rate for each CHW. One can consider many forms of policy preference, with policy makers desiring a variety of intertemporal patterns of effort. With information on time-preference parameters, a policy maker can tailor contracts for each worker to achieve specific policy objectives. In this paper, we consider two extreme forms of preferences while assuming a power, or CRRA (constant relative risk aversion), cost function. We explain the cost function and its minimization problem as well as the contracts and their maximization problem and solution.

3.1 Cost Function

We allow the CHWs' intertemporal cost to be present biased in order to follow the parametric assumptions of Andreoni and Sprenger (2012a), and we assume quasi-hyperbolic power utility (Laibson, 1997; O'Donoghue and Rabin, 2001). Hence, the quasi-hyperbolic discounted intertemporal cost function concerns working on two dates: Day 7 with allocation v_1 ($t = 1$), and Day 14 with allocation v_2 ($t = 2$). Thus, the cost function C, a power (or CRRA) function, is minimized by CHW_i as follows:

$$\min_{(v_{1i},v_{2i})} \; v_{1i}^{\gamma} + \beta_i^{\mathbf{1}_{d=1}} \delta_i \; v_{2i}^{\gamma}$$

s.t.

$$v_{1i} + R v_{2i} = m$$

Here, $\gamma > 1$ represents the stationary parameter on the convex instantaneous cost-of-effort function. The present-bias parameter, $\beta_i^{\mathbf{1}_{d=1}}$, activated when period t is the present, t=1, captures the extent to which individuals disproportionately discount the future. The parameter captures the daily discount factor over the $k = 7$ days of each considered allocation.

Here, minimizing the cost function subject to budget set and for $\gamma > 1$ yields the following intertemporal Euler equation:

$$v_{1i} = \left(\frac{\beta_i^{\mathbf{1}_{d=1}} \delta_i}{R} \right)^{\frac{1}{\gamma-1}} v_{2i} \tag{1}$$

The above equation is also known as an Euler equation.

To get the closed-form solution using Equation 1 and **??**, we get the following:

$$v_{1i}^{*}(m, R, \beta_i^{\mathbf{1}_{d=1}}, \delta_i, \gamma) = \frac{m(\beta_i^{\mathbf{1}_{d=1}} \delta_i)^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}} \delta_i)^{\frac{1}{\gamma-1}} + R^{\frac{\gamma}{\gamma-1}}} \tag{2}$$

$$v_{2i}^{*}(m, R, \beta_i^{\mathbf{1}_{d=1}}, \delta_i, \gamma) = \frac{m R^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}} \delta_i)^{\frac{1}{\gamma-1}} + R^{\frac{\gamma}{\gamma-1}}} \tag{3}$$

One can also use the Euler equation to estimate the desired parameters, but since in Round 2 of Phase 1 we experimentally varied m, we need to solve for the closed-form solution.

3.2 Maximizing Contract

The first policy objective we consider is a maximizing preference, where $P(v_{1i}, v_{2i}) = v_{1i} + v_{2i}$. With this policy preference, the policy maker desires the maximum amount of effort in total across the days. This is of great interest because policy makers often wish to maximize provision even if quality is variable. With this preference, the policy maker prefers quantity at the expense of quality. We test two treatment contracts representing extreme preferences; all other policy options lie in between these preferences. We discuss the ability of our data to speak to alternative policy preferences in Section **??**.

To derive $P(v_{1i}^*(R^*), v_{2i}^*(R^*))$, we maximize the following equation with respect to R:

$$\max_{R_{Mi}} \left\{ \frac{m {R_{Mi}}^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + R_{Mi}^{\frac{\gamma}{\gamma-1}}} + \frac{m(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + R_{Mi}^{\frac{\gamma}{\gamma-1}}} \right\}$$

Taking the first-order condition with respect to R_M and solving gives us the following:

$$\implies (\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} {R_{Mi}^*}^{\frac{2-\gamma}{\gamma-1}} + (1-\gamma){R_{Mi}^*}^{\frac{2}{\gamma-1}} - \gamma(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} {R_{Mi}^*}^{\frac{1}{\gamma-1}} = 0 \tag{6}$$

$$(6) \implies R_{Mi}^* = R_{Mi}^*(\beta_i^{\mathbf{1}_{d=1}}, \delta_i, \widehat{\gamma})$$

The above equation is nonlinear, and a closed-form solution does not exist. For each CHW using the sample estimate of $\widehat{\gamma}$=2.687 from Column (3) of the preference-elicitation results table, we constructed β_i and δ_i, using these individual estimates and employing numerical methods for each CHW $R_{Mi}^*(\beta_i^{\mathbf{1}_{d=1}}, \delta_i, \widehat{\gamma})$ is obtained. Entering this in the policy maker's objective function, we get

$$V_{Mi}^*(R_M^*(\beta_i^{\mathbf{1}_{d=1}}, \delta_i, \gamma), m) = \frac{m({R_{Mi}^*}^{\frac{1}{\gamma-1}} + (\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}})}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + {R_{Mi}^*}^{\frac{\gamma}{\gamma-1}}}. \tag{4}$$

3.3 Leontief Contract

The first policy preference we consider is a Leontief preference, in which $P(v_{1,i}(R_i), v_{2,i}(R_i)) = min[v_{1,i}(R_i), v_{2,i}(R_i)]$. With this policy preference, the policy maker desires an even amount of effort on each day. While this is an extreme preference, there is general interest in understanding mechanisms that smooth behavior—for example, for boosting saving or avoiding procrastination. This is also important from a planning perspective, particularly in countries with low state capacity or limited human or financial resources. With this preference, it is quality that is preferred over quantity. This problem has an intuitive solution. The tailored contract gives each CHW a value of R equal to their one-period discount factor.

To derive $P(v^*_{1i}(R^*), v^*_{2i}(R^*))$, consider the following setup:

$$\max_{R} \; P\left(\frac{mR^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + R^{\frac{\gamma}{\gamma-1}}}, \frac{m(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + R^{\frac{\gamma}{\gamma-1}}}\right) \tag{5}$$

Here, v^*_{1i} and v^*_{2i} are derived in Equations 2 and 3, and solving for that yields the following:

$$\max_{R_{Li}} \left\{ min\left(\frac{mR_{Li}{}^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + R_{Li}^{\frac{\gamma}{\gamma-1}}}, \frac{m(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + R_{Li}^{\frac{\gamma}{\gamma-1}}}\right) \right\}$$

$$\implies R^*_{Li}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i) = \beta_i^{\mathbf{1}_{d=1}}\delta_i$$

Substituting the above equation in $P(v^*_{1i}, v^*_{2i})$, we get the following:

$$V^*_{Li}(R^*_{Li}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i, \gamma), m) = \frac{m(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}}}{(\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{1}{\gamma-1}} + (\beta_i^{\mathbf{1}_{d=1}}\delta_i)^{\frac{\gamma}{\gamma-1}}}$$

In the above relationship, one can see that when $(\beta_i\delta_i) \to 1 \implies V^*_{Li} \to \frac{m}{2}$. Thus the total amount of work is equally divided between both dates.

Importantly, we have two contracts, where one emphasizes quality and one quantity of work. The quantity-quality trade-off is salient in economics, and our choice of contracts allows us to understand it.

3.4 Control Contracts

Each of these tailored R^*_i's was tested against the three remaining contracts: one other treatment contract and two random contracts ($R^*_{random(i)}$). The usage of the remaining three contracts as controls gives us higher power in our analysis. The values for the first random

[htbp]

Table 1: **Summary Statistics of Experimental R^*_{mi} and R^*_{Li}**

	No of Obs	Mean	Median	Std Dev	P10	P90
$R^*_{Mi}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i, \widehat{\gamma})$	436	0.29	0.29	0.02	0.28	0.32
$R^*_{Li}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i)$	436	2.43	1.14	9.21	0.86	3.11
$R^*_{random(i)}$	436	0.30	0.30	0.09	0.18	0.42
$R^{**}_{random(i)}$	436	4.71	1.96	11.63	0.32	8.62

contract were chosen from a uniform distribution of $R^*_{random(i)} \in [0.15, 0.45]$, which makes this contract similar to $R^*_{Mi}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i, \widehat{\gamma})$. The values for the second random contract were chosen from a uniform distribution of $R^{**}_{random(i)} \in [0.15, 10]$, which makes this contract similar to $R^*_{Li}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i)$. This is visible in Table 3.4, in which we show the summary statistics for the value of contracts for all 420 CHWs. The contracts follow the set intervals, with a mean value of 0.29 for the maximizing contract, 2.43 for the Leontief contract, and 0.30 and 4.71 for the two random contracts.

In Figure 2, we can see the full distribution of the same contracts. While the average CHW is not present biased, there is substantial variation around the average, which allows for a lot of variation in the contracts we see in Figure 2. The heterogeneity points to possible gains from individually tailored contracts, and we exploit this variation to test contract effectiveness.

4 Sample Details and Structural Estimates

We now explain our sample and the structural estimates calculated from the elicitation exercise. In Table 2, we provide summary statistics for our sample of CHWs. Our sample is exclusively female, mostly middle-aged and married with children, and largely without access to formal savings accounts. The CHWs are generally highly experienced with an average of 19.38 years of experience with the Department of Health. The table also provides some information on average task completion, which is roughly equal for both dates.

Table 2: **Summary Statistics**

	No of Obs	Mean	Median	Std Dev	P10	P90
Age in Years	436	47.60	48	6.56	39	56
Marital Status	436	2.25	2	0.67	2	3
Number of Children	436	3.25	3	1.67	1	5
Education Level	436	2.89	3	0.82	2	4
Had a Savings Account (=1)	436	0.09	0	0.29	0	0
Has a Savings Account (=1)	436	0.13	0	0.33	0	1
Late on Bill Payment (=1)	436	0.69	1	0.46	0	1
Participated in a Rosca (=1)	436	0.33	0	0.47	0	1
Participate in a Rosca (=1)	436	0.38	0	0.49	0	1
Years in Health Department	436	19.38	21	5.59	12	26
Assigned Area Category	436	2.31	2	0.75	1	3
Tasks Completed on Day 1	436	16.68	17	5.98	9	23
Tasks Completed on Day 2	436	17.10	18	8.04	4	27

Notes: The table presents the statistical characteristics of the participating Lady Health Workers. Marital status is coded as 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, or 5 for separated. Education level is recorded as 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelor's degree, and 6 for master's degree. Assigned-area categories are defined by the Punjab Health Department as 1 for easy, 2 for difficult, and 3 for hard. Tasks completed on Day 7 and Day 14 are for Round 2 of the experiment.

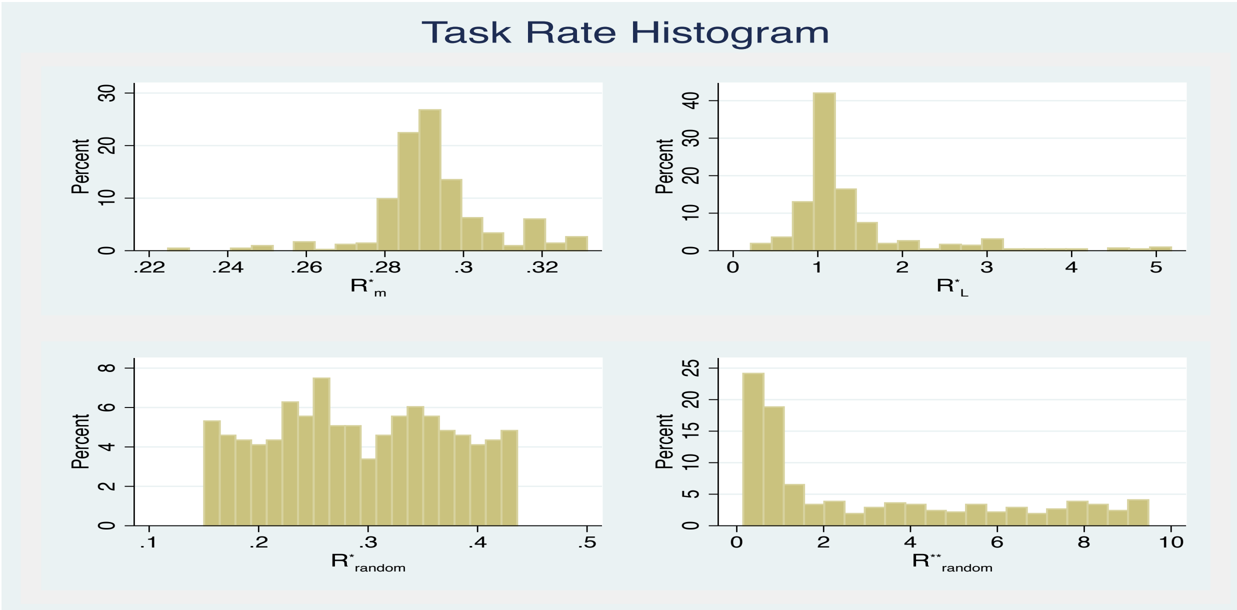

Figure 2: $R^*_{Mi}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i, \gamma)$, $R^*_{Li}(\beta_i^{\mathbf{1}_{d=1}}, \delta_i)$, R^*_{random} and R^{**}_{random} distribution

Before we present the structural estimates, we check whether the CHWs understood our experiment and responded to the experimental variation as expected. In Figure 3, we plot the task ratio (the log of the allocation to the sooner work date, v_1, over the log of the allocation to the later date, v_2) for each interest rate, for immediate and advance decisions separately. We show this for Rounds 1 and 2 in Panels A and B respectively. We see that the CHWs act rationally, as a higher task rate leads to a lower task ratio. We also observe that the immediate and advance decisions generally track each other very closely except at a few points on the curves, which visually demonstrates little possibility of present bias, a fact we confirm below using structural methods.

Finally, in Table 3, we estimate the structural parameters β, δ, and γ for both rounds using nonlinear least squares. Importantly, in Round 1, the only experimental variation comes from the different task rates, while in Round 2, both the task rate and the total number of households are experimentally varied. This leads to differences in estimates between the two rounds. We can see that the CHWs are not present biased, as the estimated β's are close to 1 in both rounds and are not statistically different from one, which implies time consistency. This is also true when we combine elicited allocations from both rounds, where

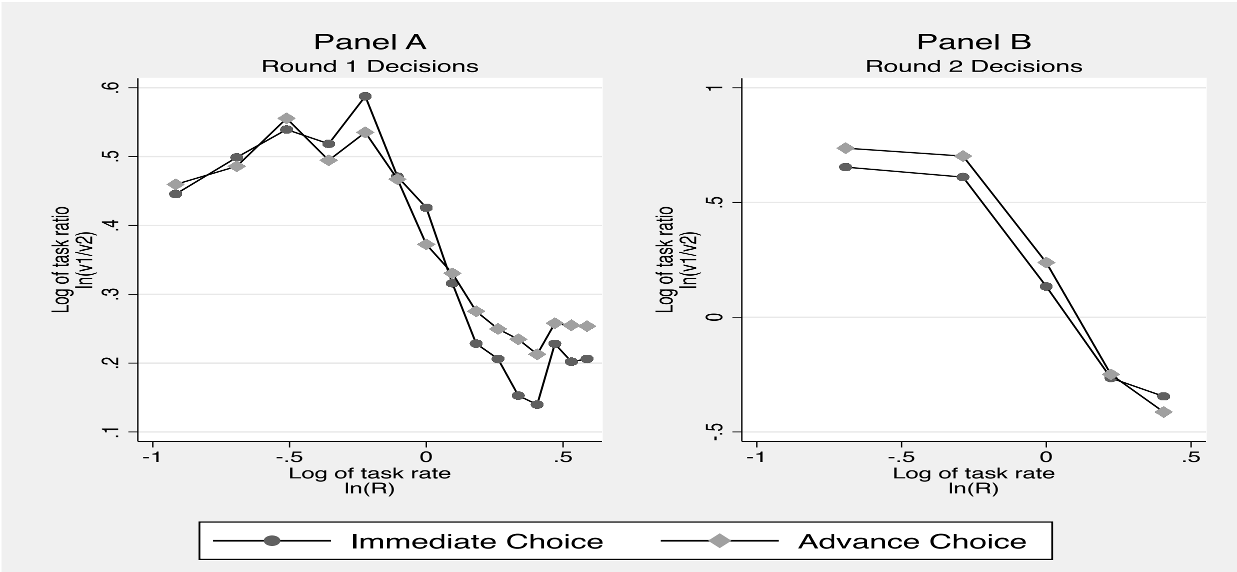

Figure 3: Discounting Behavior

Notes: Mean behavior in Round 1 and Round 2.

Column (3) includes the CHWs who were absent in the second round and Column (4) excludes them. The missing CHWs do not affect our results. We believe the reason we do not find any present bias is that the CHWs are very experienced and were selected for their technological proficiency. Thus, they are a select sample from the universe of CHWs.

A δ greater than 1 suggests the CHWs prefer to complete less work as the time after the first day of work increases. A possible explanation is that the CHWs do not want to commit to more work a week later because they face greater uncertainty about other obligations on the future date. However, we hesitate to draw firm conclusions regarding δ, as our experiment provides no variation in delay lengths to help identify δ. We identify the δ from the constant one-week delay between the work dates.

Finally, the cost-of-effort parameter is around 5 in Round 1 and around 2 in Round 2, the latter being in a very reasonable range. The Round 1 estimate is higher than the Round 2 estimate because the first time the CHWs allocate effort, they encounter substantial uncertainty about all elements of the structure of the experiment, especially the decision structure, the work and payment schedule, and the mechanism through which they will be paid. When they progress to Round 2, their earlier experience has helped them resolve these

Table 3: **Nonlinear-Least-Squares Estimates**

	Round 1 (1)	*Round* 2 (2)	*Combined* (3)	*Combined* (4)
Present-Bias Parameter: β	0.906	0.992	0.980	0.989
	(0.103)	(0.020)	(0.022)	(0.023)
Discount Factor: δ	1.196	1.006	1.024	1.024
	(0.044)	(0.003)	(0.004)	(0.004)
Cost-of-Effort Parameter: γ	5.624	2.102	2.687	2.706
	(0.770)	(0.074)	(0.107)	(0.111)
# Decisions	13,185	13,080	26,265	25,380
# of CHWs	440	436	453	423
Adjusted R^2	0.915	0.894	0.897	0.898
$RMSE$	5.22	5.93	5.78	5.76
Hypothesis				
β=1 (p-value)	0.35	0.67	0.37	0.62
δ=1 (p-value)	0	0.02	0	0
γ=1 (p-value)	0	0	0	0

Notes: The table presents the structural estimates of an intertemporal hyperbolic-discounting model using the nonlinear-least-squares estimation method. Column (1) reports the structural estimates using the CHWs' decisions from the first round. Column (2) uses the decision sets from the second round. Column (3) reports the NLS estimates using both rounds of CHWs' decision including 17 Lady Health Workers' decisions absent in the second round. Column (4) uses the Lady Health Workers' decisions in both rounds. Clustered standard errors are in parentheses. Weekly discount rate can be calculated as $(\delta)^7$. Standard errors are calculated via the delta method. Chi-squared tests are in last three rows.

uncertainties and thus their effort becomes less costly. Another reason for the change is the extra experimental variation in the total number of tasks, m, in Round 2 beyond the variation from Round 1.

5 Results: Contracts and Allocation Decisions

We evaluate whether the tailored contracts have any effect on allocative behavior. We show point estimates in tables and add in distributional changes in graphs because every CHW had a personalized contract and thus a personalized treatment.

As each of the four contracts was randomly offered to 25 percent of our sample, we must ensure balance between the groups. In Appendix 8.2, we provide evidence that all our groups are balanced for every contract.

We perform many robustness tests (shown in Appendix 8.3). First, we test for the effect of outliers to understand whether a few extreme observations drive our results. Second, we test different measures of treatment, particularly what we can tailoring intensity, a nonbinary measure of our treatment. Third, we test two outcomes. Fourth, we test the effect of restricting our sample to CHWs who worked in both rounds. Fifth, we test for counterfactual tailoring. Sixth, we use only two random contracts as comparisons for the treatment.

Finally, we test for heterogeneous effects depending on whether the CHWs are present biased (see Appendix 8.5).

5.1 Maximizing Contract

First, we present results for our first treatment contract: the maximizing contract. In Table 4, we show the effect of the maximizing contract on the log of total tasks chosen over the two weeks. Our hypothesis is that a maximizing contract will lead to more total work. Our main variable of interest is *Structural Tailored*, which is positive and statistically significant with a value of 0.335 above the control mean of 3.307 in Round 1, around a 10 percent increase in the treatment compared to the control group. We find a similarly sized and statistically significant effect in Round 2, which took place six months after we elicited preferences. This shows that the contracts were effective even in the medium term. We do not find evidence that the effect size changed in the medium term: the difference in coefficients in Rounds 1 and 2 is not statistically significant.

In Columns (2) and (4), we add further explanatory variables to understand whether immediate or advance decisions made any difference in choices. We can see that the effect is nonexistent in both rounds. The effects are similar in the last panel, in which we combine both rounds.

Table 4: The Effect of Tailoring Intertemporal Incentives for Maximizing Policy

Dependent Variable:	$\ln(w_{1,i} + w_{2,i})$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	0.335***	0.341***	0.353***	0.358***	0.345***	0.350***
	(0.020)	(0.020)	(0.017)	(0.017)	(0.017)	(0.017)
β_2 : Immediate Choice (=1)		-0.006		-0.000		-0.003
		(0.004)		(0.003)		(0.002)
β_3 : Structural Tailored x Immediate		-0.012*		-0.010		-0.011**
		(0.007)		(0.007)		(0.005)
β_0 : Constant	3.381***	3.384***	3.362***	3.362***	3.374***	3.375***
	(0.025)	(0.025)	(0.022)	(0.022)	(0.022)	(0.022)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.444	0.444	0.416	0.416	0.422	0.422
Log Likelihood	-1420.851	-1420.528	-1547.233	-1547.157	-3017.125	-3016.796
Mean in Untailored Contract	3.307	3.307	3.298	3.298	3.302	3.302
Mean in Untailored Advance		3.310		3.298		3.304
Mean in Untailored Immediate		3.304		3.297		3.301
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(3)}^{round=2}$						
$p - value$	0.183					
Hypothesis 2: $\beta_{1Col(2)}^{round=1} = \beta_{1Col(4)}^{round=2}$						
$p - value$	0.244					
Hypothesis 3: $\beta_{3Col(2)}^{round=1} = \beta_{3Col(4)}^{round=2}$						
$p - value$	0.784					

Notes: This table reports the effects of tailoring on maximum effort provision over time. For all subjects, the treatment tailored condition is defined as a dummy equal to one when one of the assigned four task rates is equal to $R^*_{Mi}(\beta_i, \delta_i, \widehat{\gamma})$. The measure $\ln(w_{1,i} + w_{2,i})$ reflects the natural logarithm of total task allocation (w_1,w_2) over two weeks. Column (1) reports a regression of this measure on the tailored condition for Round 1. Column (2) reports the full-sample estimates of Round 1, interacting the treatment with being in the immediate-choice condition. Column (3) reports a regression of this measure on the tailored condition for Round 2. Column (4) reports the full-sample estimates of Round 2, interacting the treatment with being in the immediate-choice condition. Column (5) reports a regression of this measure on the tailored condition for both rounds. Column (6) reports the full-sample estimates of both rounds, interacting treatment with being in the immediate-choice condition. Fixed-effects regressions. Heteroskedasticity-robust White standard errors are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. LHW=Lady Health Worker

We show point estimates above. However, was there a distributional shift? We offered personalized contracts and thus expect every treated individual to have changed their behavior. In Figure 4, we show the distribution of CHWs' task choices (the log of the sum of tasks chosen over both days). The shaded area shows tailored contract choices, and a clear rightward shift is visible in both rounds, showing that a distributional shift occurred; that is, all CHWs chose a larger number of tasks.

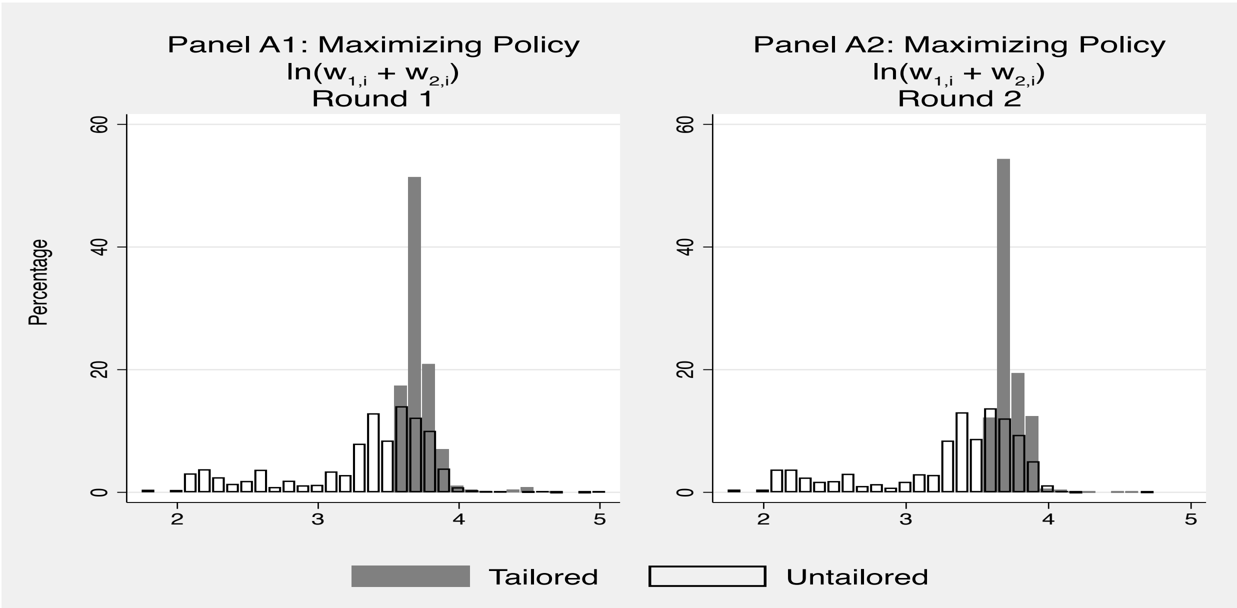

Figure 4: Maximizing Policy across Rounds

Notes: Panel A1 presents a histogram of the Maximizing Policy target, $\ln(w_{1,i} + w_{2,i})$, for Tailored and Untailored health workers' decisions in Round 1. Panel A1 presents a histogram of the Maximizing Policy target, $\ln(w_{1,i} + w_{2,i})$ for Tailored and Untailored health workers' decisions in Round 2.

Our outcome measure in Table 4 could be critiqued because, as we show in Figure X, the relationship between the number of tasks and R is inverse. Hence, it could be that even without eliciting time-preference parameters and estimating structural estimates, we can always offer a lower task rate and attain the same goal: a higher total number of tasks accomplished. Hence, a maximizing contract might not be necessary to achieve the goal.

To test whether this is the case, in Table 5, we created a new outcome measure: the absolute value of the total number of tasks predicted by the model divided by the total number of actual tasks minus one. The total number of tasks predicted by the model uses Equation 4 and inputs four values of task rates, including the actual R_M, but treats the other task rates (R_L and R_random) as pseudo-Rs_M. The denominator is the actual amount of total tasks allocated. A higher value of this variable shows that the predicted and actual tasks are more distant and thus X.

We can see consistent effects: the maximizing contract leads to a smaller difference

Table 5: The Effect of Tailoring Intertemporal Incentives for Maximizing Policy

Dependent Variable:	$\lvert \frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1 \rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.023***	-0.019***	-0.017***	-0.013**	-0.020***	-0.016***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)
β_2 : Immediate Choice (=1)		-0.004*		0.000		-0.002
		(0.002)		(0.002)		(0.001)
β_3 : Structural Tailored x Immediate		-0.008*		-0.008*		-0.008***
		(0.004)		(0.004)		(0.003)
β_0 : Constant	0.100***	0.102***	0.098***	0.097***	0.102***	0.102***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.483	0.483	0.509	0.509	0.467	0.468
Log Likelihood	2742.454	2744.189	3097.378	3098.037	5645.340	5647.353
Mean in Untailored Contract	0.127	0.127	0.122	0.122	0.125	0.125
Mean in Untailored Advance		0.129		0.121		0.125
Mean in Untailored Immediated		0.125		0.122		0.124
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: ${\beta_1}^{round=1}_{Col(1)} = {\beta_1}^{round=2}_{Col(3)}$						
$p-value$	0.246					
Hypothesis 2: ${\beta_1}^{round=1}_{Col(2)} = {\beta_1}^{round=2}_{Col(4)}$						
$p-value$	0.350					
Hypothesis 3: ${\beta_3}^{round=1}_{Col(2)} = {\beta_3}^{round=2}_{Col(4)}$						
$p-value$	0.970					

Notes: This table reports the effects of tailoring on maximum effort provision over time. For all subjects, the treatment tailored condition is defined as a dummy equal to one when one of the assigned four task rates is equal to $R^*_{Mi}(\beta_i, \delta_i, \widehat{\gamma})$. $(Total\ Task)^{predicted}$ is constructed using the parameter values $(\beta_i\delta_i, \widehat{\gamma})$ from Phase 1 and the customized assigned four values of R_i. $(Total\ Task)^{actual}$ is calculated using the actual and observed (w_1, w_2) from Phase 2. The measure $\lvert \frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1 \rvert$ (the percentage difference between model-based predicted optimal total tasks and actually chosen total weekly tasks over two weeks) reflects the distance from optimal total tasks to actual total tasks over two weeks. Column (1) reports a regression of this measure on the tailored condition for Round 1. Column (2) reports the full-sample estimates of Round 1, interacting the treatment with being in the immediate-choice condition. Column (3) reports a regression of this measure on the tailored condition for Round 2. Column (4) reports the full-sample estimates of Round 2, interacting the treatment with being in the immediate-choice condition. Column (5) reports a regression of this measure on the tailored condition for both rounds. Column (6) reports the full-sample estimates of both rounds, interacting the treatment with being in the immediate-choice condition. Fixed-effects regressions. Heteroskedasticity-robust White standard errors are reported in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. LHW=Lady Health Worker

between predicted and actual total tasks and thus performs better than just offering lower task rates to individuals. Our main explanatory variable is *Structural Tailored*, in which $R_M = 1$, which has a coefficient of -0.023 over a control mean of 0.127. In Column (2), we control for *Immediate Choice* and its interaction with *Structural Tailored*. We find that making a same-day choice when offered a maximizing contract leads to a smaller difference as well. The results are similar in Round 2.

In Figure 5, we show distributional effects. The plotted variable is the same. We can see a leftward shift overall, showing across-the-board greater task accomplishment due to the maximizing contract in both rounds.

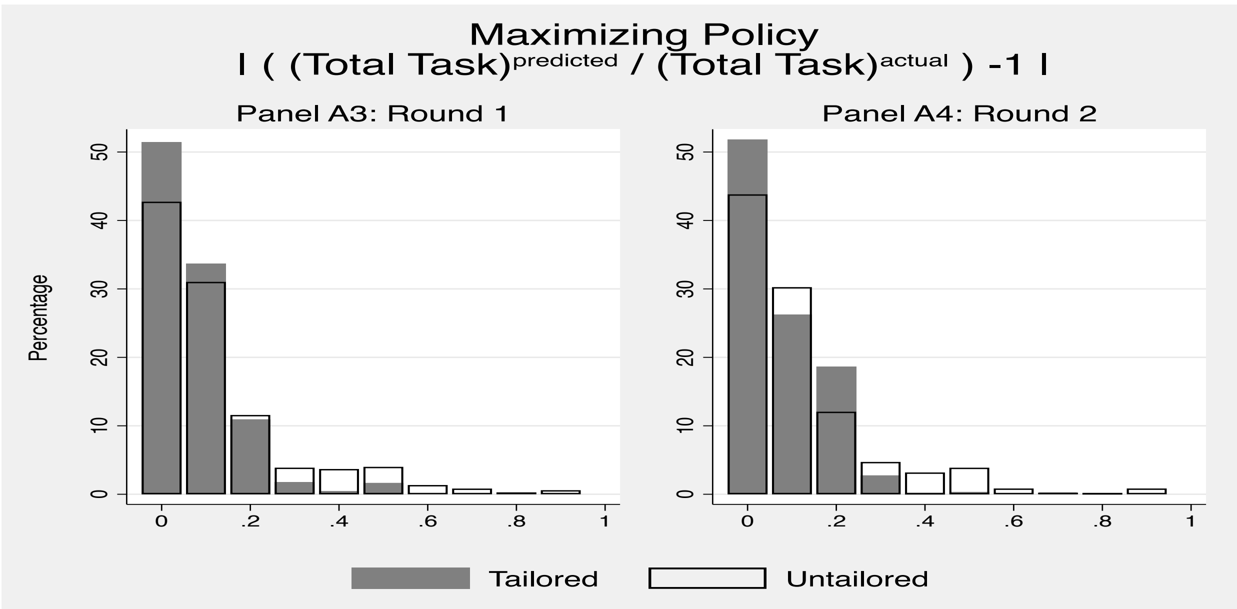

Figure 5: Maximizing Policy across Rounds

Notes: Panel A3 presents a histogram of the Maximizing Policy target, $|\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1|$, in Tailored and Untailored health workers' decisions in Round 1. Panel A4 presents a histogram of the Maximizing Policy target, $|\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1|$, in Tailored and Untailored health workers' decisions in Round 2.

In Figure 6, we plot the 45-degree line between predicted and actual tasks. Theoretically, we expect the individuals with tailored tasks to be closer to the 45-degree line. The full circles represent the tailored-contract CHWs, while the hollow circles represent random-contract CHWs. As theorized, we see the full circles near the line and the hollow circles farther away.

5.2 Leontief Contract

We present results for the Leontief contract. In Table 6, we show the effect of the contract on the absolute value of Week 1 task allocations over Week 2 tasks allocations minus one: a variable that measures how different the allocations are from each other, with 0 meaning

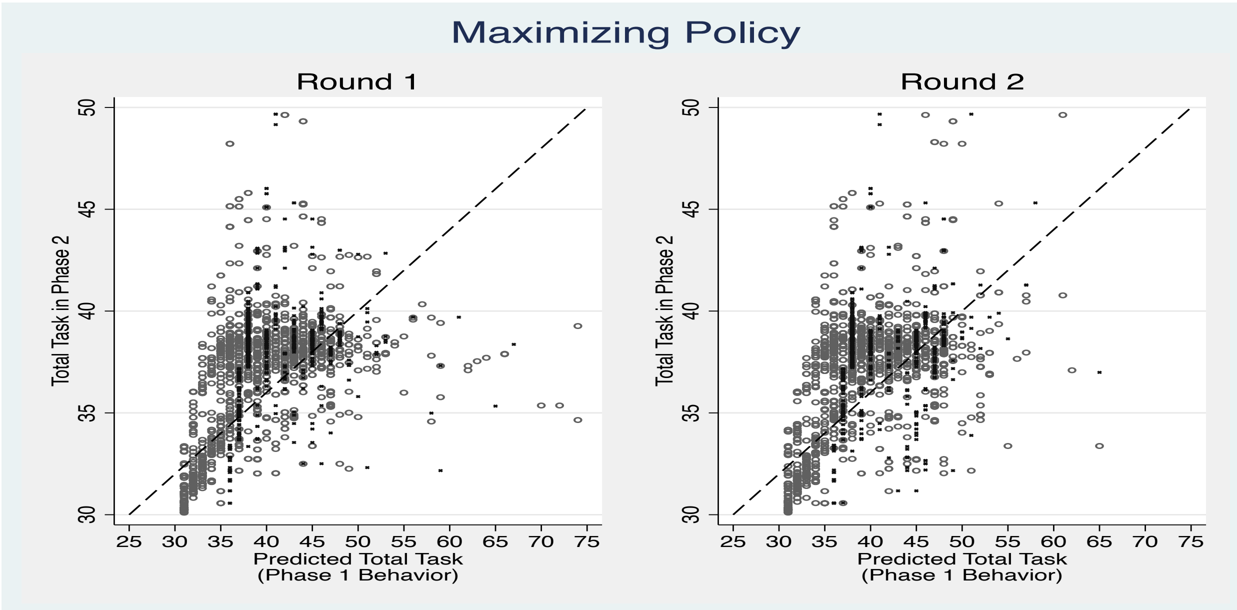

Figure 6: Comparison of Actual and Predicted Behavior in Maximizing Policy

Notes: The left panel presents the relationship between the model-based predicted Lady Health Workers' behavior and their actually chosen total tasks in the context of the Maximizing Policy target in Round 1 in the Tailored (cross) and Untailored (hollow circle) conditions. The left panel presents the relationship between the model-based predicted Lady Health Workers' behavior and their actually chosen total tasks in the context of the Maximizing Policy target in Round 2 in the Tailored (cross) and Untailored (hollow circle) conditions.

no difference. Our hypothesis is that a Leontief contract will lead to more equalization between the number of tasks allocated to each day. Our main variable of interest is *Structural Tailored*, when $R_L = 1$, which is negative and statistically significant with a value of -0.408 over a control mean of 1.054 in Round 1, which is around a 38 percent reduction in the treatment group compared to the control group. This means that the Leontief contract substantially reduced the difference in the tasks allocated to both days. We find a similarly sized and statistically significant effect in Round 2, which took place six months after we elicited preferences. This shows that the contracts are effective even in the medium term. We do not find evidence for the effect size changing in the medium term, as the difference in coefficients in Round 1 and 2 is not statistically significant.

In Round 1 and Round 2, Column (2), we add further explanatory variables to understand whether immediate or advance decisions made any difference in choices. We can see that the effect is close to nonexistent in both rounds. The effects are similar in the last panel, in which we combine both rounds.

Table 6: The Effect of Tailoring Intertemporal Incentives for Leontief Policy

Dependent Variable:	$\lvert \frac{w_{1,i}}{w_{2,i}} - 1 \rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.408***	-0.363***	-0.358***	-0.349***	-0.383***	-0.356***
	(0.088)	(0.097)	(0.055)	(0.062)	(0.054)	(0.059)
β_2 : Immediate Choice (=1)		0.063		0.082*		0.072**
		(0.052)		(0.047)		(0.034)
β_3 : Structural Tailored x Immediate		-0.091		-0.019		-0.055
		(0.073)		(0.084)		(0.055)
β_0 : Constant	0.918***	0.887***	0.844***	0.803***	0.881***	0.845***
	(0.070)	(0.076)	(0.085)	(0.088)	(0.073)	(0.075)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.399	0.399	0.485	0.485	0.395	0.395
Log Likelihood	-6042.571	-6041.954	-5720.523	-5718.868	-12061.782	-12060.099
Mean in Untailored Contract	1.054	1.054	0.984	0.984	1.018	1.018
Mean in Untailored Advance		1.022		0.941		0.981
Mean in Untailored Immediated		1.085		1.026		1.055
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(3)}^{round=2}$						
$p-value$	0.593					
Hypothesis 2: $\beta_{1Col(2)}^{round=1} = \beta_{1Col(4)}^{round=2}$						
$p-value$	0.895					
Hypothesis 3: $\beta_{3Col(2)}^{round=1} = \beta_{3Col(4)}^{round=2}$						
$p-value$	0.482					

Notes: This table reports the effects of tailoring on the equality of effort provision over time. For all subjects, the treatment tailored condition is defined as a dummy equal to one when one of the assigned four task rates is equal to $R^*_{Li}(\beta_i, \delta_i)$. The measure $\lvert \frac{w_1}{w_2} - 1 \rvert$ (the percentage difference between tasks allocated to Week 1 and Week 2 of the drive) reflects the distance from task allocation (w_1,w_2) to equality ($w_1 = w_2$). Column (1) reports a regression of this measure on the tailored condition for Round 1. Column (2) reports the full-sample estimates of Round 1, interacting the treatment with being in the immediate-choice condition. Column (3) reports a regression of this measure on the tailored condition for Round 2. Column (4) reports the full-sample estimates of Round 2, interacting the treatment with being in the immediate-choice condition. Column (5) reports a regression of this measure on the tailored condition for both rounds. Column (6) reports the full-sample estimates of both rounds, interacting the treatment with being in the immediate-choice condition. Fixed-effects regressions. Heteroskedasticity-robust White standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. LHW=Lady Health Worker

The findings of Table 6 indicate the substantial benefits of tailored contracts. For a given interest rate, matching this interest rate to individual preferences generates significantly smoother service provision compared to random contracts. The effects can be substantial and reducing distance measures by around X percent on average. This suggests that policy makers that wish to change intertemporal choices of workers may be able to achieve their goals through tailored contracts.

In Figure 7, we show the distributional effects. We show the distribution for every CHW with the same variable as Table 6. We can see a leftward shift toward zero, showing that the difference between the allocations is being reduced across the board.

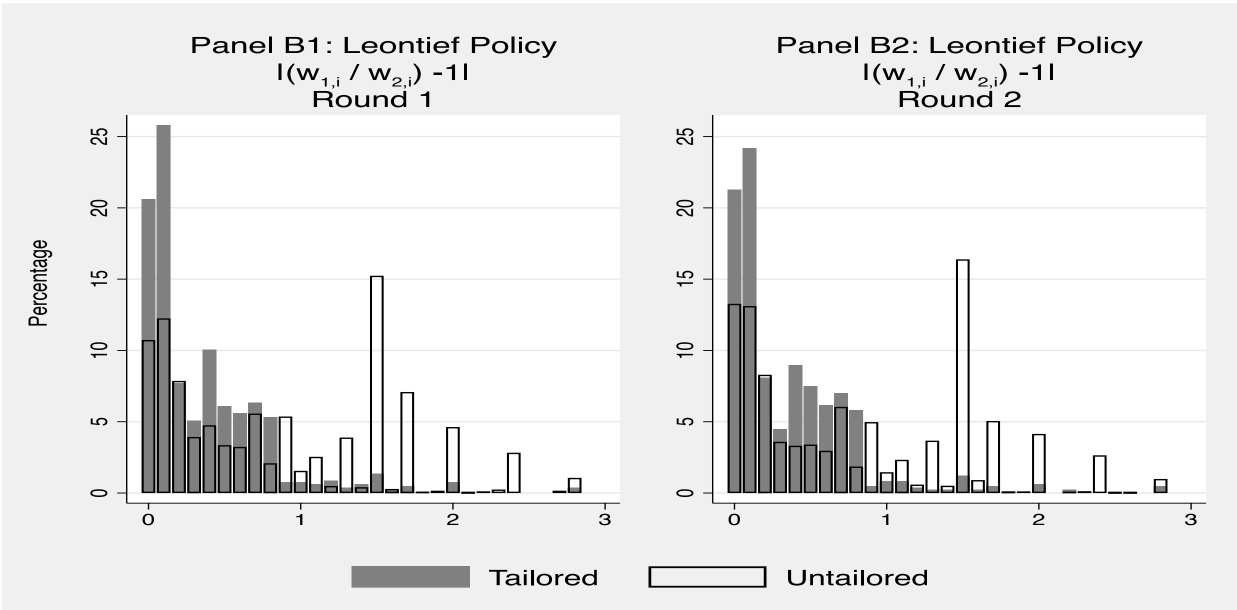

Figure 7: Leontief Policy across Rounds

Notes: Panel B1 presents a histogram of the Leontief policy target, $|\frac{w_{1,i}}{w_{2,i}} - 1|$, in Tailored and Untailored health workers' decisions in Round 1. Panel B2 presents the behavior these same health workers in the Tailored and Untailored conditions for the Leontief policy target, $|\frac{w_{1,i}}{w_{2,i}} - 1|$, in Round 2.

Table 7: The Effect of Tailoring Intertemporal Incentives for Leontief Policy

Dependent Variable:	$\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}}-1\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.458***	-0.463***	-0.508***	-0.515***	-0.485***	-0.491***
	(0.031)	(0.033)	(0.044)	(0.045)	(0.035)	(0.036)
β_2 : Immediate Choice (=1)		-0.015		-0.005		-0.011
		(0.012)		(0.016)		(0.010)
β_3 : Structural Tailored x Immediate		0.010		0.013		0.012
		(0.017)		(0.022)		(0.014)
β_0 : Constant	0.581***	0.588***	0.734***	0.737***	0.638***	0.644***
	(0.046)	(0.047)	(0.045)	(0.044)	(0.045)	(0.044)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.468	0.468	0.479	0.480	0.442	0.442
Log Likelihood	-3022.031	-3021.827	-3863.278	-3863.247	-7177.180	-7177.022
Mean in Untailored Contract	0.656	0.656	0.743	0.743	0.700	0.700
Mean in Untailored Advance		0.663		0.746		0.706
Mean in Untailored Immediated		0.649		0.741		0.695
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1}=\beta_{1Col(3)}^{round=2}$						
$p-value$	0.115					
Hypothesis 2: $\beta_{1Col(2)}^{round=1}=\beta_{1Col(4)}^{round=2}$						
$p-value$	0.108					
Hypothesis 3: $\beta_{3Col(2)}^{round=1}=\beta_{3Col(4)}^{round=2}$						
$p-value$	0.895					

Notes: This table reports the effects of tailoring on Leontief effort provision over time. For all subjects, the treatment tailored condition is defined as a dummy equal to one when one of the assigned four task rates is equal to $R^*_{Li}(\beta_i,\delta_i)$. $(Minimum\ Task)^{predicted}$ is constructed using the parameter values $\beta_i\delta_i$ of Phase 1 and the customized assigned four values of R_i. The $(Minimum\ Task)^{actual}$ is calculated using the actual and observed (w_1,w_2) in Phase 2. The measure $\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}}-1\rvert$ (the percentage difference between model-based predicted optimal minimum tasks and actually chosen minimum weekly tasks over two weeks) reflects the distance from the optimal minimum task to the actual minimum task over two weeks. Column (1) reports a regression of this measure on the tailored condition for Round 1. Column (2) reports the full-sample estimates of Round 1, interacting the treatment with being in the immediate-choice condition. Column (3) reports a regression of this measure on the tailored condition for Round 2. Column (4) reports the full-sample estimates of Round 2, interacting the treatment with being in the immediate-choice condition. Column (5) reports a regression of this measure on the tailored condition for both rounds. Column (6) reports the full-sample estimates of both rounds, interacting the treatment with being in the immediate-choice condition. Fixed-effects regressions. Heteroskedasticity-robust White standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. LHW=Lady Health Worker

6 Results: Tailored Contracts and Performance

In this section, we analyze the effect of the contracts on public service delivery by the CHWs—in our case, household visits for disease surveillance.

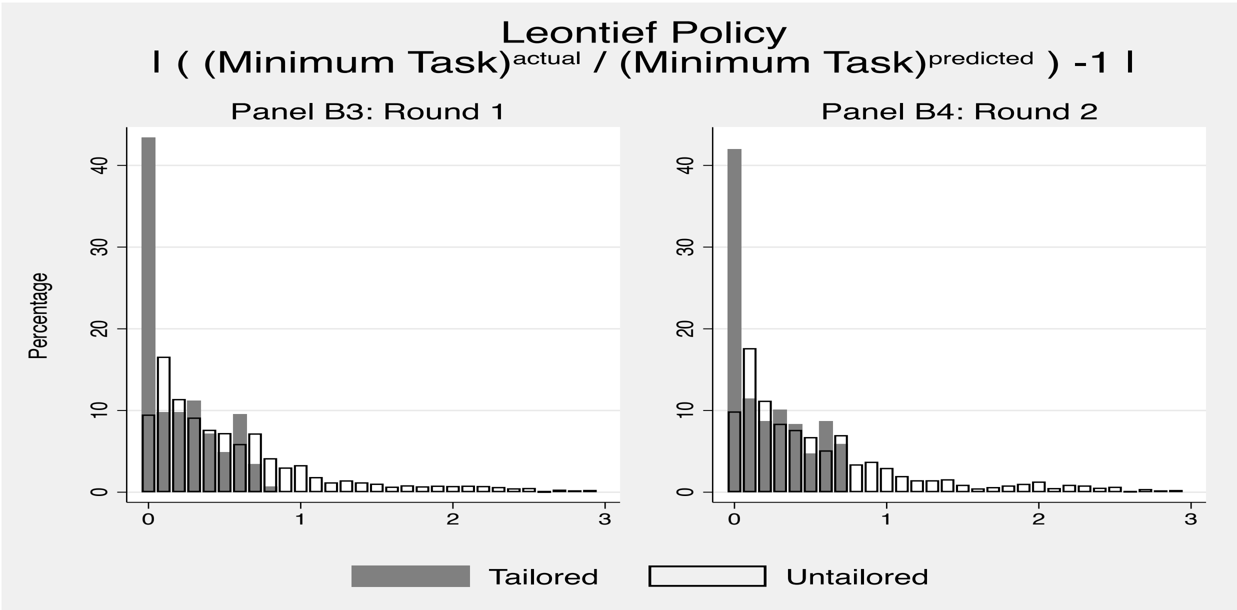

Figure 8: Leontief Policy across Rounds

Notes: Panel B3 presents a histogram of the Leontief policy target, $|\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1|$, in Tailored and Untailored health workers' decisions in Round 1. Panel B4 presents the behavior of these same health workers in the Tailored and Untailored conditions for the Leontief policy target, $|\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1|$, in Round 2.

Our first outcome of interest is the number of forms completed and submitted. The data (required by the Department of Health) on a completed form concern disease prevalence in a household. Our second outcome of interest is the distance traveled (in meters). To conduct the household surveys, the CHWs go from household to household on foot; covering ground is an important part of their job. Our final outcome of interest is the time taken between surveys (in minutes).

In Table 8, we show the effect of the individually tailored maximizing contracts on these outcome variables. We find that the maximizing contract results in 20 percent more forms being submitted, after using training-center fixed effects to control for geographic characteristics of CHWs' official assigned catchment area. We find that the contract results in a significant 162 meters more ground being covered by the CHWs, compared to a control mean of 546 meters. The CHWs were working in Lahore, which is a dense city. They were operating in low- to middle-income areas, where density is even higher than high-income areas. Considering the lack of pedestrian friendliness in developing countries, 162 meters is

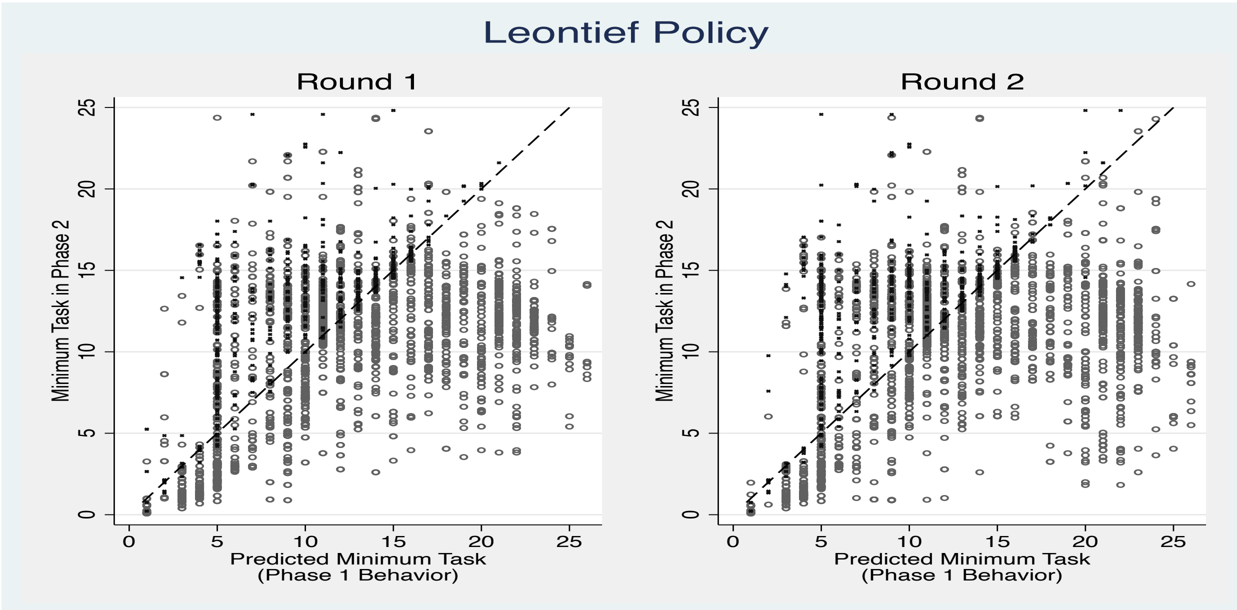

Figure 9: Comparison of Actual and Predicted Behavior in Leontief Policy

Notes: The left panel presents the relationship between the model-based predicted Lady Health Workers' behavior and their actually chosen total tasks in the context of the Leontief policy target in Round 1 in the Tailored (cross) and Untailored (hollow circle) conditions. The left panel presents the relationship between the model-based predicted Lady Health Workers' behavior and their actually chosen total tasks in the context of the Leontief policy target in Round 2 in the Tailored (cross) and Untailored (hollow circle) conditions.

economically meaningful. Finally, we find that the time taken between households declines by around a quarter of one minute compared to a control mean of three minutes. This allows the CHWs to cover more ground and take less time between houses, in turn allowing them to take breaks and be more diligent in finding houses to survey. The sample size is smaller for the last two outcomes because of connectivity issues when sharing locations on WhatsApp. With a bad connection, location data can be received very late and get bunched together, which prevents us from measuring distance traveled and time lapse accurately. However, this is a genuine problem when conducting fieldwork, and we do not expect it to be correlated with observables. We test for balance between these groups and find no statistically significant differences (See Appendix 8.2).

We see similar results in Round 2; however, these are for a smaller sample. The reason for the smaller sample is that we use data from a second experiment—in which some CHWs worked in groups and some as individuals—that explores group time preferences. Hence, there were fewer CHWs working as individuals, which shrinks our sample of completed work.

Table 8: Performance Analysis of Tailored Contracts

Dependent Variable:	*ln(#Forms)* *Submitted* (1)	*Distance* *Traveled* (2)	*Time* *Lapsed* (3)
β_1 : Maximum Structural Tailored (=1)	0.273***	75.803**	-0.186
	(0.044)	(37.672)	(0.235)
β_2 : Leontief Structural Tailored (=1)	-0.134***	-114.408***	0.605**
	(0.034)	(31.664)	(0.270)
β_0 : Constant	3.450***	545.082***	2.624***
	(0.050)	(26.011)	(0.159)
Training Center FEs	Yes	Yes	Yes
Round FEs	Yes	Yes	Yes
Winsorized 85th and 15th Percentiles	No	Yes	Yes
Mean in Untailored Contract	3.358	526.815	3.141
R-Squared	0.379	0.111	0.160
# Observations	637	637	599
# LHWs	428	428	410

Notes: The table reports the effects of Maximized and Leontief tailoring on the reported behavior of Lady Health Workers (LHWs). In Column (1), the measure *ln(#Forms) submitted* reflects the natural logarithm of the total number of submitted forms by LHWs over two weeks in Round 1 and Round 2. In Column (2) the measure *Distance Traveled* reflects the total distance (in meters) traveled by LHWs over two weeks in Round 1 and Round 2, based on the reported geo-stamped data. In Column (3) the measure *Time Lapsed* reflects the average time spent per household (in minutes) by LHWs over two weeks in Round 1 and Round 2 based on the reported time-stamped data. Table reports a regression of these measures on a dummy equal to one for subjects assigned to the two tailored conditions. Fixed-effects regressions. Heteroskedasticity-robust White standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Importantly, the choice of who does individual work was totally random, which should ensure that the groups are balanced.

We also show the effect of the individually tailored Leontief contracts on forms submitted, distance covered, and time lapsed. We find that the Leontief contract results in 16.80 percent fewer forms being submitted and 203 less meters being covered. However, the time spent increases by 1.5 minutes. This is in line with the preference for a combination of lower quantity and higher quality. We see similar results in Round 2, which had a smaller sample.

Finally, it is important to note that while there may be concerns about agents adapting their behavior and thus picking contracts of their preference, the contract that they finally have to implement is a random contract. Each agent has two random contracts and whether the random contracts are betetr or worse than the treatment contracts is unknown to everyone including the research team. Thus, the CHWs do not have complete control over what contract they are finally allocated and have no incentive to mimic any particular contract.

7 Conclusion

We conducted a field experiment with public sector health workers to test individually tailored contracts using time-preference parameters. We considered a policy maker who knows the time-preference parameters of individuals—such as their discount factor, δ, and their present-bias parameter, β—and wishes to attain a policy objective such as maximizing the amount of work or equalizing it across time.

We found two important results. First, the contracts function as theorized. The maximizing contract leads to more tasks being allocated over the period of the experiment, and the Leontief contract leads to more equalized work over the period. We see these effects in distributional terms as well, which is important because the contracts are individually tailored.

The results hold both one and six months after we elicit preferences, which shows that the time-preference parameters we estimated not only have an effect in the medium term but have an effect of similar magnitude across time, thus showing us that the parameters are stable and usable for policy purposes in the medium term. The contracts also lead to better public service delivery (in the form of household health surveys) in terms of the number of household surveys conducted, the distance traveled, and the time taken between surveys.

Finally, our theoretical model does not allow for general equilibrium effects. We test the treatment contracts against random contracts, not one-fit-for-all contracts.

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8 Appendix

8.1 Derivation of R_m^* for Maximizing Policy Maker Derivation

starting with the following

$$\max_{R_m} \left\{ \frac{m {R_m}^{\frac{1}{\gamma-1}}}{(\beta_i\delta_i)^{\frac{1}{\gamma-1}} + R_m^{\frac{\gamma}{\gamma-1}}} + \frac{m(\beta_i\delta_i)^{\frac{1}{\gamma-1}}}{(\beta_i\delta_i)^{\frac{1}{\gamma-1}} + R_m^{\frac{\gamma}{\gamma-1}}} \right\}$$

Taking the first order condition with respect to R_m, where

$$P = v_{1,i}^* + v_{2,i}^* = \frac{m {R_m}^{\frac{1}{\gamma-1}} + m(\beta_i\delta_i)^{\frac{1}{\gamma-1}}}{(\beta_i\delta_i)^{\frac{1}{\gamma-1}} + R_m^{\frac{\gamma}{\gamma-1}}}$$

Then

$$\frac{\partial P}{\partial R_m} = 0 \implies$$

solving the following equation for

$$R_m^*(\beta_i, \delta_i, \gamma)$$

$$\frac{((\beta_i\delta_i)^{\frac{1}{\gamma-1}} + R_m^{\frac{\gamma}{\gamma-1}})\, m\frac{1}{\gamma-1} R_m^{\frac{1}{\gamma-1}-1} - (m(R_m)^{\frac{1}{\gamma-1}} + m(\beta_i\delta_i)^{\frac{1}{\gamma-1}})\frac{\gamma}{\gamma-1} R_m^{\frac{1}{\gamma-1}-1}}{((\beta_i\delta_i)^{\frac{1}{\gamma-1}} + R_m^{\frac{1}{\gamma-1}})^2} = 0$$

simplifying we get the following equation for optimal R denoted as $R^*(\beta_i, \delta_i, \gamma)$

$$(\beta_i\delta_i)^{\frac{1}{\gamma-1}} {R_m^*}^{\frac{2-\gamma}{\gamma-1}} + (1-\gamma){R_m^*}^{\frac{2}{\gamma-1}} - \gamma(\beta_i\delta_i)^{\frac{1}{\gamma-1}} {R_m^*}^{\frac{1}{\gamma-1}} = 0$$

8.2 Balance Tables

Here we present all balance tables to show that our small samples with fewer CHWs are no different from the main sample.

Table 9: **Round1: Balance Table for the Maximum Structural Tailored Assignment**

	Treatment	Control	Difference p-value	No. of Obs.
Demographics				
Age in Years	48.680	47.266	0.057	420
	(0.640)	(0.371)		
Marital Status	2.220	2.272	0.481	420
	(0.063)	(0.039)		
Number of Children	3.560	3.184	0.037	420
	(0.153)	(0.094)		
Education Level	3.010	2.834	0.059	420
	(0.082)	(0.043)		
Financial Background				
Has a Savings Account (=1)	0.120	0.125	0.894	420
	(0.033)	(0.019)		
Late on Bill Payment (=1)	0.650	0.709	0.274	420
	(0.048)	(0.025)		
Participated in a ROSCA (=1)	0.300	0.344	0.410	420
	(0.046)	(0.027)		
Participate in a ROSCA (=1)	0.310	0.400	0.096	420
	(0.046)	(0.027)		
Health Work Experience				
Years in Health Department	20.050	19.138	0.156	420
	(0.561)	(0.313)		
Assigned Area Nature	2.380	2.300	0.344	420
	(0.073)	(0.042)		
Phase 1 Data				
Drive 1 Behavior:$(Rv_{1i}/v_{2i})^{\widehat{\gamma}}$	2.289	2.108	0.735	420
	(0.304)	(0.443)		
# of LHWs	100	320		

Notes: Marital status is coded as: 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, 5 for separation. Education level is recorded as: 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelors and 6 for masters level education. A ROSCA is an informal Rotating Savings and Credit Association. Assigned area categories are defined by the Punjab Health Department as: 1 being easy, 2 difficult and 3 being hard area. Uses robust standard errors. $p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: **Round2: Balance Table for the Maximum Structural Tailored Assignment**

	Treatment	Control	Difference p-value	No. of Obs.
Demographics				
Age in Years	46.969	47.697	0.441	217
	(0.808)	(0.489)		
Marital Status	2.415	2.211	0.059	217
	(0.095)	(0.051)		
Number of Children	3.415	3.151	0.323	217
	(0.229)	(0.136)		
Education Level	2.877	2.737	0.189	217
	(0.091)	(0.054)		
Financial Background				
Has a Savings Account (=1)	0.154	0.053	0.038	217
	(0.045)	(0.018)		
Late on Bill Payment (=1)	0.708	0.678	0.660	217
	(0.057)	(0.038)		
Participated in a Rosca (=1)	0.292	0.303	0.879	217
	(0.057)	(0.037)		
Participate in a Rosca (=1)	0.400	0.401	0.986	217
	(0.061)	(0.040)		
Health Work Experience				
Years in Health Department	18.692	20.158	0.068	217
	(0.664)	(0.446)		
Assigned Area Nature	2.416	3.233	0.556	217
	(0.086)	(0.059)		
Phase 1 Data				
Drive 1 Behavior:$(Rv_{1i}/v_{2i})^{\widehat{\gamma}}$	2.416	3.233	0.556	217
	(0.665)	(1.213)		
# of LHWs	65	152		

Notes: Marital status is coded as: 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, 5 for separation. Education level is recorded as: 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelors and 6 for masters level education. A ROSCA is an informal Rotating Savings and Credit Association. Assigned area categories are defined by the Punjab Health Department as: 1 being easy, 2 difficult and 3 being hard area. Uses robust standard errors. $p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11: **Round1: Balance Table for the Leontief Structural Tailored Assignment**

	Treatment	Control	Difference p-value	No. of Obs.
Demographics				
Age in Years	47.286	47.699	0.601	420
	(0.700)	(0.362)		
Marital Status	2.347	2.233	0.173	420
	(0.075)	(0.036)		
Number of Children	3.245	3.283	0.842	420
	(0.164)	(0.093)		
Education Level	3.020	2.832	0.050	420
	(0.086)	(0.043)		
Financial Background				
Has a Savings Account (=1)	0.163	0.112	0.214	420
	(0.037)	(0.018)		
Late on Bill Payment (=1)	0.694	0.696	0.973	420
	(0.047)	(0.026)		
Participated in a ROSCA (=1)	0.347	0.329	0.747	420
	(0.048)	(0.026)		
Participate in a ROSCA (=1)	0.459	0.354	0.066	420
	(0.050)	(0.027)		
Health Work Experience				
Years in Health Department	19.694	19.252	0.490	420
	(0.557)	(0.314)		
Assigned Area Nature	2.235	2.345	0.205	420
	(0.076)	(0.041)		
Phase 1 Data				
Drive 1 Behavior:$(Rv_{1i}/v_{2i})^{\widehat{\gamma}}$	1.863	2.239	0.522	420
	(0.395)	(0.433)		
# of LHWs	98	322		

Notes: Marital status is coded as: 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, 5 for separation. Education level is recorded as: 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelors and 6 for masters level education. A ROSCA is an informal Rotating Savings and Credit Association. Assigned area categories are defined by the Punjab Health Department as: 1 being easy, 2 difficult and 3 being hard area. Uses robust standard errors. $p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: **Round2: Balance Table for the Maximum Structural Tailored Assignment**

	Treatment	Control	Difference p-value	No. of Obs.
Demographics				
Age in Years	47.742	47.374	0.700	217
	(0.819)	(0.488)		
Marital Status	2.226	2.290	0.502	217
	(0.077)	(0.056)		
Number of Children	3.274	3.213	0.808	217
	(0.208)	(0.142)		
Education Level	2.726	2.800	0.472	217
	(0.086)	(0.056)		
Financial Background				
Has a Savings Account (=1)	0.048	0.097	0.184	217
	(0.027)	(0.024)		
Late on Bill Payment (=1)	0.694	0.684	0.890	217
	(0.059)	(0.038)		
Participated in a ROSCA (=1)	0.242	0.323	0.226	217
	(0.055)	(0.038)		
Participate in a ROSCA (=1)	0.339	0.426	0.230	217
	(0.060)	(0.040)		
Health Work Experience				
Years in Health Department	20.387	19.452	0.265	217
	(0.715)	(0.436)		
Assigned Area Nature	2.339	2.290	0.654	217
	(0.092)	(0.057)		
Phase 1 Data				
Drive 1 Behavior:$(Rv_{1i}/v_{2i})^{\widehat{\gamma}}$	1.469	3.596	0.085	217
	(0.178)	(1.216)		
# of LHWs	62	155		

Notes: Marital status is coded as: 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, 5 for separation. Education level is recorded as: 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelors and 6 for masters level education. A ROSCA is an informal Rotating Savings and Credit Association. Assigned area categories are defined by the Punjab Health Department as: 1 being easy, 2 difficult and 3 being hard area. Uses robust standard errors. $p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: **Balance Table for Round 1 Reported GPS Data**

	GPS Reported	GPS not Reported	Difference p-value	No. of Obs.
Demographics				
Age in Years	47.353	48.528	0.119	420
	(0.368)	(0.655)		
Marital Status	2.281	2.180	0.169	420
	(0.038)	(0.063)		
Number of Children	3.260	3.326	0.748	420
	(0.090)	(0.185)		
Education Level	2.894	2.809	0.368	420
	(0.043)	(0.084)		
Financial Background				
Has a Savings Account (=1)	0.124	0.124	0.995	420
	(0.018)	(0.035)		
Late on Bill Payment (=1)	0.671	0.787	0.023	420
	(0.026)	(0.044)		
Participated in a ROSCA (=1)	0.329	0.348	0.738	420
	(0.026)	(0.051)		
Participate in a ROSCA (=1)	0.390	0.337	0.356	420
	(0.027)	(0.050)		
Health Work Experience				
Years in Health Department	19.142	20.146	0.122	420
	(0.311)	(0.568)		
Assigned Area Nature	2.353	2.191	0.073	420
	(0.040)	(0.081)		
Performance Data				
# Forms Completed on Day1	19.589	18.449	0.270	420
	(0.455)	(0.927)		
# Forms Completed on Day2	14.571	13.180	0.212	420
	(0.631)	(0.916)		
# of LHWs	331	89		

Notes: Marital status is coded as: 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, 5 for separation. Education level is recorded as: 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelors and 6 for masters level education. A ROSCA is an informal Rotating Savings and Credit Association. Assigned area categories are defined by the Punjab Health Department as: 1 being easy, 2 difficult and 3 being hard area. Tasks completed on Day 7 and Day 14 are for the Phase 2 of the experiment. Uses robust standard errors. $p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: **Balance Table for Round 2 Reported GPS Data**

	GPS Reported	GPS not Reported	Difference p-value	No. of Obs.
Demographics				
Age in Years	47.498	47.000	0.855	217
	(0.424)	(2.693)		
Marital Status	2.278	2.125	0.485	217
	(0.047)	(0.213)		
Number of Children	3.215	3.625	0.610	217
	(0.118)	(0.793)		
Education Level	2.785	2.625	0.527	217
	(0.048)	(0.247)		
Financial Background				
Has a Savings Account (=1)	0.081	0.125	0.714	217
	(0.019)	(0.117)		
Late on Bill Payment (=1)	0.679	0.875	0.110	217
	(0.032)	(0.117)		
Participated in a ROSCA (=1)	0.301	0.250	0.744	217
	(0.032)	(0.154)		
Participate in a ROSCA (=1)	0.392	0.625	0.186	217
	(0.034)	(0.172)		
Health Work Experience				
Years in Health Department	19.799	17.625	0.318	217
	(0.378)	(2.138)		
Assigned Area Nature	2.301	2.375	0.682	217
	(0.050)	(0.172)		
Performance Data				
# Forms Completed on Day1	19.278	15.125	0.259	217
	(0.580)	(3.624)		
# Forms Completed on Day2	15.234	12.625	0.379	217
	(0.613)	(2.896)		
# of LHWs	209	8		

Notes: Marital status is coded as: 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, 5 for separation. Education level is recorded as: 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelors and 6 for masters level education. A ROSCA is an informal Rotating Savings and Credit Association. Assigned area categories are defined by the Punjab Health Department as: 1 being easy, 2 difficult and 3 being hard area. Tasks completed on Day 7 and Day 14 are for the Phase 2 of the experiment. Uses robust standard errors. $p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 15: **Balance Table for Round 1 & Round 2 Work Participation**

	Participated Both Rounds	Not Participated Both Rounds	Difference p-value	No. of Obs.
Demographics				
Age in Years	47.684	47.521	0.801	420
	(0.483)	(0.427)		
Marital Status	2.230	2.289	0.367	420
	(0.046)	(0.047)		
Number of Children	3.287	3.261	0.870	420
	(0.110)	(0.118)		
Education Level	2.962	2.791	0.027	420
	(0.060)	(0.047)		
Financial Background				
Has a Savings Account (=1)	0.158	0.090	0.035	420
	(0.025)	(0.020)		
Late on Bill Payment (=1)	0.708	0.682	0.569	420
	(0.032)	(0.032)		
Participated in a ROSCA (=1)	0.359	0.308	0.271	420
	(0.033)	(0.032)		
Participate in a ROSCA (=1)	0.349	0.408	0.219	420
	(0.033)	(0.034)		
Health Work Experience				
Years in Health Department	19.000	19.706	0.197	420
	(0.394)	(0.380)		
Assigned Area Nature	2.321	2.318	0.967	420
	(0.053)	(0.049)		
Performance Data				
# Forms Completed on Day1	19.541	19.156	0.639	420
	(0.581)	(0.577)		
# Forms Completed on Day2	13.679	14.867	0.266	420
	(0.556)	(0.909)		
# of LHWs	209	211		

Notes: Marital status is coded as: 1 for unmarried, 2 for married, 3 for widow, 4 for divorced, 5 for separation. Education level is recorded as: 1 for primary education, 2 for secondary education, 3 for matriculation, 4 for high school education, 5 for bachelors and 6 for masters level education. A ROSCA is an informal Rotating Savings and Credit Association. Assigned area categories are defined by the Punjab Health Department as: 1 being easy, 2 difficult and 3 being hard area. Tasks completed on Day 7 and Day 14 are for the Phase 2 of the experiment. Uses robust standard errors. $p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

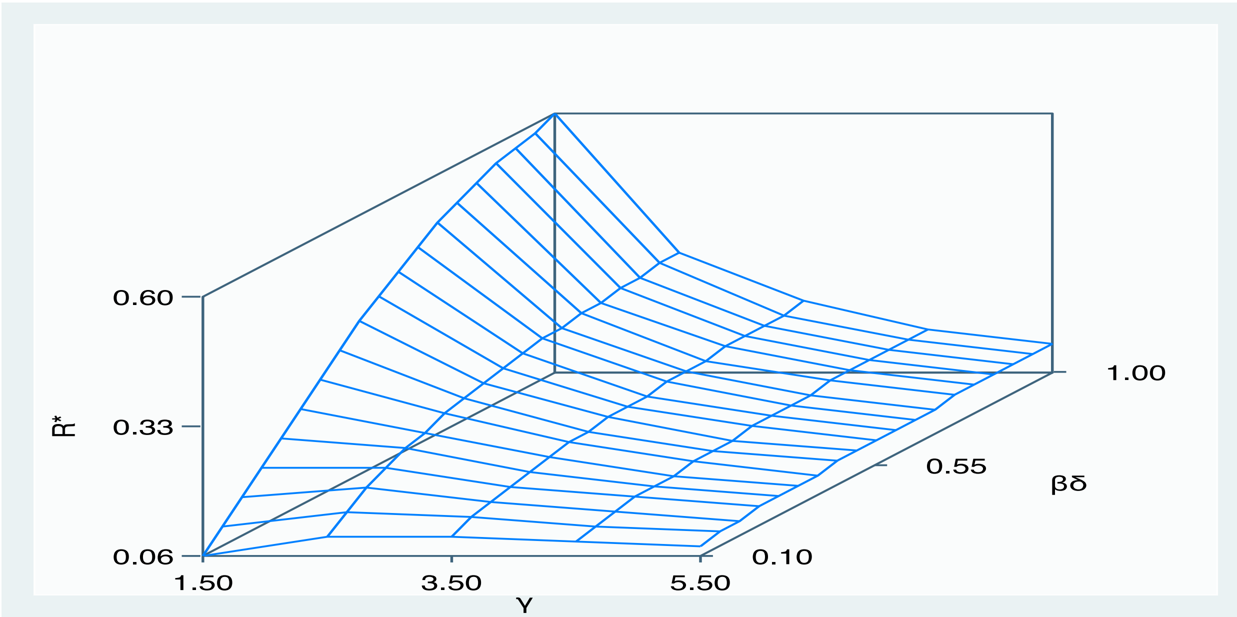

Figure 10: Parameters' Relationship in Maximizing Policy

Notes: The 3-D graph shows the relationship between R_m^* and γ and $\beta\delta$.

8.3 Robustness Tests

8.4 MLE Estimates

Here, we use different estimation methods to estimate our structural parameters.

8.4.1 Robustness Checks: Winsor

The first robust test we perform is to test whether outliers drive our results. We winsorize our sample at the X percent. We find the same results qualitatively.

8.4.2 Robustness Checks: Tailoring Intensity

The second robustness test we perform is to test whether using tailoring intensity, rather than a binary tailored contract, effects our results. We define tailoring intensity as the absolute difference between optimally customized value of R and four assigned values of R_i. Theoretically, we would expect stronger effects with higher tailoring intensity, which is exactly what we observe in our results.

Table 16: **Maximum Likelihood Estimates Adapted for Censoring**

	Round 1 (1)	*Round 2* (2)	*Combined* (3)	*Combined* (4)
Present-Bias Parameter: β	0.944	0.992	0.984	0.991
	(0.060)	(0.017)	(0.018)	(0.021)
Discount Factor: δ	1.120	1.009	1.024	1.024
	(0.016)	(0.003)	(0.003)	(0.003)
Cost of Effort Parameter: γ	3.581	1.898	2.248	2.263
	(0.268)	(0.064)	(0.094)	(0.095)
σ	6.095	6.664	6.601	6.571
	(0.197)	(0.244)	(0.216)	(0.222)
# Decisions	13,185	13,080	26,265	25,380
# of LHWs	440	436	453	423
Log Likelihood	-38009.16	-39557.13	-78276.65	-75593.51
Hypothesis				
β=1 (p-value)	0.35	0.62	0.37	0.67
δ=1 (p-value)	0	0.01	0	0
γ=1 (p-value)	0	0	0	0

Notes: The table presents the structural estimates of intertemporal hyperbolic-discounting model using nonlinear least squares estimation method adapted for censoring, recognizing that v_1 will be censored in the interval of $[5, m-3]$. Column 1: reports the structural estimates using the LHWs' decisions from the first round. Column 2: uses the decisions sets from second round. Columns 3: reports the NLS estimates using both rounds of LHWs' decision including 17 LHWs' decisions absent in the second round. Columns 4: uses the LHWs' decisions present in both rounds. Clustered standard errors in parentheses. Weekly discount rate can be calculated as $(\delta)^7$. (A parameter δ greater than one suggests that people prefer to complete less work as the duration from the first day of work increases. Possible explanation for this finding is that LHWs do not want to commit to more work farther in the future because there is greater uncertainty about other obligations on these dates.). Standard errors calculated via the delta method. Chi-squared tests in last three rows.

8.4.3 Robustness Checks: Different Outcomes

The third robustness test we perform is to test alternative dependent variables. We run the same regressions with the logged square root of the total number of forms plus total number of forms squared as well as the log of the minimum of tasks on both days. We find that the results are the same qualitatively.

8.4.4 Robustness Checks: Restricted Sample

The fourth robustness test we perform is to test if a restricted sample yields the same result. We restrict our sample to CHWs who participated in both rounds of Phase 2. Our results are the same qualitatively.

8.4.5 Robustness Checks: Coutnerfactual Tailoring

We test counterfactual tailoring contracts. Instead of using the remaining three contracts as the control group, we simply use one of the random contracts as the counterfactual contract

Table 17: The Effect of Tailoring for Maximizing Policy on Winsorized Sample

Dependent variable:	$\ln(w_{1,i} + w_{2,i})$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	0.330***	0.333***	0.350***	0.352***	0.341***	0.344***
	(0.018)	(0.018)	(0.016)	(0.016)	(0.016)	(0.016)
β_2 : Immediate Choice (=1)		-0.003		-0.000		-0.002
		(0.003)		(0.003)		(0.002)
β_3 : Structural Tailored x Immediate		-0.006		-0.005		-0.006
		(0.005)		(0.006)		(0.004)
β_0 : Constant	3.372***	3.374***	3.360***	3.360***	3.366***	3.367***
	(0.023)	(0.023)	(0.020)	(0.020)	(0.020)	(0.020)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.425	0.425	0.399	0.399	0.405	0.405
Log Likelihood	-1287.606	-1287.507	-1460.706	-1460.679	-2784.741	-2784.635
Mean in Untailored Contract	3.305	3.305	3.303	3.303	3.304	3.304
Mean in Untailored Advance		3.307		3.303		3.305
Mean in Untailored Immediated		3.304		3.302		3.303
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1}{}^{round=1}_{Col(1)} = \beta_{1}{}^{round=2}_{Col(3)}$						
$p-value$	0.151					
Hypothesis 2: $\beta_{1}{}^{round=1}_{Col(2)} = \beta_{1}{}^{round=2}_{Col(4)}$						
$p-value$	0.174					
Hypothesis 3: $\beta_{3}{}^{round=1}_{Col(2)} = \beta_{3}{}^{round=2}_{Col(4)}$						
$p-value$	0.916					

Notes: This table reports the effects of tailoring on the maximum effort provision over time. The measure $\ln(w_{1,i} + w_{2,i})$ reflects the natural logarithm of total task allocation (w_1, w_2) over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

(the one that mimics the treatment contract).

8.5 Heterogeneity Effect

We now analyze our main results to understand whether they are heterogeneous based on the existence of present bias.

Table 18: The Effect of Tailoring for Leontief Policy on Winsorized Sample

Dependent variable:	$\lvert\frac{w_{1,i}}{w_{2,i}} - 1\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.469***	-0.450***	-0.410***	-0.401***	-0.439***	-0.425***
	(0.029)	(0.034)	(0.029)	(0.035)	(0.023)	(0.026)
β_2 : Immediate Choice (=1)		0.024		0.041*		0.032*
		(0.023)		(0.025)		(0.017)
β_3 : Structural Tailored x Immediate		-0.038		-0.018		-0.028
		(0.034)		(0.038)		(0.025)
β_0 : Constant	0.907***	0.895***	0.849***	0.829***	0.889***	0.873***
	(0.010)	(0.015)	(0.010)	(0.015)	(0.013)	(0.016)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.404	0.405	0.419	0.420	0.332	0.332
Log Likelihood	-2828.296	-2827.643	-2839.151	-2837.143	-6105.885	-6103.983
Mean in Untailored Contract	0.902	0.902	0.854	0.854	0.878	0.878
Mean in Untailored Advance		0.890		0.833		0.861
Mean in Untailored Immediated		0.914		0.875		0.894
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1\,Col(1)}^{round=1} = \beta_{1\,Col(3)}^{round=2}$						
$p - value$	0.061					
Hypothesis 2: $\beta_{1\,Col(2)}^{round=1} = \beta_{1\,Col(4)}^{round=2}$						
$p - value$	0.214					
Hypothesis 3: $\beta_{3\,Col(2)}^{round=1} = \beta_{3\,Col(4)}^{round=2}$						
$p - value$	0.668					

Notes: This table reports the effects of tailoring on the equality of effort provision over time. The measure $\lvert\frac{w_{1,i}}{w_{2,i}} - 1\rvert$ (the percentage difference between tasks allocated to Week 1 and Week 2 of the drive) reflects the distance of the task allocation (w_1,w_2) from equality ($w_1 = w_2$). Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

8.6 Context: Community Health Workers

CHWs are instrumental in delivering essential health care services worldwide, including in developed countries like the United States. It is estimated that approximately five million CHWs are active within the global health care system (Perry et al. 2014). The role of these workers has garnered particular attention in low- and middle-income countries since the

Table 19: The Effect of Tailoring for Maximum Policy on Winsorized Sample

Dependent variable:	$\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.025***	-0.021***	-0.020***	-0.016***	-0.023***	-0.019***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
β_2 : Immediate Choice (=1)		-0.002		-0.000		-0.001
		(0.002)		(0.002)		(0.001)
β_3 : Structural Tailored x Immediate		-0.009**		-0.007*		-0.008***
		(0.004)		(0.004)		(0.003)
β_0 : Constant	0.103***	0.104***	0.101***	0.102***	0.103***	0.104***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.369	0.369	0.357	0.357	0.333	0.334
Log Likelihood	3035.987	3037.488	3233.214	3233.873	6113.162	6115.104
Mean in Untailored Contract	0.118	0.118	0.114	0.114	0.116	0.116
Mean in Untailored Advance		0.119		0.114		0.117
Mean in Untailored Immediated		0.117		0.115		0.116
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1\,Col(1)}^{round=1} = \beta_{1\,Col(3)}^{round=2}$						
$p - value$	0.066					
Hypothesis 2: $\beta_{1\,Col(2)}^{round=1} = \beta_{1\,Col(4)}^{round=2}$						
$p - value$	0.283					
Hypothesis 3: $\beta_{3\,Col(2)}^{round=1} = \beta_{3\,Col(4)}^{round=2}$						
$p - value$	0.595					

Notes: This table reports the effects of tailoring on the maximum effort provision over time. The $(Total\ Task)^{predicted}$ is constructed using the parameter values $(\beta_i\delta_i, \gamma)$ of Phase 1 and the customized assigned four values of R_i. The $(Minimum\ Task)^{actual}$ is calculated using the actual and observed (w_1,w_2) in Phase 2. The measure $\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1\rvert$ (the percentage difference between model based predicted optimal total tasks and actual chosen total of weekly tasks over two weeks) reflects the distance of the optimal total task from the actual total task over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

1970s, where there was a significant shortage of trained health care professionals to promote preventive health care aimed at achieving sustainable development goals (Scott et al. 2018).

In Pakistan, CHWs serve as the backbone of the preventive and primary health care system, particularly in rural areas. These workers operate under a dedicated division of the

Table 20: The Effect of Tailoring for Leontief Policy on Winsorized Sample

Dependent variable:	$\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.381***	-0.384***	-0.401***	-0.413***	-0.391***	-0.399***
	(0.020)	(0.022)	(0.023)	(0.024)	(0.019)	(0.020)
β_2 : Immediate Choice (=1)		-0.012		-0.015		-0.014*
		(0.011)		(0.012)		(0.008)
β_3 : Structural Tailored x Immediate		0.007		0.023		0.015
		(0.016)		(0.019)		(0.012)
β_0 : Constant	0.561***	0.567***	0.602***	0.610***	0.570***	0.577***
	(0.012)	(0.014)	(0.011)	(0.012)	(0.011)	(0.012)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.341	0.341	0.361	0.361	0.330	0.331
Log Likelihood	-2010.120	-2009.889	-2273.753	-2273.390	-4403.108	-4402.550
Mean in Untailored Contract	0.589	0.589	0.623	0.623	0.606	0.606
Mean in Untailored Advance		0.595		0.630		0.613
Mean in Untailored Immediated		0.583		0.615		0.599
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(3)}^{round=2}$						
$p-value$	0.271					
Hypothesis 2: $\beta_{1Col(2)}^{round=1} = \beta_{1Col(4)}^{round=2}$						
$p-value$	0.300					
Hypothesis 3: $\beta_{3Col(2)}^{round=1} = \beta_{3Col(4)}^{round=2}$						
$p-value$	0.842					

Notes: This table reports the effects of tailoring on the Leontief effort provision over time. The $(Minimum\ Task)^{predicted}$ is constructed using the parameter values $\beta_i\delta_i$ of Phase 1 and the customized assigned four values of R_i. The $(Minimum\ Task)^{actual}$ is calculated using the actual and observed (w_1,w_2) in Phase 2. The measure $\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\rvert$ (the percentage difference between model based predicted optimal minimum tasks and actual chosen minimum of weekly tasks over two weeks) reflects the distance of the optimal minimum task from the actual minimum task over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Department of Health known as the Lady Health Workers program, established in 1993, with a total workforce of 96,000 individuals nationwide (Jalal 2011). Since 2014, they have been officially recognized as full-time public sector employees with job security akin to other government personnel.

Table 21: The Effect of Tailoring Intensity on Intertemporal Incentives for Maximum Policy

Dependent variable:	$\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Tailoring Intensity	0.461***	0.447***	0.388***	0.378***	0.421***	0.409***
	(0.042)	(0.046)	(0.037)	(0.040)	(0.033)	(0.037)
β_2 : Immediate Choice		-0.002		0.001		-0.001
		(0.003)		(0.002)		(0.002)
β_3 : Tailoring Intensity x Immediate		-0.014**		-0.010*		-0.012**
		(0.007)		(0.006)		(0.005)
β_0 : Constant	0.220***	0.219***	0.199***	0.197***	0.211***	0.210***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.504	0.505	0.527	0.527	0.487	0.487
Log Likelihood	2812.656	2816.628	3161.298	3163.095	5769.800	5775.272
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(3)}^{round=2}$						
$p-value$	0.198					
Hypothesis 2: $\beta_{1Col(2)}^{round=1} = \beta_{1Col(4)}^{round=2}$						
$p-value$	0.240					
Hypothesis 3: $\beta_{3Col(2)}^{round=1} = \beta_{3Col(4)}^{round=2}$						
$p-value$	0.526					

Notes: This table reports the effects of tailoring on the maximum effort provision over time. The $(Total\ Task)^{predicted}$ is constructed using the parameter values $(\beta_i\delta_i, \gamma)$ of Phase 1 and the customized assigned four values of R_i. The $(Minimum\ Task)^{actual}$ is calculated using the actual and observed (w_1,w_2) in Phase 2. The measure $\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1\rvert$ (the percentage difference between model based predicted optimal total tasks and actual chosen total of weekly tasks over two weeks) reflects the distance of the optimal total task from the actual total task over two weeks. Column (1) reports a regression of this measure on tailoring intensity (measured as the absolute difference between optimally customized value of R and four assigned values of R_i) for Round 1. Column (2) reports the full sample estimates of Round 1 interacting tailoring intensity with being in the immediate choice condition. Column (3) reports a regression of this measure on tailoring intensity for Round 2. Column (4) reports the full sample estimates of Round 2 interacting tailoring intensity with being in the immediate choice condition. Column (5) reports a regression of this measure on tailoring intensity for both rounds. Column (6) reports the full sample estimates of both rounds interacting tailoring intensity with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

All CHWs in Pakistan are women hired by the Department of Health to work in specific communities within each district. While they are affiliated with a health clinic for administrative purposes, their primary responsibility is to deliver services directly to a defined community outside the clinic setting. They do not overlap with other CHWs in their geographic area of responsibility, nor do they have systematic interactions with other health

Table 22: The Effect of Tailoring Intensity on Intertemporal Incentives for Leontief Policy

Dependent variable:	$\left\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\right\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Tailoring Intensity	0.092***	0.089***	0.082***	0.080***	0.086***	0.084***
	(0.014)	(0.013)	(0.009)	(0.009)	(0.010)	(0.009)
β_2 : Immediate Choice		0.046***		0.070***		0.058***
		(0.012)		(0.016)		(0.010)
β_3 : Tailoring Intensity x Immediate		-0.231***		-0.289***		-0.262***
		(0.028)		(0.031)		(0.022)
β_0 : Constant	0.333***	0.343***	0.398***	0.403***	0.339***	0.347***
	(0.019)	(0.019)	(0.029)	(0.029)	(0.019)	(0.019)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.646	0.653	0.641	0.648	0.624	0.631
Log Likelihood	-2339.481	-2304.172	-3218.516	-3182.721	-5829.066	-5761.940
# Decisions	3360	3360	3472	3472	6832	6832
# LHWs	420	420	400	400	432	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(3)}^{round=2}$						
$p - value$	0.457					
Hypothesis 2: $\beta_{1Col(2)}^{round=1} = \beta_{1Col(4)}^{round=2}$						
$p - value$	0.469					
Hypothesis 3: $\beta_{3Col(2)}^{round=1} = \beta_{3Col(4)}^{round=2}$						
$p - value$	0.079					

Notes: This table reports the effects of tailoring on the Leontief effort provision over time. The $(Minimum\ Task)^{predicted}$ is constructed using the parameter values $\beta_i\delta_i$ of Phase 1 and the customized assigned four values of R_i. The $(Minimum\ Task)^{actual}$ is calculated using the actual and observed (w_1,w_2) in Phase 2. The measure $\left\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\right\rvert$ (the percentage difference between model based predicted optimal minimum tasks and actual chosen minimum of weekly tasks over two weeks) reflects the distance of the optimal minimum task from the actual minimum task over two weeks. Column (1) reports a regression of this measure on tailoring intensity (measured as the absolute difference between optimally customized value of R and four assigned values of R_i) for Round 1. Column (2) reports the full sample estimates of Round 1 interacting tailoring intensity with being in the immediate choice condition. Column (3) reports a regression of this measure on tailoring intensity for Round 2. Column (4) reports the full sample estimates of Round 2 interacting tailoring intensity with being in the immediate choice condition. Column (5) reports a regression of this measure on tailoring intensity for both rounds. Column (6) reports the full sample estimates of both rounds interacting tailoring intensity with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

care professionals in their day-to-day duties. This organizational setup contributes to the study's focus by minimizing the potential for information spillovers and facilitating the precise measurement of performance.

CHWs in Pakistan predominantly function as outreach workers, necessitating monthly household visits. Their central duty revolves around providing preventive and basic health care services directly to citizens at their homes. Consequently, the delivery of any service

Table 23: The Effect of Tailoring on Alternative Measures

Dependent variable:	$\ln\sqrt{(total_i + total_i{}^2)}$		$\ln(min[w_{1,i}, w_{2,i}])$	
	(1)	(2)	(3)	(4)
β_1 : Structural Tailored (=1)	0.345***	0.350***	-0.146***	-0.153***
	(0.017)	(0.017)	(0.020)	(0.021)
β_2 : Immediate Choice (=1)		-0.003		-0.014*
		(0.002)		(0.009)
β_3 : Structural Tailored x Immediate		-0.011**		0.014
		(0.005)		(0.015)
β_0 : Constant	4.067***	4.069***	2.456***	2.464***
	(0.022)	(0.022)	(0.018)	(0.019)
LHW FEs	Yes	Yes	Yes	Yes
Round FEs	Yes	Yes	Yes	Yes
R-Squared	0.422	0.422	0.440	0.440
Log Likelihood	-3017.125	-3016.796	-4047.139	-4046.449
Mean in Untailored Contract	3.995	3.995	2.396	2.396
Mean in Untailored Advance		3.997		2.404
Mean in Untailored Immediated		3.994		2.388
# Decisions	6832	6832	6832	6832
# LHWs	432	432	432	432

Notes: This table reports the effects of tailoring on the alternative measures of effort provision over time. $\ln\sqrt{(total_i + total_i{}^2)}$ and $\ln(min(w_{1,i}, w_{2,i}))$ are used as alternative for maximizing and Leontief policy measures respectively. Column (1) reports a regression of the alternate measure of maximizing policy maker on a dummy equal to one for subjects in the tailored group. Column (2) reports the estimates of interacting treatment with being in the immediate choice condition. Column (3) reports a regression of the alternate measure of Leontief policy maker on a dummy equal to one for subjects in the tailored group. Column (4) reports the estimates of interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

hinges on these workers making regular household visits. These visits are vital for staying informed about the community's health status and educating household members on disease prevention. During these interactions, CHWs offer guidance on family planning, conduct antenatal checks to monitor expectant mothers' health, and provide postnatal follow-ups to advise on disease prevention and nutrition. To fulfill these responsibilities, CHWs must consistently visit households to keep track of important events such as marriages.

Table 24: The Effect of Tailoring Intertemporal Incentives for Maximizing Policy-Restricted Sample

Dependent variable:	$\ln(w_{1,i} + w_{2,i})$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	0.335***	0.342***	0.352***	0.356***	0.344***	0.350***
	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)	(0.019)
β_2 : Immediate Choice (=1)		-0.005		-0.001		-0.003
		(0.004)		(0.003)		(0.002)
β_3 : Structural Tailored x Immediate		-0.015**		-0.009		-0.011**
		(0.007)		(0.007)		(0.005)
β_0 : Constant	3.378***	3.381***	3.363***	3.363***	3.374***	3.376***
	(0.024)	(0.024)	(0.028)	(0.028)	(0.025)	(0.025)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.435	0.435	0.412	0.412	0.416	0.416
Log Likelihood	-1295.936	-1295.619	-1489.013	-1488.951	-2824.523	-2824.214
Mean in Untailored Contract	3.301	3.301	3.301	3.301	3.301	3.301
Mean in Untailored Advance		3.303		3.303		3.303
Mean in Untailored Immediated		3.300		3.300		3.300
# Decisions	3040	3040	3324	3324	6364	6364
# LHWs	380	380	380	380	380	380
Hypothesis 1: $\beta_{1\,Col(1)}^{round=1} = \beta_{1\,Col(3)}^{round=2}$						
$p - value$	0.156					
Hypothesis 2: $\beta_{1\,Col(2)}^{round=1} = \beta_{1\,Col(4)}^{round=2}$						
$p - value$	0.277					
Hypothesis 3: $\beta_{3\,Col(2)}^{round=1} = \beta_{3\,Col(4)}^{round=2}$						
$p - value$	0.473					

Notes: This table reports the effects of tailoring on the maximum effort provision over time. The measure $\ln(w_{1,i} + w_{2,i})$ reflects the natural logarithm of total task allocation (w_1,w_2) over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

8.7 Other

Finally, in Figure 34, we show the relationship between different demographic variables and the discount factor. We can see that the existence of a savings around leads to a lower discount rate.

Table 25: The Effect of Tailoring Intertemporal Incentives for Leontief Policy-Restricted Sample

Dependent variable:	$\lvert \frac{w_{1,i}}{w_{2,i}} - 1 \rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.455***	-0.413***	-0.346***	-0.335***	-0.398***	-0.372***
	(0.076)	(0.087)	(0.058)	(0.065)	(0.050)	(0.057)
β_2 : Immediate Choice (=1)		0.074		0.086*		0.081**
		(0.056)		(0.048)		(0.036)
β_3 : Structural Tailored x Immediate		-0.083		-0.022		-0.051
		(0.079)		(0.087)		(0.058)
β_0 : Constant	0.908***	0.871***	0.827***	0.784***	0.891***	0.851***
	(0.072)	(0.078)	(0.087)	(0.090)	(0.079)	(0.081)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.392	0.392	0.495	0.496	0.396	0.396
Log Likelihood	-5367.280	-5366.488	-5491.293	-5489.568	-11147.149	-11145.064
Mean in Untailored Contract	1.016	1.016	1.016	1.016	1.016	1.016
Mean in Untailored Advance		0.976		0.976		0.976
Mean in Untailored Immediated		1.056		1.056		1.056
# Decisions	3040	3040	3324	3324	6364	6364
# LHWs	380	380	380	380	380	380
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(3)}^{round=2}$						
$p-value$	0.194					
Hypothesis 2: $\beta_{1Col(2)}^{round=1} = \beta_{1Col(4)}^{round=2}$						
$p-value$	0.414					
Hypothesis 3: $\beta_{3Col(2)}^{round=1} = \beta_{3Col(4)}^{round=2}$						
$p-value$	0.572					

Notes: This table reports the effects of tailoring on the equality of effort provision over time. The measure $\lvert \frac{w_1}{w_2} - 1 \rvert$ (the percentage difference between tasks allocated to Week 1 and Week 2 of the drive) reflects the distance of the task allocation (w_1,w_2) from equality ($w_1 = w_2$). Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 26: The Effect of Tailoring Intertemporal Incentives for Maximizing Policy-Restricted Sample

Dependent variable:	$\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.025***	-0.020***	-0.017***	-0.014**	-0.021***	-0.017***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
β_2 : Immediate Choice (=1)		-0.003		0.000		-0.001
		(0.002)		(0.002)		(0.001)
β_3 : Structural Tailored x Immediate		-0.010**		-0.007		-0.009***
		(0.005)		(0.005)		(0.003)
β_0 : Constant	0.101***	0.102***	0.097***	0.097***	0.101***	0.102***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.493	0.493	0.496	0.496	0.466	0.466
Log Likelihood	2489.482	2491.029	2945.977	2946.516	5254.799	5256.591
Mean in Untailored Contract	0.125	0.125	0.125	0.125	0.125	0.125
Mean in Untailored Advance		0.125		0.125		0.125
Mean in Untailored Immediated		0.124		0.124		0.124
# Decisions	3040	3040	3324	3324	6364	6364
# LHWs	380	380	380	380	380	380
Hypothesis 1: $\beta_{1\,Col(1)}^{\,round=1} = \beta_{1\,Col(3)}^{\,round=2}$						
$p-value$	0.065					
Hypothesis 2: $\beta_{1\,Col(2)}^{\,round=1} = \beta_{1\,Col(4)}^{\,round=2}$						
$p-value$	0.238					
Hypothesis 3: $\beta_{3\,Col(2)}^{\,round=1} = \beta_{3\,Col(4)}^{\,round=2}$						
$p-value$	0.678					

Notes: This table reports the effects of tailoring on the maximum effort provision over time. The $(Total\ Task)^{predicted}$ is constructed using the parameter values $(\beta_i\delta_i, \gamma)$ of Phase 1 and the customized assigned four values of R_i. The $(Minimum\ Task)^{actual}$ is calculated using the actual and observed (w_1,w_2) in Phase 2. The measure $\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}} - 1\rvert$ (the percentage difference between model based predicted optimal total tasks and actual chosen total of weekly tasks over two weeks) reflects the distance of the optimal total task from the actual total task over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 27: The Effect of Tailoring Intertemporal Incentives for Leontief Policy-Restricted Sample

Dependent variable:	$\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\rvert$					
	Round 1		*Round 2*		*Combined*	
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.465***	-0.474***	-0.510***	-0.518***	-0.489***	-0.498***
	(0.033)	(0.035)	(0.042)	(0.043)	(0.036)	(0.037)
β_2 : Immediate Choice (=1)		-0.017		-0.011		-0.014
		(0.013)		(0.016)		(0.010)
β_3 : Structural Tailored x Immediate		0.018		0.016		0.017
		(0.018)		(0.021)		(0.014)
β_0 : Constant	0.586***	0.595***	0.702***	0.707***	0.622***	0.629***
	(0.049)	(0.049)	(0.054)	(0.054)	(0.051)	(0.051)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	No	No	Yes	Yes
R-Squared	0.474	0.474	0.466	0.466	0.443	0.443
Log Likelihood	-2810.527	-2810.298	-3614.797	-3614.722	-6623.422	-6623.170
Mean in Untailored Contract	0.700	0.700	0.700	0.700	0.700	0.700
Mean in Untailored Advance		0.707		0.707		0.707
Mean in Untailored Immediated		0.693		0.693		0.693
# Decisions	3040	3040	3324	3324	6364	6364
# LHWs	380	380	380	380	380	380
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(3)}^{round=2}$						
$p - value$	0.069					
Hypothesis 2: $\beta_{1Col(2)}^{round=1} = \beta_{1Col(4)}^{round=2}$						
$p - value$	0.104					
Hypothesis 3: $\beta_{3Col(2)}^{round=1} = \beta_{3Col(4)}^{round=2}$						
$p - value$	0.918					

Notes: This table reports the effects of tailoring on the Leontief effort provision over time. The $(Minimum\ Task)^{predicted}$ is constructed using the parameter values $\beta_i\delta_i$ of Phase 1 and the customized assigned four values of R_i. The $(Minimum\ Task)^{actual}$ is calculated using the actual and observed (w_1,w_2) in Phase 2. The measure $\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\rvert$ (the percentage difference between model based predicted optimal minimum tasks and actual chosen minimum of weekly tasks over two weeks) reflects the distance of the optimal minimum task from the actual minimum task over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 1. Column (2) reports the full sample estimates of Round 1 interacting treatment with being in the immediate choice condition. Column (3) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for Round 2. Column (4) reports the full sample estimates of Round 2 interacting treatment with being in the immediate choice condition. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group for both rounds. Column (6) reports the full sample estimates of both rounds interacting treatment with being in the immediate choice condition. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 28: The Effect of Counterfactual Tailoring Intertemporal Incentives for Maximum Policy

Dependent variable:	$\ln(w_{1,i}+w_{2,i})$			$\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$		
	Round 1	*Round 2*	*Combined*	*Round 1*	*Round 2*	*Combined*
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Alt. Structural Tailored (=1)	0.405***	0.402***	0.405***	0.030***	0.021***	0.025***
	(0.020)	(0.017)	(0.017)	(0.007)	(0.006)	(0.006)
β_2 : Immediate Choice (=1)	-0.006	-0.002	-0.004	-0.004*	-0.001	-0.002
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
β_3 : Alt. Structural Tailored x Immediate	-0.013	-0.004	-0.008*	-0.008	-0.003	-0.006*
	(0.008)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)
β_0 : Constant	3.366***	3.350***	3.361***	0.089***	0.088***	0.091***
	(0.024)	(0.021)	(0.021)	(0.006)	(0.004)	(0.005)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	Yes	No	No	Yes
R-Squared	0.479	0.442	0.452	0.485	0.510	0.468
Log Likelihood	-1311.907	-1466.768	-2830.317	2748.858	3099.745	5651.469
Mean in Untailored Contract	3.291	3.286	3.288	0.116	0.113	0.114
Mean in Untailored Advance	3.294	3.287	3.290	0.117	0.113	0.115
Mean in Untailored Immediated	3.288	3.285	3.286	0.114	0.113	0.113
# Decisions	3360	3472	6832	3360	3472	6832
# LHWs	420	400	432	420	400	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(2)}^{round=2}$						
$p-value$	0.973					
Hypothesis 2: $\beta_{3Col(1)}^{round=1} = \beta_{3Col(2)}^{round=2}$						
$p-value$	0.672					
Hypothesis 3: $\beta_{1Col(4)}^{round=1} = \beta_{1Col(5)}^{round=2}$						
$p-value$	0.342					
Hypothesis 4: $\beta_{3Col(4)}^{round=1} = \beta_{3Col(5)}^{round=2}$						
$p-value$	0.715					

Notes: This table reports the effects of counterfactual tailoring on the maximum effort provision over time. The treatment tailored variable is defined as dummy equal to one for LHW's lowest assigned R. In the first three columns, the measure $\ln(w_{1,i}+w_{2,i})$ reflects the natural logarithm of total task allocation (w_1,w_2) over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (2) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (3) reports the results for the combined samples. In the last three columns, the measure $\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$ (the percentage difference between model based predicted optimal total tasks and actual chosen total of weekly tasks over two weeks) reflects the distance of the optimal total task from the actual total task over two weeks. Column (4) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (6) reports the results for the combined samples. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 29: The Effect of Counterfactual Tailoring Intertemporal Incentives for Maximum Policy

Dependent variable:	$\ln(w_{1,i}+w_{2,i})$			$\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$		
	Round 1	*Round* 2	*Combined*	*Round* 1	*Round* 2	*Combined*
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Alt. Structural Tailored (=1)	0.351***	0.341***	0.346***	0.030***	0.026***	0.028***
	(0.025)	(0.025)	(0.024)	(0.008)	(0.007)	(0.007)
β_2 : Immediate Choice (=1)	-0.008*	-0.002	-0.005**	-0.006**	-0.001	-0.003**
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
β_3 : Alt. Structural Tailored x Immediate	0.001	-0.001	-0.000	0.000	-0.002	-0.001
	(0.008)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
β_0 : Constant	3.392***	3.392***	3.396***	0.085***	0.081***	0.084***
	(0.030)	(0.031)	(0.030)	(0.007)	(0.007)	(0.007)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	Yes	No	No	Yes
R-Squared	0.498	0.493	0.489	0.474	0.479	0.449
Log Likelihood	-1227.004	-1265.639	-2534.522	2787.090	3185.588	5787.224
Mean in Untailored Contract	3.297	3.294	3.295	0.113	0.109	0.111
Mean in Untailored Advance	3.301	3.295	3.298	0.116	0.109	0.112
Mean in Untailored Immediated	3.292	3.292	3.292	0.110	0.108	0.109
# Decisions	3336	3432	6768	3336	3432	6768
# LHWs	417	396	428	417	396	428
Hypothesis 1: $\beta_{1Col(1)}^{round=1}=\beta_{1Col(2)}^{round=2}$						
$p-value$	0.774					
Hypothesis 2: $\beta_{3Col(1)}^{round=1}=\beta_{3Col(2)}^{round=2}$						
$p-value$	0.359					
Hypothesis 3: $\beta_{1Col(4)}^{round=1}=\beta_{1Col(5)}^{round=2}$						
$p-value$	0.302					
Hypothesis 4: $\beta_{3Col(4)}^{round=1}=\beta_{3Col(5)}^{round=2}$						
$p-value$	0.434					

Notes: This table reports the effects of counterfactual tailoring on the maximum effort provision over time. The treatment variable (Alt. Structural Tailored) is defined as dummy equal to one for LHW's R if it is equal to $R^*_{random(i)}$ which is different from $R^*_{Mi}(\beta_i,\delta_i,\widehat{\gamma})$. In the first three columns, the measure $\ln(w_{1,i}+w_{2,i})$ reflects the natural logarithm of total task allocation (w_1,w_2) over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (2) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (3) reports the results for the combined samples. In the last three columns, the measure $\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$ (the percentage difference between model based predicted optimal total tasks and actual chosen total of weekly tasks over two weeks) reflects the distance of the optimal total task from the actual total task over two weeks. Column (4) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (6) reports the results for the combined samples. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 30: The Effect of Tailoring Intertemporal Incentives for Maximum Policy Using only Two Task Rates

Dependent variable:	$\ln(w_{1,i}+w_{2,i})$			$\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$		
	Round 1	*Round* 2	*Combined*	*Round* 1	*Round* 2	*Combined*
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.022***	-0.009*	-0.015***	-0.036***	-0.025***	-0.030***
	(0.007)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
β_2 : Immediate Choice (=1)	-0.007	-0.003	-0.005	-0.005	-0.003	-0.004
	(0.007)	(0.005)	(0.004)	(0.005)	(0.003)	(0.003)
β_3 : Structural Tailored x Immediate	-0.010	-0.007	-0.009	-0.007	-0.005	-0.006*
	(0.009)	(0.007)	(0.005)	(0.006)	(0.005)	(0.003)
β_0 : Constant	4.000***	3.953***	3.978***	0.254***	0.221***	0.238***
	(0.020)	(0.015)	(0.012)	(0.016)	(0.015)	(0.012)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	Yes	No	No	Yes
R-Squared	0.719	0.700	0.533	0.666	0.648	0.484
Log Likelihood	1874.400	2379.877	3373.569	2449.122	2789.903	4515.531
Mean in Untailored Contract	3.729	3.718	3.723	0.118	0.109	0.113
Mean in Untailored Advance	3.733	3.719	3.726	0.120	0.111	0.115
Mean in Untailored Immediated	3.725	3.716	3.721	0.115	0.108	0.111
# Decisions	1680	1736	3416	1680	1736	3416
# LHWs	420	400	432	420	400	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1}=\beta_{1Col(2)}^{round=2}$						
$p-value$	0.123					
Hypothesis 2: $\beta_{3Col(1)}^{round=1}=\beta_{3Col(2)}^{round=2}$						
$p-value$	0.730					
Hypothesis 3: $\beta_{1Col(4)}^{round=1}=\beta_{1Col(5)}^{round=2}$						
$p-value$	0.061					
Hypothesis 4: $\beta_{3Col(4)}^{round=1}=\beta_{3Col(5)}^{round=2}$						
$p-value$	0.767					

Notes: This table reports the effects of tailoring on the maximum effort provision over time using the allocation decisions from $R^*_{random(i)}$ and $R^*_{Mi}(\beta_i,\delta_i,\widehat{\gamma})$. In the first three columns, the measure $\ln(w_{1,i}+w_{2,i})$ reflects the natural logarithm of total task allocation (w_1,w_2) over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (2) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (3) reports the results for the combined samples. In the last three columns, the measure $\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$ (the percentage difference between model based predicted optimal total tasks and actual chosen total of weekly tasks over two weeks) reflects the distance of the optimal total task from the actual total task over two weeks. Column (4) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (6) reports the results for the combined samples. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $*p<0.1$, $**p<0.05$, $***p<0.01$.

Table 31: The Effect of Tailoring Intertemporal Incentives for Leontief Policy Using only Two Task Rates

Dependent variable:	$\lvert\frac{w_{1,i}}{w_{2,i}} - 1\rvert$			$\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\rvert$		
	Round 1	*Round* 2	*Combined*	*Round* 1	*Round* 2	*Combined*
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.271*	-0.222**	-0.250***	-0.414***	-0.471***	-0.445***
	(0.161)	(0.093)	(0.091)	(0.056)	(0.072)	(0.060)
β_2 : Immediate Choice (=1)	0.109	0.197	0.152	0.003	0.006	0.004
	(0.159)	(0.128)	(0.095)	(0.018)	(0.014)	(0.011)
β_3 : Structural Tailored x Immediate	-0.138	-0.135	-0.136	-0.007	0.001	-0.003
	(0.170)	(0.140)	(0.102)	(0.021)	(0.020)	(0.014)
β_0 : Constant	0.868***	0.838***	0.886***	0.420***	0.464***	0.435***
	(0.163)	(0.072)	(0.094)	(0.068)	(0.101)	(0.081)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	Yes	No	No	Yes
R-Squared	0.640	0.711	0.600	0.827	0.824	0.816
Log Likelihood	-3108.710	-2879.984	-6366.309	-769.280	-848.129	-1703.340
Mean in Untailored Contract	1.129	1.016	1.071	0.871	0.909	0.891
Mean in Untailored Advance	1.074	0.916	0.994	0.870	0.904	0.887
Mean in Untailored Immediated	1.183	1.117	1.150	0.873	0.915	0.894
# Decisions	1680	1736	3416	1680	1736	3416
# LHWs	420	400	432	420	400	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1} = \beta_{1Col(2)}^{round=2}$						
$p - value$	0.901					
Hypothesis 2: $\beta_{3Col(1)}^{round=1} = \beta_{3Col(2)}^{round=2}$						
$p - value$	0.987					
Hypothesis 3: $\beta_{1Col(4)}^{round=1} = \beta_{1Col(5)}^{round=2}$						
$p - value$	0.780					
Hypothesis 4: $\beta_{3Col(4)}^{round=1} = \beta_{3Col(5)}^{round=2}$						
$p - value$	0.745					

Notes: This table reports the effects of tailoring on the Leontief effort provision over time using the allocation decisions from $R^{**}_{random(i)}$ and $R^{*}_{Li}(\beta_i, \delta_i)$. In the first three columns, the measure $\lvert\frac{w_1}{w_2} - 1\rvert$ (the percentage difference between tasks allocated to Week 1 and Week 2 of the drive) reflects the distance of the task allocation (w_1,w_2) from equality ($w_1 = w_2$). Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (2) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (3) reports the results for the combined samples. In the last three columns, the measure $\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}} - 1\rvert$ (the percentage difference between model based predicted optimal minimum tasks and actual chosen minimum of weekly tasks over two weeks) reflects the distance of the optimal minimum task from the actual minimum task over two weeks. Column (4) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 1. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being in the immediate choice condition for Round 2. Column (6) reports the results for the combined samples. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 32: The Heterogeneous Effect of Tailoring Intertemporal Incentives for Maximum Policy

Dependent variable:	$\ln(w_{1,i}+w_{2,i})$			$\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$		
	Round 1	*Round 2*	*Combined*	*Round 1*	*Round 2*	*Combined*
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	0.352***	0.365***	0.360***	-0.020***	-0.017***	-0.019***
	(0.020)	(0.017)	(0.017)	(0.006)	(0.005)	(0.005)
β_2 : Structural Tailored x Present Biased (=1)	-0.129***	-0.091***	-0.110***	-0.018	-0.002	-0.010
	(0.030)	(0.034)	(0.029)	(0.014)	(0.012)	(0.011)
β_0 : Constant	3.380***	3.362***	3.374***	0.100***	0.098***	0.102***
	(0.024)	(0.022)	(0.022)	(0.005)	(0.004)	(0.004)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	Yes	No	No	Yes
R-Squared	0.445	0.417	0.423	0.483	0.509	0.468
Log Likelihood	-1416.350	-1545.071	-3010.749	2743.484	3097.394	5645.981
Mean in Untailored Contract	3.307	3.298	3.302	0.127	0.122	0.125
Mean in Untailored Present Biased (=0)	3.278	3.274	3.276	0.123	0.120	0.122
Mean in Untailored Present Biased (=1)	3.490	3.454	3.472	0.152	0.136	0.144
# Decisions	3360	3472	6832	3360	3472	6832
# LHWs	420	400	432	420	400	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1}=\beta_{1Col(2)}^{round=2}$						
$p-value$	0.329					
Hypothesis 2: $\beta_{2Col(1)}^{round=1}=\beta_{2Col(2)}^{round=2}$						
$p-value$	0.443					
Hypothesis 3: $\beta_{1Col(4)}^{round=1}=\beta_{1Col(5)}^{round=2}$						
$p-value$	0.268					
Hypothesis 4: $\beta_{2Col(4)}^{round=1}=\beta_{2Col(5)}^{round=2}$						
$p-value$	0.424					

Notes: This table reports the effects of tailoring on the maximum effort provision over time. In the first three columns, the measure $\ln(w_{1,i}+w_{2,i})$ reflects the natural logarithm of total task allocation (w_1,w_2) over two weeks. Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ (estimated in Phase 1) less than 0.9 for Round 1. Column (2) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ less than 0.9 (estimated in Phase 1) for Round 2. Column (3) reports the results for the combined samples. In the last three columns, the measure $\lvert\frac{(Total\ Task)^{predicted}}{(Total\ Task)^{actual}}-1\rvert$ (the percentage difference between model based predicted optimal total tasks and actual chosen total of weekly tasks over two weeks) reflects the distance of the optimal total task from the actual total task over two weeks. Column (4) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ (estimated in Phase 1) less than 0.9 for Round 1. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ less than 0.9 (estimated in Phase 1) for Round 2. Column (6) reports the results for the combined samples. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. $*p<0.1$, $**p<0.05$, $***p<0.01$.

Table 33: Heterogeneous Effect of Tailoring Intertemporal Incentives for Leontief Policy

Dependent variable:	$\lvert\frac{w_{1,i}}{w_{2,i}}-1\rvert$			$\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}}-1\rvert$		
	Round 1	*Round* 2	*Combined*	*Round* 1	*Round* 2	*Combined*
	(1)	(2)	(3)	(4)	(5)	(6)
β_1 : Structural Tailored (=1)	-0.476***	-0.427***	-0.451***	-0.474***	-0.519***	-0.498***
	(0.094)	(0.056)	(0.055)	(0.034)	(0.050)	(0.040)
β_2 : Structural Tailored x Present Biased (=1)	0.498*	0.516***	0.506***	0.119	0.077	0.098
	(0.260)	(0.187)	(0.177)	(0.076)	(0.087)	(0.075)
β_0 : Constant	0.918***	0.843***	0.906***	0.581***	0.734***	0.638***
	(0.070)	(0.085)	(0.075)	(0.046)	(0.045)	(0.045)
LHW FEs	Yes	Yes	Yes	Yes	Yes	Yes
Round FEs	No	No	Yes	No	No	Yes
R-Squared	0.401	0.486	0.397	0.468	0.480	0.442
Log Likelihood	-6038.287	-5714.219	-12051.240	-3020.551	-3862.868	-7175.696
Mean in Untailored Contract	1.054	0.984	1.018	0.656	0.743	0.700
Mean in Untailored Present Biased (=0)	1.048	0.999	1.023	0.655	0.749	0.703
Mean in Untailored Present Biased (=1)	1.087	0.885	0.986	0.663	0.706	0.685
# Decisions	3360	3472	6832	3360	3472	6832
# LHWs	420	400	432	420	400	432
Hypothesis 1: $\beta_{1Col(1)}^{round=1}=\beta_{1Col(2)}^{round=2}$						
$p-value$	0.207					
Hypothesis 2: $\beta_{2Col(1)}^{round=1}=\beta_{2Col(2)}^{round=2}$						
$p-value$	0.909					
Hypothesis 3: $\beta_{1Col(4)}^{round=1}=\beta_{1Col(5)}^{round=2}$						
$p-value$	0.129					
Hypothesis 4: $\beta_{2Col(4)}^{round=1}=\beta_{2Col(5)}^{round=2}$						
$p-value$	0.447					

Notes: This table reports the effects of tailoring on the Leontief effort provision over time. In the first three columns, the measure $\lvert\frac{w_1}{w_2}-1\rvert$ (the percentage difference between tasks allocated to Week 1 and Week 2 of the drive) reflects the distance of the task allocation (w_1,w_2) from equality ($w_1=w_2$). Column (1) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ (estimated in Phase 1) less than 0.9 for Round 1. Column (2) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ less than 0.9 (estimated in Phase 1) for Round 2. Column (3) reports the results for the combined samples. In the last three columns, the measure $\lvert\frac{(Minimum\ Task)^{actual}}{(Minimum\ Task)^{predicted}}-1\rvert$ (the percentage difference between model based predicted optimal minimum tasks and actual chosen minimum of weekly tasks over two weeks) reflects the distance of the optimal minimum task from the actual minimum task over two weeks. Column (4) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ (estimated in Phase 1) less than 0.9 for Round 1. Column (5) reports a regression of this measure on a dummy equal to one for subjects in the tailored group interacted with being a present-biased a dummy equal to one for subjects having $\beta\delta$ less than 0.9 (estimated in Phase 1) for Round 2. Column (6) reports the results for the combined samples. Fixed effects regressions. Heteroskedasticity robust White standard errors reported in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$.

Table 34: **Relation between LHW demographic and one-period discount factor**

Dependent variable						$\beta\delta$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age in Years	-0.047											-0.023
	(0.049)											(0.040)
Marital Status		-0.348										-0.296
		(0.286)										(0.271)
Number of Children			0.164									0.058
			(0.118)									(0.132)
Education Level				-0.851								-0.959
				(0.568)								(0.667)
Had a Savings Account (=1)					-1.017**							-0.746
					(0.511)							(0.632)
Has a Savings Account (=1)						-1.071**						-0.624
						(0.527)						(0.482)
Late on Bill Payment (=1)							0.778					0.655
							(0.663)					(0.643)
Participated in a Rosca (=1)								0.589				0.454
								(1.041)				(0.840)
Participate in a Rosca (=1)									0.625			0.514
									(0.962)			(0.731)
Years in Health Department										-0.063		-0.058
										(0.078)		(0.094)
Assigned Area Nature											-0.629	-0.469
											(0.728)	(0.747)
p-value	0.34	0.22	0.17	0.13	0.05	0.04	0.24	0.57	0.52	0.42	0.39	0.86
# LHW	436	436	436	436	436	436	436	436	436	436	436	436

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table shows the predictors of one-period discount factor $\beta\delta$. Uses robust standard errors.

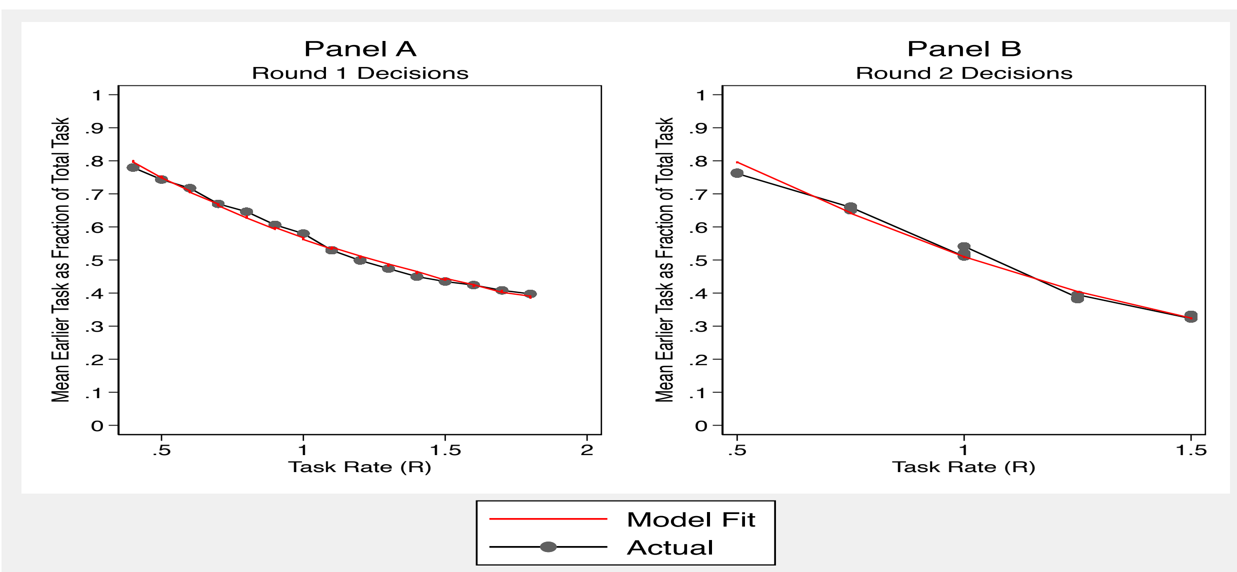

Figure 11: Discounting Behavior

Notes: Mean Experimental Responses Over Task Rates in Round 1 and Round 2.