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When do reminders work?
Memory constraints and medical adherence[*]

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Abstract

An extensive literature shows that reminders can successfully change behavior. Yet, there exists substantial unexplained heterogeneity in their effectiveness, both: (i) across studies, and (ii) across individuals within a particular study. This paper investigates when and why reminders work. We develop a theoretical model that highlights three key mechanisms through which reminders may operate. To test the predictions of the model, we run a nationwide field experiment on medical adherence with over 4000 pregnant women in South Africa and document several key results. First, we find an extremely strong baseline demand for reminders. This demand increases after exposure to reminders, suggesting that individuals learn how valuable they are for freeing up memory resources. Second, stated adherence is increased by pure reminders and reminders containing a moral suasion component, but interestingly, reminders containing health information reduce adherence in our setting. Using a structural model, we show that heterogeneity in memory costs (or, equivalently, annoyance costs) is crucial for explaining the observed behavior.

Keywords: Nudging, Reminders, Memory, Attention, Medication adherence, Structural model
JEL codes: D04, D91, C93, I12

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1 Introduction

Reminders provide a powerful tool for behavior change. A large body of work has demonstrated that reminders can successfully capture our attention and influence our behavior in many domains, such as *gym attendance* (Calzolari & Nardotto 2017), *electricity consumption* (Allcott & Rogers 2014, Gilbert & Zivin 2014), *personal saving* (Karlan et al. 2016), *take-up of social benefits* (Bhargava & Manoli 2015), *tax payments* (Antinyan & Asatryan 2019), *court appearances* (Fishbane et al. 2020) and *adherence to medical treatment* (Vervloet et al. 2012, Altmann & Traxler 2014, Milkman et al. 2021, Campos-Mercade et al. 2021). However, most studies find substantial heterogeneity across participants in their responsiveness to reminders. Many studies also find that subtle changes to the design of the reminder can also lead to considerable variation in their effectiveness. These studies typically fail to fully explain why and for whom reminders work. This heterogeneity in effectiveness is illustrated by the fact that studies that have looked at unsubscriptions (Damgaard & Gravert 2018) or negative willingness to pay for additional reminders (Allcott & Kessler 2019) show that while reminders are effective for some receivers, the same reminder can backfire on others. Therefore, despite their low direct costs compared to the large hoped-for benefits of the targeted behavior change, poorly designed reminders can be ineffective or even lower receiver welfare by causing annoyance or diverting attention from more important behaviors. Nevertheless, mainly due to their low direct costs compared to the commonly observed behavior change, there has been a proliferation in the use of reminders as a policy tool. Given that reminders may backfire, an important question to ask is: How do we know ex-ante whether a reminder will have an overall welfare improving effect?

As with other types of nudges, one potential solution for identifying the most effective reminders before implementing them as policy, is to directly test an array of possible reminders in the specific context of interest and implement the winners (as seen in recent megastudies such as Milkman et al. (2021)). This approach requires enormous amounts of resources and thus defeats the idea of nudges being cost-effective and practical complements to the policy toolkit. And, while this approach may be effective for a specific setting, the findings may not transfer to other contexts. (List 2022). Moving away from "what works", we need to develop an understanding of why, how and for whom different types of reminders work to change behavior.

This paper contributes to this endeavor by studying three mechanisms that may contribute to the observed heterogeneity in the effectiveness of reminders. Specifically, we develop a theoretical framework that decomposes the broader class of reminders into the following three constituent components that may influence their effectiveness: (i) focusing attention, (ii) providing information, and (iii) moral suasion. The first mechanism is the one most often stressed in the existing literature (see, e.g., Karlan et al. (2016)). Reminders redirect attention towards a desired behavior—often at the particular moment when the desired action needs to be taken. The other two mechanisms focus on persuasion. By providing information about the desired behavior, reminders are meant to affect beliefs about how important or beneficial an action is (as in several information interventions such as those in Fishbane et al. (2020) and Milkman et al. (2021)). Moral suasion components, such as social comparisons or norms (used for example in the tax nudging literature, see Antinyan & Asatryan (2019)), can serve to shift the psychological utility from carrying out, or failing to carry out, the desired behavior.

While the model we develop is relatively general and may be applied to different settings where individuals wish to repeatedly engage in a particular desirable behavior, we focus on the application to medication adherence. Medication adherence is particularly interesting because it is characterized by a particular set of features that reflect a class of situations where reminders may play an crucial role. Specifically, adherence to medication requires repeatedly taking an action that: (i) has large benefits, (ii) often requires very little effort, conditional on remembering to do it, and (iii) is often time-sensitive (e.g., taking a pill at the same time every day). Despite the large benefits and low cost of taking the action, medication adherence rates are often less than 50%, implying a huge welfare loss to individuals and public health systems around the world (Haynes et al. 2002, Organization 2003). These observations point towards memory constraints and excessive demands on an individual's attention as potential underlying factors generating this pattern of behavior. Such contexts seem well-suited for reminders to play a welfare-improving role by reducing the demands on an individual's memory. In addition, some patients may lack an understanding of the importance of regular medication intake. Thus, repeated persuasive reminders could increase adherence over time.

To provide evidence on the mechanisms discussed in our model, we conducted a field experiment studying medication adherence of over 4000 pregnant women in South Africa. To implement a large-scale experiment of this nature, we collaborated with MomConnect, a mobile health platform that services over 60% of pregnant women and new mothers in South Africa (Barron et al. 2018, Peter et al. 2018). At the time of the experiment, nearly 2 million women had joined MomConnect since its inception, making it one of the largest global m-Health programs of its kind. The primary focus of the field experiment is to study the factors influencing the engagement with the mobile health app to increase adherence to iron supplements during pregnancy.[1] Anemia dur-

[1]The South African National Department of Health (NDoH) supplies free iron supplements to all pregnant women in South Africa. Health workers are instructed to provide pregnant woman with a supply of the supplements at the

ing pregnancy has negative health effects for both mothers and babies—e.g., it is associated with maternal mortality, pre-term delivery, and low birth weight (see, e.g., Rioux & LeBlanc 2007, Mbhenyane & Cherane 2017). The World Health Organization (2020) estimates that the rate of anemia among women of reproductive age in 2016 was around 25% in South Africa and 33% globally.

We invited a random sample of 18,400 pregnant women who were already signed up on the mobile health platform to take part in our incentivized, text-message based study over the course of three months. Of these, 4226 women opted into our study and were randomized into one of the six treatment arms, five of which are presented in this paper.[2] The core features of the treatment variation involved the following. The *Baseline* condition received no reminders to take supplements, a *Pure Reminders* condition received basic reminders twice a week for four weeks, an *Informational Reminder* condition received reminders at the same frequency, but with additional health information content, a *Promise* condition received a prompt to promise their unborn child to take the supplements, but no further reminders, and the final treatment *Informational Reminders and Promise* combined the informational reminders with the promise treatment. We measure the participants' engagement with the program by measuring the unsubscription rate, the frequency of responding to questions and tasks, and their stated adherence.[3]

Using the data from this large-scale field experiment, we document several findings. First, our results show that overall there was very high engagement with the program. The unsubscription rate from the reminders is 0.5%, which is below our initial expectations and far below attrition in similar field studies (see for example Cohen et al. (2017)). Active engagement is very high with 82.2% of women still responding to the survey two months after opting in. Taken together, this suggests that the mothers find the reminders useful for supporting a healthy pregnancy and are motivated to contribute to the research study.

Second, we then test our model-informed hypotheses on stated adherence. We find a high baseline stated adherence of taking the pills (on average 6.5 out of 7 pills per week). In line with our model, receiving additional reminders has a significant positive effect on adherence of 2-3 percentage points. Also in line with our hypotheses, receiving a moral prompt has a marginally significant positive effect on stated adherence. However, contrary to our hypotheses, receiving additional health information with the reminders has a significant negative effect.

first antenatal visit and to follow-up by checking for signs of anemia during the second visit (Mbhenyane & Cherane 2017).

[2]The sixth treatment arm is described in the companion paper (Barron et al. 2020). That paper presents a novel time preference elicitation task which aims to help predict which individuals are less likely to adhere to medication.

[3]In all treatment conditions, the expectant mothers each received a sequence of reminder messages, belief elicitations, survey questions and knowledge quizzes as well as a willingness-to-pay elicitation for additional reminders after having been exposed to our treatments.

While caution is necessary when drawing conclusions from self-reported adherence, when we investigate which covariates correlate with self-reported adherence, our findings indicate that the results from self-reported adherence are reasonable. For example, mothers who report that free pills are not always accessible at their clinic report lower adherence as do women who state that they have difficulty remembering to take the pills. The main results are robust to including control variables. Further, experimenter demand effects should have been most relevant in the information treatment, which emphasizes the importance of taking the pills, and yet, we find a significant negative effect of information on self-reported adherence.

Third, reminders can create annoyance costs that reduce the demand for reminders if the anticipated annoyance is larger than the anticipated benefits (Damgaard & Gravert 2018). To identify the influence of exposure to reminders on the subsequent demand for reminders, we elicit each woman's willingness to pay (WTP) for additional reminders after four weeks of receiving reminders.[4] We document several striking findings. We show that there is an extremely high baseline demand for additional reminders—the women appear to really value these reminders. Specifically, we find that if there is no difference in the monetary payment associated with receiving or not receiving reminders, 82.95% of women choose to receive the reminders. This share increases to 95% when it is cheaper to receive reminders than to not receive them (i.e., there is a cost associated with not receiving reminders). However, when there is a cost that must be paid to receive reminders, the share that wants the reminders is still very high at around 40%. Furthermore, in line with the model, we find that being exogenously exposed to attention focusing reminders during the experimental period significantly increases the demand for further reminders.

The very high demand for costly reminders after the experimental period, despite the minor change in adherence from reminders is a striking finding. If the women are already taking their pills most of the time, why would they want daily notifications? To explore this question further, we conduct a structural estimation in which we investigate how the reminders affect the weight of the different components of the utility function of our model. We focus in particular on the annoyance costs that we assume are associated with every reminder (although we estimate their magnitude). Our structural estimation shows that to fit our model with the empirical data, we need to assume variation in initial annoyance costs and, surprisingly, that being exposed to attention

[4]We designed a multiple-price list (MLP) task that could be implemented in our text-message based setting. Every participant received only one line of the MPL and her decision was implemented as chosen. Because the assignment to rows was random and orthogonal to the treatments, we can use their answers to approximate a willingness-to-pay for the treatment group. The women randomly receive one of four text messages that ask them to choose between a monetary amount and no reminders and a different amount and daily reminders for the next two weeks. This increases the reminder frequency compared to the weeks before from bi-weekly to daily.

focusing reminders leads to a positive shift in annoyance costs. The women learn to appreciate the reminders.

Our findings indicate that there can be (welfare) benefits to receiving reminders even in contexts where the rate of compliance with the desired behavior is already high in the absence of the reminders. A natural explanation for this is that remembering to engage in a particular type of desirable behavior expends valuable cognitive resources—reminders can be used to free up these resources for other purposes. This is important as it highlights that the value of reminders cannot always be directly read from the impact on the desirable behavior—reminders may be extremely valuable even without having any significant effect on the target behavior. Our paper demonstrates that these indirect effects ("hidden benefits") of reminders are crucial to keep in mind due to the positive externalities they may generate.

Our paper makes three key contributions to the literature. First, we develop a novel model examining the effect of reminders on attention. We complement the existing theoretical work studying the effect of reminders on attention (see, e.g., Karlan et al. 2016, Taubinsky 2013, Damgaard & Gravert 2018) by extending the model to allow for more permanent changes in beliefs and utility in addition to the temporary increase in attention and annoyance when receiving a reminder. Second, we provide empirical evidence on the demand for reminders. We show that reminders for medication adherence are beneficial and desired by our target group. Importantly, in our setting the interests of the sender (South African Department of Health) and the recipients (the pregnant women) of the reminders are aligned and the effort costs of taking an action after receiving the reminder are comparably low. This could explain the differences in unsubscription rates (0,5% vs. 3.7%) compared to the reminders to donate in Damgaard & Gravert (2018) where the interests of senders and receivers might not have been fully aligned or the lower adherence in Calzolari & Nardotto (2017) where the effort costs of going to the gym were likely much higher. Our reminder nudge fits the original intention of nudges to help individuals overcome internalities and making the decision makers better off as judged by themselves (Thaler & Sunstein 2003). This is in contrast to nudges aiming to reduce externalities (see e.g. Carlsson et al. (2021) for an overview). Finally, we contribute to the limited literature on adherence to antenatal care in Sub-Saharan Africa. Esopo et al. (2020) found only five randomized controlled trials focusing on antenatal care in Sub-Saharan Africa, whereof only two focus on adherence.

The rest of the paper proceeds as follows. Section 2 describes our theoretical framework and develops testable hypotheses. Section 3 presents the experimental design. In Section 4, we present our reduced form results on the response to reminders. We then turn to the demand for reminders, which we investigate in Section 5, both in terms of model predictions and reduced-form results. In

Section 6, we use data from the experiment to structurally estimate our model to understand the importance of each of the parameters for decision-making. Section 7 discusses the policy relevance of our results. Finally, Section 8 concludes.

2 Theoretical Framework

We are interested in the three potential roles of reminders: reminders as a tool for 1) focusing attention on a behavior, 2) providing key information, and 3) providing moral suasion. In this section, we develop our theoretical framework which captures these three roles of reminders.[5] Our model informs our experimental design and hypotheses which will allow us to 1) understand the extent to which each of these three mechanisms drives the reminder response in our setting[6] and 2) enhance our understanding of the demand for reminders. We look at both intended behavior change, in this case adherence, as well as unintended consequences of the reminders, namely disengagement and unsubscriptions.

2.1 The setup

Consider a T period model with repeated interaction between the expectant mother and the reminder service. In each period, individual i may receive a reminder message and the individual has to choose both her medical adherence and her level of engagement with the reminder service. We model the medical adherence as a binary action variable a_{it}, where $a_{it} = 1$ if the individual takes supplements.[7] We model engagement with the reminder service as a binary unsubscription variable u_{it}, where $u_{it} = 1$ if the individual unsubscribes from future messages, and a binary read variable r_{it}, where $r_{it} = 1$ if the individual reads the reminder message. The decision to unsubscribe is considered irreversible and eliminates all future messages from MomConnect, i.e., $u_{it+\tau} = 1$ if $u_{it} = 1$ for any $\tau \in \{1, 2, ..., T-t\}$.

Let the instantaneous utility of being attentive in period t be given by

$$\mathscr{U}(r_{it}, a_{it}, u_{it}) = \gamma b(a_{it}) + m(a_{it}) - e_{it}(\eta a_{it} + r_{it} + u_{it}). \quad (1)$$

[5] We combine the attention and reminder models of Karlan et al. (2016), Taubinsky (2013) and Damgaard & Gravert (2018) with the nudging model of Allcott & Kessler (2019) and the norm compliance model of Fehr & Schurtenberge (2018).

[6] Our model is specifically designed to fit the context we are studying: iron intake by expectant mothers in South Africa who have signed up to receive text messages from MomConnect. However, our model can easily be reinterpreted to fit other types of reminders aimed at encouraging healthy habits.

[7] In the empirical work we will only have access to self-reported measures of adherence.

Here, $b(a_{it})$ denotes the health benefits of taking iron supplements, and we assume that $b(a_{it})$ is an increasing function of a_{it}, for the choice range we are interested in, and that $b(0) = 0$. Following Allcott & Kessler (2019), we assume that the individual may have inaccurate or biased benefits due to lack of information or a behavioral bias such as present-bias or inattention. We let $\gamma \geq 1$ capture the inaccuracy and let $\gamma b(a_{it})$ denote the perceived health benefits of adherence to the recommended iron supplements regime. That is we can also interpret γ as the subjective weight on health benefits.

The function $m(a_{it})$ captures the moral suasion effects of the messages and could include guilt of failing to take supplements. Conceptually, this is closely related to preferences for norm compliance: in our setting, compliance with the moral obligation to take daily supplements. Therefore we model the term following the norm compliance model of Fehr & Schurtenberge (2018) and assume that $m(a_{it}) = \mu \left(\frac{k_{it-1}+a_{it}}{t} - I\right)^2$ where $k_{it} = k_{it-1} + a_{it}$ is a state variable which captures the the number of iron pills taken until time t, $I = 1$ is the appropriate action rate, $\frac{k_{it-1}+a_{it}}{t}$ is the actual action rate until time t, implying that the term is equal to the squared difference between the actual and appropriate action rate. $\mu \leq 0$ denotes the weight on moral suasion effects and contribution of the term is non-positive which is to reflect feelings of guilt or regret at not having acted as one should have. $m(a_{it})$ is increasing in a_{it} which captures that there is a moral benefit to taking action. $m(a_{it})$ is also increasing in k_{it-1} which can be interpreted as utility from pride in having done the morally right thing in the past.

The final term in Equation 1 is the effort cost function. For simplicity, we assume a linear cost function with a unit cost of e_{it} which is identically and independently distributed according to the cumulative distribution function F. That is, we assume that individual and time heterogeneity is captured by the effort costs. $\eta \geq 1$ is a scaling factor which implies that the effort required to take action (i.e. to take the supplements) is equal to η times the effort required to unsubscribe and read a message,[8] i.e. individual i has effort costs $e_{it}(\eta a_{it} + u_{it} + r_{it})$.

We allow for limited attention and, as in the inattention models of Karlan et al. (2016) and Taubinsky (2013), we assume that the individual is sophisticated and therefore aware of her inattention.[9] The MomConnect program sends messages in some but not all periods and not all messages are related to iron supplements. We use p_t to denote the probability that a message about iron supplements is sent in period t and $\theta_0 \in [0,1)$ to denote the baseline probability of being

[8]This assumption is for simplicity and the assumption can easily be relaxed.

[9]However, the model does allow for overconfidence about prospective memory, as studied by for example Ericson (2011) and Letzler & Tasoff (2014), by interpreting θ as the individual's subjective belief about the likelihood of remembering if not reminded.

attentive in any period where no message is received. Conditional on receiving a message about iron supplements, individuals may choose whether they read the message and whether they want to unsubscribe from future messages. Following Damgaard & Gravert (2018), if an individual unsubscribes, she faces the baseline probability of being attentive θ_0 in all future periods. However, as messages from MomConnect may be on various topics, we allow the reminder value to depend on whether it is read. We assume that receiving a message may increase the probability of being attentive to the (iron supplement) choice even if the individual does not read the message but to a lower degree than if the message had been read. In particular we assume that

$$\theta(r_{it}) = \begin{cases} \theta_m & \text{if } r_{it} = 0 \\ 1 & \text{if } r_{it} = 1 \end{cases} \tag{2}$$

where $\theta_m \in [\theta_0; 1]$. Furthermore, we follow Damgaard & Gravert (2018) and assume that receiving a message involves an annoyance cost, Λ, regardless of whether the message is read or not. This can capture the mental cost of having to deal with the message and decide whether to read it or not. In the present model Λ does not capture the effort cost of reading the message or moral effects because we model these costs separately in the effort and moral utility terms.

Finally, we abstract from consumption utility derived from other activities because there is no monetary cost of taking supplements, reading messages or unsubscribing and as a result there is no direct effect on consumption utility.[10] Under these assumptions, conditional on being attentive in period t the expectant mother's inter-temporal optimization problem is

$$\begin{aligned} \max_{r_{it},a_{it},u_{it}} \mathscr{U}(r_{it},a_{it},u_{it}) + E_t\Big[\sum_{\tau=t}^{T} \delta^{\tau-t}(p_\tau(1-u_{i\tau-1})\theta(r_{i\tau}) + (1-p_\tau(1-u_{i\tau-1}))\theta_0)\mathscr{U}(r_{i\tau},a_{i\tau},u_{i\tau}) \\ -p_\tau(1-u_{i\tau-1})\Lambda\Big] \end{aligned} \tag{3}$$

where $0 < \delta < 1$ is the inter-temporal discount factor, and E_t denotes the expectation given period t information. The expression in expectations is the unconditional instantaneous utility in future periods. This term takes into account that the expectant mother may not be attentive in future periods. The first term in the expectations capture the probability of being attentive multiplied by the utility from being attentive in period τ. The second term captures the expected annoyance cost (i.e. the probability of receiving a message multiplied by the cost). Note that the annoyance cost in period t is sunk from the point of view of period t. We assume that the expectant mother is

[10]We note that there may be a small opportunity cost as the time spent on these activities may potentially have been spent doing more productive activities. We let the effort cost capture this cost.

rational in the sense that she knows her preferences, the timing of events, how she will respond to messages in future periods, and forms rational expectations regarding MomConnect's message strategy, i.e, $\{p_t\}_{t=1}^{T}$. If an expectant mother has not unsubscribed in period t but does not receive a message because $p_t = 0$, then she has no opportunity to unsubscribe, and we, therefore, let $u_{it} = 0$. Similarly, we assume that an expectant mother reads the messages and takes supplements if she is indifferent between doing so or not. Finally, we assume that if the expectant mother is not attentive to the decision problem in period t then she does not take action nor does she unsubscribe i.e. $a_{it} = u_{it} = 0$, and she derives no immediate utility from the decision problem, i.e. $\mathscr{U}(r_{it}, a_{it}, u_{it}) = 0$.

2.2 Deriving hypotheses from model simulations

We design our experimental treatments to target three parameters of interest: γ (the subjective weight on health benefits), μ (the weight on moral utility) and p_t (the probability of receiving a message on iron supplements in period t). The former two are potentially affected permanently and the latter is influenced only temporarily. To inform our treatment design and develop testable hypotheses, we simulate the marginal effects of changes in these parameters on the choice variables using a Monte Carlo simulation.[11] Figure 1 shows the effect of changes in the parameters γ, μ and p as well as the effect of a change in the state variable, cumulative adherence k, on the probability of taking action, $P(a_{T-1} = 1)$, the probability of unsubscribing, $P(u_{T-1} = 1)$, and the probability of reading a given message, $P(r_{T-1}|message) = 1$, holding all other parameters constant.[12]

The top left panel of Figure 1 shows that an increase in γ, the subjective weight on health benefits, raises the perceived benefits of taking action. This shift leads to an increase in the likelihood of taking action and an increase in engagement with the reminder service, i.e. a higher probability of reading a message conditional on getting one, and a lower probability of unsubscribing. These effects are robust to changes in the value of Λ (see Figure 11 in Appendix section 9.3) and k_{T-2} (see Figure 12 in the appendix) and are present even in the absence of moral utility (see Figure 9 in the appendix). However, the variance in γ only matters if individuals are not fully attentive (see Figure 8 in the appendix section 9.3).

The top right panel of Figure 1 shows that an increase in μ, the moral utility from taking action, raises the costs of not taking action. Our simulation predicts that individuals will make choices to

[11] See appendix section 9.2 for technical details on how we solve the model and section 9.3 for how we simulate the model.

[12] Note that responding to the text messages, requires that the recipient has read the message. The model includes reading the messages as a choice variable and we make the additional assumption that a fixed proportion of the individuals who read the message respond to it. That is we assume that this proportion is independent of the treatment.

avoid these costs. They either choose to increase their adherence to avoid these costs or they choose to ignore the reminders. We term this effect the disengagement effect of reminders. These effects of changes in μ are robust to changes in the value of Λ, k and γ (see Figures 11, 12 and 10 in the Appendix section 9.3). As before, the variance only matters when individuals are not fully attentive.

The bottom left panel of Figure 1 shows that an increase in p, the probability of receiving a message, also leads to an increase in the probability of taking action because it increases the probability of remembering. Furthermore, an increase in p increases the probability of unsubscribing and lowers the probability of reading the message conditional on receiving one. The intuition is that every reminder message is unpleasant (due to the annoyance cost or a moral cost of being behind target) and hence the expectant mother may prefer to unsubscribe when there is a higher frequency of messages. Similarly, by not reading the message, the expectant mother can, with some positive probability, avoid to think about the problem and hence avoid these costs. With the exception of the unsubscription effect, these effects arise only when individuals are not fully attentive (Figure 8). The unsubscription results arises even with full attention because of the presence of the annoyance cost. The direction of the results are robust with respect to the size of Λ, k, γ and μ (see Figures 12, 11, 10 and 9 in section 9.3).

As can be seen from the preceding discussion, treatments that increase γ, μ and/or p may lead to an improvement in adherence and this in turn leads to increases in k. The last panel of Figure 1 (bottom right) shows the effect of such an increase in past adherence. An increase in k has a negligible effect on the action rate of taking the pill. However, an increase in k improves engagement, i.e. the conditional probability of reading a message increases and the probability of unsubscribing decreases, because a large value of k implies that the moral costs of paying attention are relatively small, and so the expectant mother is more likely to engage positively with the reminder service.

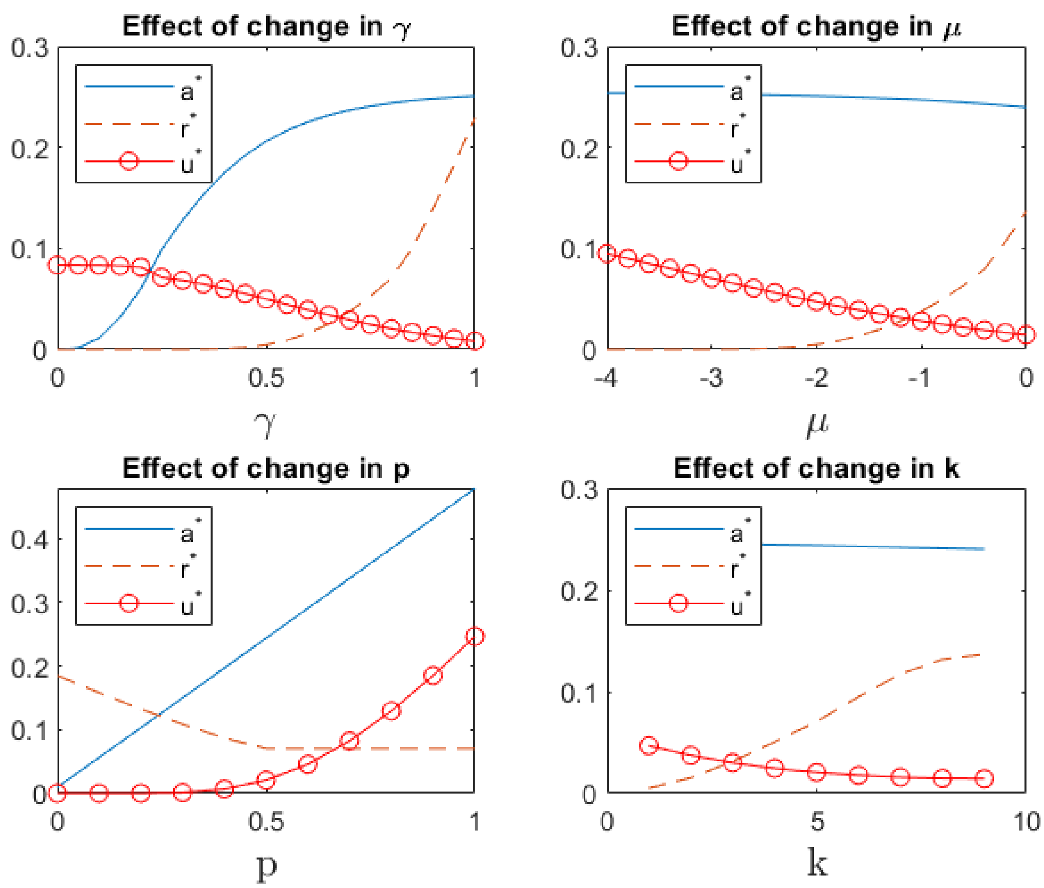
Table 1 concisely summarizes our hypotheses derived from the model predictions:

Table 1: Summary of hypotheses

	Information provision	Moral suasion	Attention focusing
$P(a_t^* = 1)$	+	+	+
$P(u_t^* = 1)$	-	+	+
$P(r_t^* = 1 \vert message)$	+	-	-

+ indicates a positive association and - indicates a negative association.

Figure 1: Sensitivity of simulated $P(a_{T-1}=1), P(u_{T-1}=1)$ and $P(r_{T-1}=1|message)$ with respect to changes in γ, μ, p and k



Notes: $P(a_{T-1}=1)$ and $P(u_{T-1}=1)$ are unconditional probabilities and $P(r_{T-1}=1|message)$ is the probability of reading a given message i.e. conditional on getting a message. Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1,0.5]$, $b(a_t)=a_t$, $T=10$, the model parameters are calibrated to $(\delta,\theta_0,\theta_m,\gamma,\mu,p,\Lambda)=(0.99963,0.01,0.5,0.8,0.5,0.5,0.5)$ and $k_{T-2}=4$. Expectations are evaluated numerically using Monte Carlo Simulations with 100.000 simulations.

First, we expect all factors to positively affect the probability of taking the pills (adherence). Second, unsubscriptions are expected to increase in the frequency of reminders and when moral suasion content is included. Unsubscriptions are expected to decrease when providing more information. Third, including information positively affects the reading rate, given that a message is received, while increasing the moral suasion component and the frequency of reminders decreases the reading rate conditional on receiving a message. In the following section, we describe how our experimental treatments generate exogenous variation in these parameters to test our hypotheses.

3 Experimental design and procedure

Our field experiment is designed to test our model predictions. The following section describes the technology and incentives, the experimental treatments, and our sampling procedure.

3.1 Technology and Incentives

We use simple text messaging (SMS) for the experiment.[13] Women are familiar with this type of communication from the health service. The experiment was programmed in RapidPro, which is a software designed for sending text message campaigns to mobile phones. All of MomConnect's communication is programmed in RapidPro and all women signed up to MomConnect could easily be sampled from. We incentivize responses by using airtime for the women's phones. This can be easily done through the phone company and is a frequently used reward for completing surveys. We vary the reward based on the time it will take to answer the messages. We pay between 5 ZAR for a simple answer and 20 ZAR for a longer task. At the time of the experiment, 15 ZAR correspond to 0.9 Euro. The minimum wage in South Africa is 20 ZAR per hour. Given that many messages could be replied to in a matter of seconds, the incentives were reasonably high.[14] The participants had no costs. All replies were covered by us. Overall, women who answered all messages earned on average 87 ZAR over the time of the experiment.

[13] While some of the women would have been able to receive messages through WhatsApp, which would have also allowed us to register whether a message had been read, an even better fit with the model, the sample of women signed up with WhatsApp was too small for our experiment.

[14] It was not possible to pay the women at the very end of the experiment due to ethical and practical reasons. Once they unsubscribed we would not be able to follow up with them.

3.2 Treatments

Our experiment has a baseline condition and four treatment conditions: 1) pure reminders (PR), 2) informational reminders (IR), 3) a promise prompt (PP) and 4) a combination of the promise prompt and the informational reminders (PP+IR). We designed the treatments to identify the effect of a variation in each of our parameters of interest: p_t, γ, μ. The reminder treatments (1,2 and 4) experimentally vary p_t, because they increase the probability of the mother being attentive to the task compared to the baseline condition. The informational reminders (2 and 4) provide information about the benefit of adherence which in the model translates into a change in γ. Finally, the promise prompt (3 and 4) is designed to increase the moral suasion component which translates into an increase the absolute value of μ.

3.2.1 Baseline Condition

We will start by explaining the baseline condition which is the minimum communication every participant received. A simple structure of the experimental design is shown in Figure 2. On day 105 before their estimated due date, the mother received a text messages asking her to opt in to a study on health behavior of pregnant women running over the next three months and consisting of several text messages. The women are told that they will receive monetary compensation in form of airtime and that there will be no costs to them. If they are interested in participating, they can reply "JOIN" and are enrolled in the study. They could unsubscribe anytime by texting "STOP".

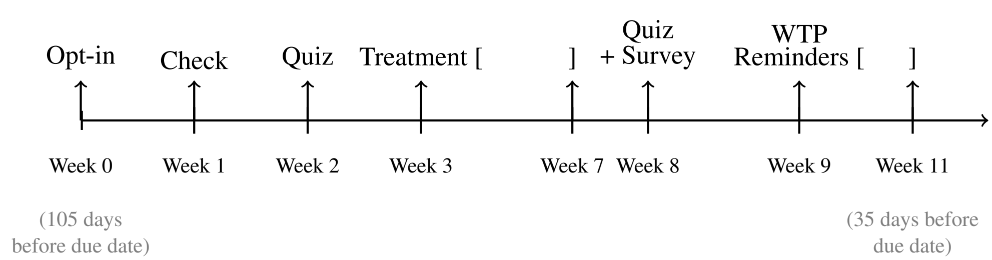
After opting in to the study and being randomized into one of the treatment arms, we asked the women about the number of kids they already had and how important they thought iron supplements were for a healthy mother and baby on a scale from 0 to 7. They received 5 ZAR for answering. All questions can be found in Appendix Table 12.

Six days later, they received a text message asking them for the last four digits of their social security number, which corresponds to their birth month and year. This was done to both measure basic response rates for a simple task and to make sure that the person responding to the text message is indeed the woman we randomized into the treatment. We have their birth date from when they first signed up to MomConnect at the health care facility. If they answered the message, the received 5 ZAR. Another six days later, the mothers were invited to take part in a short quiz to test their iron supplement knowledge. They were asked four true or false questions about the health effects of iron supplements such as whether taking iron pills would make the baby bigger. Regardless of whether the answers were wrong or right, the women received 10 ZAR airtime for participating. There was then a break in messages for the control group, while the treatment groups received more messages over the next month, as we will explain below. Thirty three days later, the women received the next text message asking them again about the last four digits in their social security number. Again they received 5 ZAR for replying. Another three days later, they were asked to take part in the second quiz. Again they were presented with four true or false questions. These were different to the first quiz. Answering all four questions resulted in 10 ZAR airtime. Three days later (54 days before the estimated due date) we sent a ten questions survey to the participants. We asked them about their adherence to the pills in the past week (0 to 7 days), some questions about how they were feeling and whether pills were available at their clinic. The women received 15 ZAR in airtime, if they responded to all the questions. There were no right or wrong answers. We ask the women about their adherence during the past seven days, rather than the more common question of how many days or what share of their pregnancy they have taken the pills. We trade off the risk of the past week being untypical for a woman with the accuracy gained by asking only about the past week.

We then asked them to participate in a willingness to pay elicitation for additional reminders for the following two weeks. Details of this tasks will be discussed in section 5, where we look at the demand for reminders.

35 days before their estimated due date, all women received a final thank you message letting them know that the study was over.

Figure 2: Basic timeline of the experiment



3.2.2 Pure and informational reminder treatment

The pure and the informational reminder treatments have all the components of the baseline. In addition, the women received eight reminders, one message every three days between the first quiz and the second check of the social security number. This doubles the amount of messages they would be receiving from the general MomConnect program. In the pure reminder treatment, the messages had no informational value, such as “It is easy to forget to take iron pills when you are busy. Remember to take them every day.”. Thus, the treatment is only attention focusing. In the informational message treatment, the messages provided health facts around iron pills: "Eat vitamin C rich fruits and vegetables such as tomato, guava, mango, pineapple, orange and other citrus fruits. They help suck up iron.". These messages increased information provision. All informational messages were designed in collaboration with local health care professionals and pre-tested with a small sample. For both reminder treatments the probability that MomConnect sends a message is temporarily higher i.e. $p_t^R > p_t^0$ during the treatment period where p_t^0 is the baseline level in the baseline group. To calibrate beliefs, the temporary increase in the frequency of messages is announced to the mothers in a text message and after the treatment period the probability of receiving a message about iron supplements is again at the baseline level of p_t^0. For the informational reminder group, we hypothesize that the messages permanently shifts the percieved health benefits by $\Delta\gamma = \gamma_I - \gamma_0$ from a baseline of γ_0 to γ_I.[15]

3.2.3 Promise

The promise treatment also had all the components of the baseline. On top, 15 days after the first quiz the women received the following message: "Dear mama, please take a moment to think about your baby and what you can do now to give your baby a better life. One thing you can do is to take your iron pills. Think about making a promise to your baby to do your best to take your iron pills, daily. Did you make a promise to take your iron pills daily? Reply "Yes" or "No"." The message uses moral suasion to increase the moral costs of not taking the pills.[16] Regardless of the answer, the women received the following message after replying: "Your actions matter for your baby's health. Think about your promise to help you to remember to take your iron pills!". In terms of model parameters, the promise permanently increases the weight on moral utility by $\Delta\mu = \mu_P - \mu_0$ from a baseline μ_0 to μ_P.[17]

3.2.4 Informational Reminder and Promise:

The last group combined the informational reminders with the promise treatment by sending the prompt and the informational messages. That is the treatment is expected to permanently raise μ and γ to μ_P and γ_I, and temporarily raise p_t to p_t^R. After the treatment period the probability of receiving a message about iron supplements is again at the baseline level of p_t^0.

[15] Technically, the improvement in accuracy $\Delta\gamma$ is achieved by sending n informational messages.

[16] Typical messages using moral suasion in reminders are for example: "9 out of 10 people pay their taxes on time. You are currently not one of them." Or "Get your flu shot to protect others."

[17] We note that the moral effects in our model also capture a preference for keeping the promise in line with the findings of Vanberg (2008).

3.3 Outcomes

The first two outcomes measures engagement with the MomConnect service and are: the probability of having unsubscribed from reminders (Outcome 1) and the probability of responding to a message conditional on getting a message (Outcome 2), which we use as a proxy for the probability of reading the messages. In addition to these measures of engagement, we have survey measures of self-reported adherence which we use as a proxy for the action rate (Outcome 3)[18]. We measure response rate and self-reported adherence after completion of the treatment period. We measure unsubscription rates during the treatment period for all groups and after completion of treatment.

3.4 Sampling

The data collection for this study took place from the 19th of March to the 29th of June 2019. A sample of 18,400 women was drawn randomly from the population of MomConnect users. We used the following criteria: i) their expected due date was 130-105 days away on 19th of March 2019 ii) they were 18 or older. We sampled from the whole country and did not place a restriction on language. We have information on their preferred language, whether they live in an urban or rural area and whether they signed up with a smart phone or a traditional mobile phone (proxied by whether they preferred text messages or WhatsApp). We chose the time frame of 105 days before due date, since most women only join the program around three to four month into their pregnancy, when they see a health care professional for the first time. The time frame also gives us enough time to message the mothers. All mothers received the first message from us, the invitation to join the study, 105 days before their due date. That means we have a rolling enrollment over 25 days and that the mothers receive treatment messages on different days of the week.

In line with our pre-study expectations, approximately 24% (4226) of the women contacted opted to participate. 72 women could not be paid based on a technical failure and are thus excluded from the analysis. This leaves us with 4154 women in our final sample. After giving consent to take part in the study, we then randomize the women into one of six treatment arms.

[18] We note that the experimental setting does not allow for reliable measurement of whether the women take iron supplements. In principle, highly noisy measurements of adherence could be obtained at considerable cost, but the focus of the current paper is to understand mechanisms of behavioral responses to reminders not to assess health benefits of the particular reminders provided in this paper. Research suggests that self-reported estimates tend to be upward biased (Wilson et al. 2009). However, stated measures for medication adherence are widely used in the medication field and have been found to correlate strongly with objective measures. See for example the review for HIV medication by Simoni et al. (2006) who find significant correlations between individual's self-reported adherence and virus levels in 85% of the reviewed cases. Further, we are interested in treatment effects rather than absolute levels.

Five of these arms are used for this paper. One additional arm with 694 women is the basis of Barron et al. 2020. 3460 women make up the final sample for this paper.[19] Given the high usage of the MomConnect program by pregnant women all over South Africa, we end up with a fairly representative distribution of pregnant women from all over the country. Table 11 in the Appendix shows descriptive statistics on who opted in to the experiment. Women who live in urban areas, are younger, have English as their preferred language and are signed up to MomConnect by Whatsapp are significantly more likely to opt in to study. Given the high number of observations, the differences are statistically significant for all four variables, but only meaningfully different for English vs. other languages and for being registered by Whatsapp. Both of which is not surprising given that the study was conducted in English and required frequent phone access. We find no systematic differences based on region.[20]

The women were randomly allocated to the treatment conditions. Control (683), Pure Reminder (737), Information (716), Information and Promise (674) and Promise (650). Differences in number of participants in each group comes from the technological and timing constraint, that for every consenting participant a randomization was run at the time of opt-in to assign her to a treatment.

In addition to the messages from our study, the women continued to receive messages from the main MomConnect service. They received informational messages twice per week as well as messages reminding them of their doctor's appointments. These messages come from a different phone number and we make clear, that unsubscribing from the experiment does not unsubscribe mothers from MomConnect in general. For privacy reasons, we have no data on their interaction outside of our experiment.

4 Reduced form results for unsubscriptions, response rate and adherence

The average woman in our sample was born in 1992, making her 27 years old at the time of data collection. Thirty-five percent of our sample has English as their preferred language. Twenty-nine percent of the women live in urban areas and they have on average one child already. Table 2 shows a balance check for the main control variables. Columns 1-5 show the means for each group and columns 6-9 show the differences between control and each treatment group. As expected

[19] In the regressions estimating the effect on adherence after three months and including most of our control variables, we still have 2747 women (79% of the original sample).

[20] Results available upon request

with this number of statistical tests, we find some small significant differences. Participants in the Pure Reminder treatment are slightly more likely to have selected English as their preferred language and state a marginally significantly higher belief about the importance of vitamins for healthy mothers. Participants in the Information treatment are slightly more likely to live in an urban area. Mothers in the Information and Promise treatment have marginally more kids already. However, there are no consistent or economically large differences. Hence we are certain that the randomization worked as intended. Where relevant, we will run robustness checks for our regressions controlling for these variables. It was not possible for the women to switch into a different treatment group and neither is it likely that there are any spillover effects. The women would need to have an estimated due date within 25 days to each other and be close enough friends to discuss medical details with each other. Since we sampled from the whole country, this is highly unlikely.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Means					Difference	
Variable	Mean Control	Mean Pure	Mean Info	Mean Info+Promise	Mean Promise	Pure vs. C	Info vs. C	InfoPromise vs. C	Promise vs. C
Urban	0.319	0.354	0.388	0.334	0.335	0.035	0.069***	0.015	0.016
	(0.467)	(0.479)	(0.488)	(0.472)	(0.472)	(0.025)	(0.026)	(0.025)	(0.026)
English	0.637	0.688	0.675	0.653	0.632	0.051**	0.038	0.016	-0.005
	(0.481)	(0.464)	(0.469)	(0.476)	(0.483)	(0.025)	(0.025)	(0.026)	(0.026)
Age	26.959	27.023	27.458	27.423	27.240	0.064	0.499	0.464	0.281
	(5.752)	(5.462)	(5.620)	(5.673)	(5.758)	(0.298)	(0.304)	(0.310)	(0.315)
Nr. Kids	1.011	1.070	1.060	1.114	1.046	0.059	0.050	0.103*	0.035
	(1.022)	(1.114)	(1.093)	(1.134)	(1.088)	(0.058)	(0.057)	(0.060)	(0.059)
Important for Mom	6.470	6.619	6.478	6.414	6.563	0.149*	0.008	-0.056	0.093
	(1.569)	(1.249)	(1.522)	(1.631)	(1.450)	(0.077)	(0.085)	(0.089)	(0.085)
Important for Baby	6.394	6.502	6.477	6.427	6.520	0.108	0.083	0.033	0.126
	(1.634)	(1.382)	(1.463)	(1.525)	(1.379)	(0.084)	(0.087)	(0.090)	(0.086)
Pre-Quiz Score	2.879	2.908	2.890	2.835	2.891	0.029	0.011	-0.044	0.012
	(0.714)	(0.683)	(0.708)	(0.716)	(0.730)	(0.040)	(0.041)	(0.041)	(0.042)
Observations	683	737	716	674	650	1,420	1,399	1,357	1,333

Table 2: Balance Table

To test the model predictions, we used our treatments to create dummies that measure the marginal effect of additional messages, additional information, and additional moral costs. For example, the pure reminder, the informational reminder and the promise with informational reminder treatments send more messages to the mothers than the baseline condition, but the informational reminder treatments also adds information. Rather than comparing the treatments directly, this approach allows us to understand the mechanisms better and test our hypotheses from our model. We thus set our information dummy equal to one for individuals who were assigned to treatments Pure Reminders, Informational Reminders and Promise + Informational Reminders. Information is set equal to one for Informational Reminders and Promise + Informational Reminders. Finally Moral is set to one for Promise and Promise + Informational Reminders.

4.1 Outcome 1 and 2: Unsubscriptions and Engagement

We have a very high participation rate over the course of the experiment. Only 18 out of 3460 women unsubscribed by texting "STOP".[21] While this is great news for the program, this does not allow us to test for treatment differences in unsubscriptions. The attrition rates in our experiment are, with 0.5%, unusually low[22]. In Damgaard & Gravert (2018) the unsubscription rate was approximately three percent per reminder, which would have corresponded to 138 unsubscriptions in this experiment.

We, therefore, turn to our second outcome variable, engagement with the program. Overall, 53.21% of participants answered every text message, we sent out. To measure engagement as a result of treatment we estimate the effect of our treatment dummies on the probability of responding to the first incentivized message post treatment. The women were asked to send the last four digits of their social security number and received 5 ZAR for their response. This was a purposely easy task and did not depend on information or adherence. Table 3 shows the marginal effects of attention, information and moral on the probability of reading/ responding to this message. The estimation is a basic OLS regression with robust standard errors. While the estimates for attention and moral are positive and the effect of additional information is negative, we find no statistically significant difference in engagement. In column 2, we control for stated adherence (number of pills taken the past 7 days) to show that adherence does not affect our estimates. Overall, 82.89%

[21] Only 9 participants unsubscribed prior to the WTP elicitation.

[22] Compare for example with 28% attrition in a field survey study with pregnant women in Kenya, who were followed up with in person (Cohen et al. 2017). In a mobile health weight loss intervention with young adults, only 20.2% of participants replied to all text messages. 53.7% replied to at least half of the 16 messages (Partridge et al. 2015). The required number of messages is similar to our intervention

of women responded to this question. Thus, it is not only the case that women did not unsubscribe, but the large majority was still engaged after several weeks.

Table 3: Probability of responding to the first incentivized post-treatment message

	Prob of response	Prob of response
Attention	0.017	0.023
	(0.019)	(0.017)
Information	-0.005	-0.001
	(0.018)	(0.016)
Moral	0.004	0.008
	(0.015)	(0.013)
Days taken, 0-7		0.015^{***}
		(0.005)
Constant	0.819^{***}	0.780^{***}
	(0.013)	(0.035)
Observations	3460	3034
R^2	0.000	0.006

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Marginal effect of mechanism dummies on the probability of responding to the first incentivized post-treatment message the mothers received after being exposed to the treatment. Attention, Information and Moral are dummy variables to measure marginal effects."Days taken" measures self-reported adherence during the week prior to the survey conducted after treatment.

4.2 Outcome 3: Stated Adherence

Fifty days after the opt-in and after the individuals in the treatments have received their treatment, we sent a ten question survey to the mothers. We asked them out of how many days in the past week they had taken their iron pills. On average, the women state that they have taken their pills on 6.50 (SD 1.37) out of 7 days. In Table 4, we show the regression results from an OLS regression with robust standard errors in which we regress the three treatment dummies and additional control variables on the first question from the survey, the stated adherence. The outcome variable is equal to 1 if the mother reported full adherence and zero otherwise. In column 1, we show the pure effect of the treatments. In column 2, we add control variables from before the treatment period, that is the number of kids, whether the mother lives in an urban area, whether she prefers another language than English, her age, and her beliefs about how important she thinks taking the pills is for a healthy mother and child. The characteristics were all elicited when the mothers joined the experiment. In column 3, we then add a combination of questions from the two quizzes. “Knows health benefits” is a dummy equal to one, if the mother correctly answered the three questions relating to the health benefits of taking iron pills. “Knows correct adherence” is a dummy equal to one if the mother correctly answered three questions related to correct adherence. The final column (4) estimates the full model by including the other nine survey questions, two of which are a repeated belief elicitation. We only lose a few observations with each column, given that most mothers, if they answered the first survey question, which is our outcome variable, also answered the other questions.

We find that having received additional messages compared to the control group has a significant positive effect on stated adherence. We estimate a 3.4 percentage points increase in the probability of having full adherence in the week prior to the survey. The marginal effect of additional information is significantly negative. The effect of an additional moral component is positive and significant on the 5-percent level. The estimate is half of the size of the effect of attention (1.7 percentage points). The estimates of the marginal treatment dummies are robust to the addition of control variables.

There are no significant effects of where the mother lives, whether she prefers messages in English, and whether she already has kids on stated adherence. The estimate for age is small and not robust to including further controls. These results indicate that medication adherence and self-reporting of adherence does not systematically vary with basic demographics. We find that mothers who believe that iron pills are important to stay healthy during their pregnancy report significantly higher adherence. There are no independent effects for their beliefs about the importance of pills for having a healthy baby, but these two beliefs are also strongly correlated (Corr. 0.43).

As we see in column 3, being well informed about the health benefits and about the correct adherence of taking the pills have independently significant positive effects on adherence, independently of our treatment dummies and independently of the beliefs about the importance of taking the pills. Correctly answering all questions about health benefits on the quizzes increases adherence by 2.5 percentage points, which is similar to the effect of the reminders.

In line with our expectations, mothers who state that they have a hard time remembering to take the pills are significantly less likely to have a high adherence rate (column 4). This is the largest estimate we find with 7.9 percentage points. Pills being available at the clinic for free has a significant positive effect on adherence. We again elicit the mother’s beliefs about the importance

Table 4: Stated Adherence - Probability of taking the pill out of 7 days

	(1) Prob full adh	(2) Prob full adh	(3) Prob full adh	(4) Prob full adh
Attention	0.034***	0.025**	0.026***	0.023**
	(0.010)	(0.010)	(0.010)	(0.010)
Information	-0.038***	-0.035***	-0.035***	-0.031***
	(0.010)	(0.010)	(0.010)	(0.010)
Moral	0.017**	0.016*	0.016*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)
Urban		0.010	0.009	0.006
		(0.007)	(0.007)	(0.007)
English		0.012	0.010	0.009
		(0.008)	(0.008)	(0.008)
Age		0.002***	0.002***	0.001
		(0.001)	(0.001)	(0.001)
Has kids		0.002	0.004	0.005
		(0.009)	(0.009)	(0.009)
Important for Mom - Pre		0.016***	0.015***	0.012***
		(0.004)	(0.004)	(0.004)
Important for Baby - Pre		0.006	0.005	-0.004
		(0.004)	(0.004)	(0.003)
Knows health benefits			0.025***	0.016**
			(0.008)	(0.007)
Knows correct adherence			0.014*	0.006
			(0.008)	(0.008)
Difficulty Remembering				-0.079***
				(0.013)
Free pills				0.038***
				(0.013)
Important for Mom - Post				0.030***
				(0.009)
Important for Baby - Post				0.023***
				(0.008)
Feel bad				-0.007
				(0.014)
Tired and dizzy				-0.004*
				(0.002)
Doctor visits				0.034*
				(0.018)
Low iron				-0.029*
				(0.016)
Years of schooling				-0.000
				(0.002)
Constant	0.917***	0.710***	0.695***	0.417***
	(0.007)	(0.036)	(0.037)	(0.075)
Observations	3034	2823	2823	2747
R^2	0.005	0.031	0.037	0.118

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Results from a LPM regression. Details about the variables can be found in Table 12 in the Appendix.

of the pills for them and their child. The association to adherence is now stronger than with the initial elicitation. In this second elicitation the belief about the importance for the baby is also significant.

We elicited several proxies for health outcomes related to iron levels. Because mothers might be less likely to take them if they feel constipated (a common side effect of iron supplements), we asked them whether they feel bad when taking the pills. There was no significant correlation between their answer and stated adherence. Stating to feel tired and dizzy was marginally significantly negatively correlated with stated adherence. Having seen a doctor in the past four weeks has a marginally significant positive effect. Mothers who say that they have been told that they have low iron levels are interestingly also more likely to state that they have low adherence. This might be an indication that they have other reasons for not taking the pills. Finally, there is no effect of schooling on adherence.

Stated adherence might be influenced by desirability bias or flawed recall. However, given that we ask about the past seven days, it should make it easier for the women to correctly recall the number of pills that they took. Further, the estimated effects we find on stated adherence from our covariates, such as whether free pills are available, the knowledge about the health effects and whether they had adhered to their doctor's appointments, seem reasonable. The overall high engagement with the program is further evidence that the women had trust in the program and that their answers are honest. Nevertheless, the levels might be inflated so more attention should be on the differential effects, not the absolute levels of adherence.

4.3 Reduced form results - Model hypotheses

Table 5 summarizes our results visually. It shows for each outcome and each mechanism our estimated effect and in brackets the hypothesized effect. We start with column 1 and the effect of information. We had hypothesized that adding information to the reminders would increase adherence, decrease unsubscriptions, increase the read/ response rate. Instead we find that information decreases adherence, while having no effect on the read/ response rate. Due to insufficient unsubscriptions we cannot test the second hypothesis.

Our predictions for moral suasion and attention focusing (columns 2 and 3) are confirmed for adherence, insignificant for engagement and cannot be tested for unsubscriptions.

Table 5: Summary of results with hypotheses in brackets

	Information provision	Moral suasion	Attention focusing
$P(a_t^* = 1)$	-(+)	+(+)	+(+)
$P(u_t^* = 1)^{\S}$	(-)	(+)	(+)
$P(r_t^* = 1\|message)$	0(+)	0(-)	0(-)

+ indicates a positive association and - indicates a negative association.

§ indicates that there was insufficient variation in the empirical data to test the hypotheses.

5 Willingness to pay for reminders

Given that we saw close to no unsubscriptions in response to the treatments we might conclude that the reminders were desired by the recipients. A more direct approach to estimate the demand for reminders and whether it varies between types of reminders is to implement a multiple price list to elicit the willingness to pay for reminders. This approach gives us an additional, and in light of the low unsubscription rate, valuable insight into the demand for reminders.

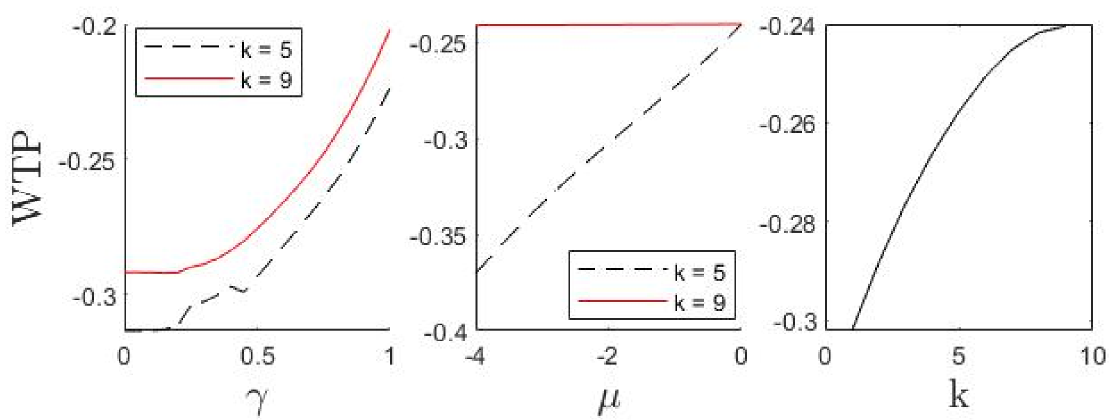
We designed a willingness to pay task based on Allcott & Kessler (2019). Normally, a willingness to pay elicitation would present participants with a list of trade-offs. For each row the participants need to choose one option and in the end one row is chosen as the row that counts. Since it was not possible to send the women a multiple price list over text message and further explain the process of randomization for payoff, we randomized women into one of four price comparisons. Because of random allocation this allows us to estimate the willingness to pay under each condition for each treatment. In our design the participants only need to make a choice between two options, which are directly implemented.

Each participant faces the following question: "Would you like A) X ZAR in airtime + A daily reminder for the next two weeks to take iron pills Or B) Y ZAR in airtime and no reminders? Reply A or B!". We vary the incentives in the following way: 1) Receive 10 ZAR to receive reminders vs. 15 ZAR and no reminders (WTP for reminders is 5). 2) Receive 15 ZAR either way (WTP 0). 3) Receive 15 ZAR and reminders vs. receive 10 ZAR and no reminders (WTP -5). 4) Receive 15 ZAR and reminders vs. 5 ZAR and no reminders (WTP -10). If the women replied A, they received the airtime offered and a daily reminder for the following 14 days. If they replied B, they received the airtime and no reminders.

All women received a message after one week and after two weeks asking them how many pills they had taken the past seven days. This gives us two further stated adherence measures.

To simulate the gain in utility from getting reminders for sure and to derive testable predictions on the willingness to pay, we again use our theoretical model from section 2. As before, we are interested in the marginal effects of increases in μ and γ (weights on moral utility and perceived health benefits, respectively) which are shown in Figure 3.[23] We also display the effect on the gain in utility from an increase in k which can capture improvements in past adherence e.g. due to previous treatment effects. The WTP is increasing in γ in all cases because receiving more precise information increases the benefit of remembering to take supplements. WTP is increasing in μ when there is low past adherence. When μ is very negative, then there is a large moral penalty from not taking the supplements. In that case, reminders could be painful as they trigger a moral cost. In a situation, with high past adherence (k high) there is little or no moral penalty from failing to take the pill and an increase in μ may lead to a slight reduction in WTP if the lower weight on the moral obligation makes the individual shift away from the desired action. In all cases, the effect of μ is greater for smaller values of k because this implies the the moral cost is amplified.

Figure 3: Sensitivity of simulated $WTP = \Delta V_i$ with respect to γ, μ, and k



Notes: ΔV_i is the gain in utility when getting reminders with probability $p_{T-1} = 1$ compared to a baseline probability of $p_{t-1} < 1$. Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$. In the baseline calibration, the model parameters are calibrated to $(\delta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 0.01, 0.5, 0.8, 0.5, 0.5, 0.5)$ and $k_{T-2} = 4$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations. We show optimal behavior in period $T-1$ conditional on being attentive.

5.1 Empirical Results of Willingness to Pay

Since we only have one trade-off per woman, we cannot estimate the willingness to pay for each individual woman. This also implies that we cannot estimate the average WTP by treatment or

[23] In Figure 13 in the appendix we switch off the moral and informational channels, respectively.

content type without making additional assumptions. Hence we defer this to our structural analysis in section 6. In this section, our reduced form analysis focuses on the demand for reminders as captured by the probability of choosing reminders for different price levels. To do so, we regress the probability of choosing reminders (captured by a dummy which is one if the mother chose to receive reminders (replies "A") and zero if not) on the price dummies $I_{p=x}$ for $x = \{-10, -5, 5\}$ and all interactions with the content dummies I_{Att}, I_{Info} and I_{Moral}. Based on the regression coefficient, we then calculated the mean acceptance rate for each price-content combination. The downward sloping demand curves are shown in Figure 4. The x-axis starts from getting 10 ZAR along with the reminders (essentially a price of -10 ZAR for reminders) and goes over to a price of 5 ZAR to receive reminders.

Point zero shows the average share of women who opt-in to reminders when they are free. 82.95% of the women who responded to this trade-off wanted the reminder when they were free (72.63% of all the women who were sent this trade-off text message). Clearly, we see a high interest in receiving reminders. The financial incentive to receive reminders increases the demand to over 94 percent. We can already see from Figure 4 that the only significant differences are in the condition where women would need to forgo some airtime in order to receive the reminders. Compared to the control condition, the attention focusing content significantly increases the willingness to pay. The information content decreases it but insignificantly so and the moral suasion component slightly but insignificantly increases the willingness to pay compared to the control.

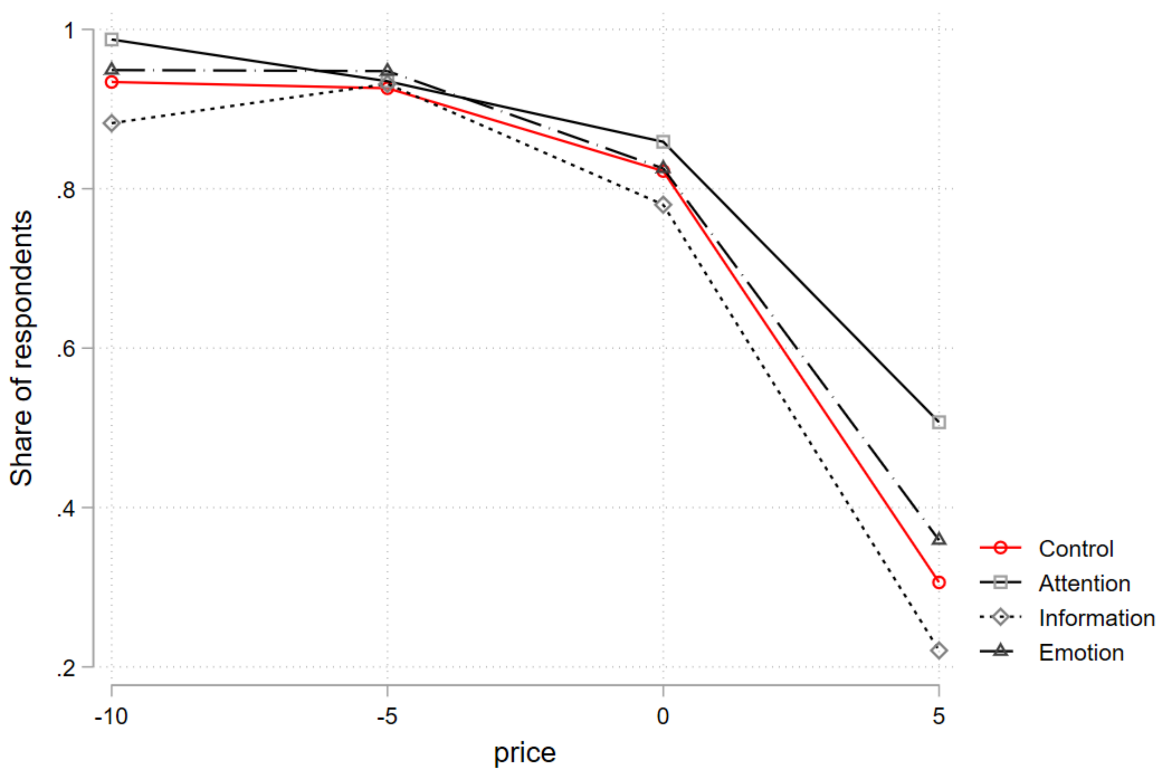
Our model suggests that the positive effect on WTP of attention focusing should arise through the observed increase in past adherence (k increases) as the attention focusing content should have no other lasting effect beyond the treatment period.

For the other content, our model suggests that the effects consist of 1) a direct effect stemming from changes in the parameters γ and μ, and 2) an indirect effect coming from changes in past adherence (k in the model and simulations).

The small positive effect of moral suasion compared to the control condition may be explained by both the direct and the indirect effect: First, given the high adherence in our sample, adding the moral suasion content (i.e. lowering the value of μ) could slightly increase the willingness to pay. Second, moral suasion content also led to improved past adherence (i.e. an increase in k) which works to raise the WTP.

With respect to the informational effect on WTP, we would, as illustrated by the simulations in Figure 3, have expected a positive direct and indirect effect if the information content had led to an increase in γ and an increase in past adherence. Instead, we see a negative effect on willingness to pay which is in line with the finding that past adherence actually decreased when information content was provided.

Figure 4: Demand for reminders based on marginal effects



Notes: Points in the figures are calculated from the regression coefficients from the following regression: $WantReminders = \alpha_1 I_{p=5} + \alpha_2 + \alpha_3 I_{p=-5} + \alpha_4 I_{p=-10} + \beta_1 I_{p=5} I_{Att} + \beta_2 I_{Att} + \beta_3 I_{p=-5} I_{Att} + \beta_4 I_{p=-10} I_{Att} + \delta_1 I_{p=5} I_{Info} + \delta_2 I_{Info} + \delta_3 I_{p=-5} I_{Info} + \delta_4 I_{p=-10} I_{Info} + \eta_1 I_{p=+5} I_{Moral} + \eta_2 I_{Moral} + \eta_3 I_{p=-5} I_{Moral} + \eta_4 I_{p=-10} I_{Moral} + \varepsilon$ where $I_{p=x}$ are price dummies for $x = \{-10, -5, 5\}$ and I_{Att}, I_{Moral} and I_{Info} are content dummies. Our reference category is the condition in which reminders are available for free and the women in the control condition.

We further explore the treatment effects in a linear probability regression with additional controls. We regress the marginal treatment dummies on a dummy which is one if the mother chose to receive reminders (replies “A”) and zero if not. Our baseline is the condition in which reminders are available for free and the women in the control condition. In column 2, we add additional controls and in column 3 we estimate the effect of prices on the demand for reminders. In line with Figure 4, we find that having received attention focusing messages has a significant positive effect on the demand for reminders (7.4 percentage points), while having received additional information has a significant negative effect (6.1 percentage points). Having been exposed to the moral suasion of the promise treatment has a marginally significant positive effect on wanting additional reminders (3.2 percentage points).

Stating that one finds it difficult to remember taking the pills has a marginally significant negative effect of 4 percentage points, while having stated less than perfect adherence in the survey, has a significant positive effect on wanting reminders, by 6 percentage points. There are no significant effects of living in an urban area, having English as a preferred language, age, having kids or having been told to be iron deficient. Our results from the treatments are in line with the results we find for self-reported adherence.

In column 3, we see the price effect from having to pay for reminders and receiving money for taking reminders. Being randomly allocated to the 5 ZAR trade-off reduces willingness to pay for reminders by 41 percentage points. Receiving money for choosing reminders leads to a 11 and 12 percentage point increase, respectively, compared to receiving free reminders.

Table 6: WTP for Reminders - LPM

	(1) Want Reminders	(2) Want Reminders	(3) Want Reminders
Attention	0.074***	0.079***	
	(0.021)	(0.022)	
Information	-0.061***	-0.074***	
	(0.021)	(0.022)	
Moral	0.032*	0.034*	
	(0.017)	(0.018)	
Urban		-0.002	
		(0.017)	
English		-0.015	
		(0.017)	
Age		-0.001	
		(0.002)	
Has kids		0.012	
		(0.019)	
Low iron		0.026	
		(0.026)	
Diff. Remembering		-0.039*	
		(0.023)	
Imperfect Adherence		0.059***	
		(0.021)	
WTP +5			-0.412***
			(0.023)
WTP -5			0.112***
			(0.016)
WTP -10			0.122***
			(0.016)
Constant	0.758***	0.785***	0.829***
	(0.015)	(0.046)	(0.014)
Observations	2964	2687	2964
R^2	0.004	0.009	0.279

Standard errors in parentheses.

The outcome measures whether women opted-in to receiving reminders (by texting ”A” or not.)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Adherence after reminders

While not part of our theoretical hypotheses given the self-selection into reminders, we were curious whether self-selected reminders have an effect on adherence. We asked all mothers, regardless of whether they chose to receive reminders or not for the two weeks, about their adherence after week one and week two. The questions were identical to the stated adherence question we had asked in the survey before the willingness to pay task. "Hi Mama, how many times did you take your iron pills these past 7 days? Reply with a number from 0 to 7." Because receiving the reminders is endogenous, we conduct a two-stage-least-squares IV regression using the price that the mothers were offered for the reminders as an instrument. Table 7, Column 1 shows our significant first stage. The more expensive the reminders were, the less likely it was that the mothers selected into them. Columns 2 and 4 then show OLS regressions in which we use the variable "Want Reminder" as an explanatory variable. Column 3 shows the IV regression in which "Want Reminders" is instrumented by "Reminder Price". Overall, we find only minor differences between our two regression approaches. Whether the women received reminders has a statistically significant effect on self-reported adherence (probability of full adherence) in the second week of receiving reminders. Receiving reminders increases the probability of full adherence by about 3 percentage points. While the marginal treatment effects are in line with our other results they are not significant. In line with Table 4, there are no significant effects of whether they live in an urban area, whether they prefer English, their age, or whether they already have kids. Women who previously stated that they had imperfect adherence, have been told by their doctor that they have low iron levels and say that they have a hard time remembering taking the pills have lower stated adherence. In column 4, we add two interaction effects to see whether receiving reminders had an effect on those who reported that they had difficulty remembering and those who had been told that they have low iron levels. We find that for the group who have low iron levels and select into reminders, the effect on adherence is negative. It is likely that these women have a particular reason for not taking the pills as regularly even when they are reminded.

However, we find that for those who stated that they had difficulty remembering to take the pills and who did not opt in for reminders, the effect on adherence is significantly negative with 11 percentage points, while those who opted in to reminders report a higher adherence of about 7 percentage points. Thus, reminders are clearly effective for the group that struggles with adherence.

Table 7: Stated Adherence - After Reminders

	(1) Want Reminders OLS	(2) Prob full adh OLS	(3) Prob full adh 2SLS	(4) Prob full adh OLS
WTPIV	-0.034***			
	(0.001)			
Want Reminders		0.031***	0.035**	0.027***
		(0.010)	(0.017)	(0.010)
Attention		0.011	0.011	0.011
		(0.010)	(0.010)	(0.010)
Information		-0.005	-0.005	-0.005
		(0.010)	(0.010)	(0.010)
Moral		0.011	0.011	0.011
		(0.008)	(0.008)	(0.008)
Urban		-0.001	-0.001	0.000
		(0.007)	(0.007)	(0.007)
English		0.012	0.012	0.010
		(0.008)	(0.008)	(0.008)
Age		0.001	0.001	0.000
		(0.001)	(0.001)	(0.001)
Has kids		-0.003	-0.003	-0.002
		(0.008)	(0.008)	(0.008)
Diff. Remembering		-0.061***	-0.060***	-0.111***
		(0.014)	(0.014)	(0.037)
Low Iron		-0.037**	-0.037**	0.018
		(0.016)	(0.016)	(0.030)
Imperfect Adherence		-0.074***	-0.074***	-0.075***
		(0.014)	(0.014)	(0.014)
DiffRem*Want				0.067*
				(0.040)
LowIron*Want				-0.070**
				(0.036)
Constant	0.701***	0.913***	0.910***	0.920***
	(0.009)	(0.022)	(0.024)	(0.021)
Observations	2964	2196	2196	2196
R^2	0.215	0.065	0.065	0.070

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ WTPIV is the price variation that the women were randomized into in the WTP task. Want Reminders is a dummy variable if the mother opted-in to reminders. Attention, Information and Moral are dummy variables to measure marginal effects. Prob full adh is a dummy variable equal to one if the mother reported full adherence during the past week.

6 Structural Estimation

Our reduced form results reveal a high general level of engagement with the reminder service (i.e. almost no unsubscriptions and high response rates post treatment) as well as a high baseline medicaton adherence rate. Despite the high baseline adherence, we do, however, see that attention focusing reminders (and to a lesser extent reminders including moral suasion) can improve adherence *and* the demand for additional reminders even further, whereas information provision, in our setting, has the opposite effect. Intuitively, one might think that women who already remember to take their iron pills even without reminders would not want additional reminders because they create annoyance costs for the mothers, while not leading to a meaningful change in behavior. Further, given that irrelevant information could easily be ignored, it is surprising that we find significant negative effects an adherence and demand from the information provision. It seems that information provision might have had a negative effect on the perceived health benefits of taking the iron pills.

Ex-ante and in our model and hypotheses development, we did not assume attention focusing to have lasting effects on the weighting of the different components of the utility function. In line with prior attention models, we assumed that attention focusing reminders increase attention temporarily, right after receiving a reminder. We also expected annoyance costs of receiving a reminder to be fixed over time.

In this section, we therefore investigate whether our initial assumptions are supported by our data or whether the exposure to attention focusing reminders led to a shift in our key model parameters and potentially a "build up" of annoyance or even a reduction in annoyance as the reminders prove helpful.

To investigate these questions, we complement the reduced form analysis with a structural estimation of the model parameters. The key question in our structural analysis is how the different content of the nudges *alter* the weight on the different components of the utility function and if so in what way. Our interest is in the *change* of the key model parameters: i) γ the weight on health benefits, ii) μ the weight on moral utility, and iii) the annoyance cost Λ. Since we do not explicitly vary the annoyance costs of the reminders in the experiment, the structural estimation helps us to understand whether the annoyance costs are affected by our treatments and whether they change over time of exposure.

6.1 Estimation setup

For our structural estimation, we need a few assumptions extending our original model. To estimate a possible shift in the model parameters, we assume that F is the lognormal distribution with $N[\alpha_e, \sigma_e]$, i.e. the effort costs are identically and independently distributed according to the uniform distribution on the unit interval. Furthermore, to accommodate the reduced form result that the willingness to receive reminders depends on individual specific factors such as the perceived difficulty of remembering to take the supplements, we also assume individual level variation in the annoyance cost Λ and assume that it is normally distributed with mean Λ_0 and variance σ^2_Λ. We also allow repeated messages to influence the size of the average annoyance cost and let $\Delta\Lambda_R$ denote the change in the mean annoyance cost coming from an increase number of messages.

In addition, we assume a simple linear benefit function, i.e. $b(a_t) = a_t$. We calibrate some of the model parameters to fit the experimental setting: 1) We let $T = 8$ which corresponds to the end of the 8 week experimental period at which time we measure outcomes. That is we let $T - 1$ denote the period of outcome measurement. 2) We let the weekly discount rate $\delta = 0.99963$ which corresponds to an annual real interest rate of 2%. 3) We let $p^0_t = 0.019$ and $p^R_t = 0.305$. This makes p_t the message intensity with 2 weekly messages at baseline from MomConnect drawn from a pool of 74 messages with 5 being about iron supplements and an additional 2 weekly messages about iron supplements in the pure reminder, information and information+promise treatments. 4) We set the starting value for the state variable $k_{T-2} = 6,4$ which corresponds to an initial adherence of around 91.6% which is close to the adherence rate in the control condition. When calculating WTP moments from the model, we update k to the model-implied adherence in order to allow the model to capture the effect that altered adherence has on the WTP for future reminders. 6) We assume that $\eta = 1$ implying that the effort cost of taking one pill is approximately the same as the effort cost of responding to a message. 5) Finally, we take into account that for our measure of reading/responding to messages we provide an incentive of 5 ZAR, hence we introduce a price for responses $q = 5$ in period $T - 1$ where outcomes are measured.

As our focus is on changes in the parameters, we calibrate their levels. We normalize $\Lambda_0 = 1$[24] and set $\mu_0 = 0$ such that relative to the normalized annoyance cost the parameter γ_0 captures the total initial value of taking a pill both from perceived health benefits and from moral and emotional factors. Based on trial runs of the model we set $\gamma_0 = 90$ in all estimations.[25]. This is equivalent to

[24] This implies an annoyance cost approximately a factor 30 smaller than that reported by Damgaard & Gravert (2018) who have significantly more unsubscriptions

[25] Preliminary results reveal that we are unable to jointly identify γ_0, Λ and μ. However, even with $\Lambda = 1$ and $\mu_0 = 0$, identification of the exact magnitude of γ_0 is difficult as the objective function in the estimation is approximately flat in γ_0 above $\gamma_0 = 70$ and above $\gamma_0 = 90$ improvements in the objective function are at the fourth decimal or below. Trial

a perceived health benefit of 5.4 Euro per week of iron pills taken at the time of the experiment or 0.77 Euro per pill taken.

We estimate the remaining parameters. There are three key parameters of interest: i) $\Delta\gamma$, the change in the weight on health benefits induced by the provision of information, ii) $\Delta\mu$, the change in the weight on moral utility induced by the promise, and iii) $\Delta\Lambda_R$, the change in average annoyance costs caused by additional reminder messages, and iv) $\sigma\Lambda$, the change in average annoyance costs caused by informational content. We also estimate the following auxiliary five parameters: i) i) θ_0, the rate of recall with no messages, ii) θ_m, the rate of recall when receiving but not reading a message, iii) α_e in the effort cost distribution, iv) σ_e in the effort cost distribution, v) σ_Λ the variance in the annoyance cost distribution. In total we estimate eight parameters that are placed in the vector ψ.

For the estimation, we use data from all treatments reported in this paper as well as data from an auxiliary experiment on a different sample of MomConnect users. In the auxiliary experiment, we varied the incentives offered for participants to respond to the message "A simple question to start! Please reply with the first 4 digits of your ID number fx. 9311 You will get X in airtime for responding." with participants randomly allocated to one of three treatments that offered $X = 2$, $X = 5$ or $X = 10$ as payment. This is a direct measure of the effort cost of responding to the messages and we use this to also proxy for the effort costs associated with reading and unsubscribing to messages and when scaled by η to capture the effort cost of taking an iron pill.

The parameters are estimated using a simulated method of moments (SMM) estimator following McFadden (1989). The estimator minimizes the distance $(m(\psi) - \hat{m})'W(m(\psi) - \hat{m})$ where the vector $m(\psi)$ contains the model-implied moments which depend on the estimated parameters. To calculate the model-implied moments we solve the model by backwards induction evaluating expectations numerically with a simulated population of 100.000 individuals per run. The vector $\hat{m}$ contains the corresponding observed moments. We use a total of 33 moments calculated from the control and treatment conditions and from the auxiliary experiment. Let $j = \{C, PR, IR, PP, PP + IR\}$ denote the control, pure reminder, informational reminder, promise prompt, and promise prompt + informational reminder conditions, respectively. We use as moments : i) the probability of taking the pill, $P(a_{it} = 1)_j$, ii) the probability of responding to a message, $P(r_{it} = 1)_j$, iii) the probability of unsubscribing $P(u_{it} = 1)_j$, iv) the probability of a WTP of 5 or more, $P(WTP_{it} \geq 5)_j$, v) the probability of a WTP of 0 or more $P(WTP_{it} \geq 0)_C$, v) the probability of a WTP of minus 5 or more $P(WTP_{it} \geq -5)_j$, vi) the probability of effort costs

runs of the model for different values of γ_0 clearly show that the model fit is much improved if γ_0 is greater than 10 but that there is little improvement in the model fit for values of γ_0 larger than 70. See table 13 in the Appendix.

smaller than or equal to 2, $P(e_{it} \leq 2)$, vii) the probability of effort costs smaller than or equal to 5, $P(e_{it} \leq 5)$, and viii) the probability of effort costs smaller than or equal to 10, $P(e_{it} \leq 10)$.[26]

The parameters in the effort cost distribution α_e and σ_e are identified from the behaviour in the auxiliary experiment combined with the response rate $P(r_{it} = 1)$ and action rate $P(a_{it} = 1)$ in the control condition. The variation in annoyance costs, σ_Λ, is identified from the WTP moments in the control condition. Identification of the remaining parameters comes from the treatment differences. The attention parameters θ_0 and θ_m are identified from the differences in $P(a_{it} = 1)$ and $P(r_{it} = 1)$ between the control treatment and the PR treatment. The changes $\Delta\gamma$ and $\Delta\mu$ are identified from variation in $P(a_{it} = 1)$ and $P(r_{it} = 1)$ in the informational and promise prompt treatments, respectively.

6.2 Structural estimates

To investigate whether variance in annoyance costs can explain our experimental findings, we estimate three different versions of the model, shutting off any change in the annoyance costs and any heterogeneity. Table 8 contains the structural estimates for the three different versions of the model and Table 9 compare the moments implied by the structural estimates to the empirical moments. The full model is our preferred model as it obtains the a good fit of the model to the empirical moments, although we do not fully capture the effect of the promise prompts.[27] In model 1, we assume no learning of annoyance costs from messages and set $\Delta\Lambda_R = 0$. With this modification the model can no longer capture the attention effects. Further, the moments implied by model 1 for the control treatment and the pure reminder treatment are identical which is in contrast to the empirical results. In model 2, we maintain $\Delta\Lambda_R = 0$ and in addition assume $\sigma_\Lambda = 0$, i.e. no variance in annoyance costs. Clearly, with this additional assumption, the model is unable to capture the variation in the WTP estimates that we observe empirically. This suggest that heterogeneity and learning in annoyance costs is important in order to rationalize the empirical findings, particularly the attentional effects and the heterogeneity in the demand for reminders as captured by the WTP.

The structural estimates from the full model confirm the reduced form results that suggested a negative impact of information provision in our experiment. We estimate $\Delta\gamma = -11.42$ which

[26] We do not use the probability of a WTP of minus 10 ZAR or more because there is no meaningful variation across treatments in WTP of less than 0 and hence we do not want to put too much emphasis on the small differences that do exist in the estimation.

[27] We see this as the model implied moments of the Control condition are similar to that of the Promise Prompt treatment and similarly the model implied moments for the Information treatment and the combined Information and Promise Prompt treatments are very similar.

amounts to a 12.7% decrease in the perceived benefits due to the provided information. We estimate $\Delta\mu = -2.78$ suggesting that the promise prompt did lead to an increase in the weight on moral utility. With respect to annoyance costs, we estimate a substantial standard deviation in the annoyance cost distribution and notably additional messages lead to a reduction - not an increase - in the average annoyance costs. Hence, in addition to the positive attention effect on the probability of taking iron pills, there also appears to be a downward correction of annoyance costs when the expectant mothers receive additional messages. This suggests that the expectant mothers learn that messages are helpful reminders. Figure 5 illustrates both the baseline distribution of annoyance costs implied by our structural estimates and the shift of the distribution caused by learning.

Learning through exposure to reminders in our setting increases the demand for reminders while information reduces the demand for reminders. Hence if we do not allow for learning in annoyance costs (Models 1 and 2), then the size of the $\Delta\gamma$ increases and becomes statistically insignificant because learning in annoyance cost has the opposite effect of an increase in $\Delta\gamma$ in the informational treatments where both effects are present in the full model.

Variation in annoyance costs is important to capture the variation in the empirical data. If we remove this source of variation (Model 2) then the estimate of the variation in the effort cost increases because this now is the only source of variation. At the same time the estimate of $\Delta\mu$ increases in absolute terms. This also leads to more variation in behaviour but as mentioned above the model fit is substantially worsened.

In terms of the auxiliary parameters, we find that the rate of natural recall is quite high at $\theta_0 = 0.966$ this is in line with a the high control group adherence. Second, the rate of recall with an unread message, θ_m is practically 1. Finally we estimate the mean and standard deviation in the lognormal effort cost distribution to $\alpha_e = -1.998$ and $\sigma_e = 3.862$, respectively.

In summary, we need learning about annoyance costs, as well as heterogeneity in annoyance costs to fit our model to the empirical results.

6.3 Estimates and decomposition of WTP

Given that our experimental design did not allow for a multiple price list approach via text message, we were unable to calculate individual WTP or the average WTP by treatment or by content type. Given our structural assumptions and estimates we can now calculate these averages. Further, we are interested in understanding whether the WTP is driven by future expectations of behavior change or is more influenced by past exposure to reminders in our experiment. To estimate welfare effects of our intervention, we need to understand what components are driving the willingness to

Table 8: Structural estimates

	Full model	Model 1	Model 2
Change in weight on health benefits, $\Delta\gamma$	-11.422	5.474	-0.011
	(5.380)	(3.764)	(0.011)
Change in weight on moral utility, $\Delta\mu$	-2.784	-4.136	-6.437
	(1.105)	(1.597)	(2.568)
Standard deviation of annoyance cost, σ_Λ	4.429	4.498	–
	(0.301)	(0.301)	
Learning of annoyance from additional messages, $\Delta\Lambda_R$	-0.779	–	–
	(0.176)		
Rate of natural recall, θ_0	0.966	0.962	0.988
	(0.002)	(0.002)	(> 0.001)
Rate of recall with message but without reading it, θ_m	0.999	0.998	1.000
	(0.002)	(0.002)	(> 0.001)
Mean of the effort cost's natural logarithm, α_e	-1.998	-1.920	-2.455
	(0.407)	(0.408)	(0.043)
Standard deviation of the effort cost's natural logarithm, σ_e	3.862	3.797	4.533
	(0.357)	(0.356)	(0.005)

Notes: SMM estimates of the model parameters with bootstraped standard errors in brackets. The number of bootstrap draws is 250. We assume that $T = 8$, $\delta = 0.99963$, $p_t^0 = 0.019$, $p_t^R = 0.305$, $k_{T-2} = 6.4$, $\eta = 1$, $\gamma_0 = 90$, $\mu = 0$, $\Lambda_0 = 1$, and that the price for responses is $q = 5$ in the period when outcomes are measured.

pay. We decompose the willingness to pay into two different components: i) the expected *future* change in behavior in response to the two additional weeks of reminders, and ii) the *prior* exposure to our experiment. The latter is again decomposed into: a) an *indirect effect* coming from behavior change during the experiment, and b) a *direct effect* from changes in the weighting parameters Λ, γ and μ when exposed to attention focusing, information provision and moral suasion, respectively.

Table 10 shows the average WTP for two weeks of daily reminders in the control group and if exposed to messages with attention focusing, information provision, or moral suasion content. The averages and the decomposition are calculated using simulated data and the structural parameter estimates from the full model in Table 8.

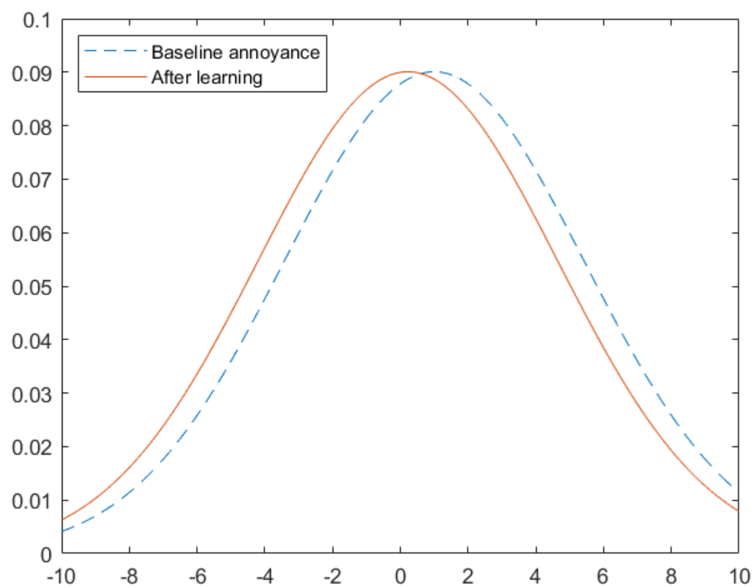
To decompose the WTP estimates, we use WTP in the control condition to measure the value of the participants' expected change in behavior when faced with additional reminders. In the control condition the average WTP for two weeks of additional reminders is estimated to ZAR 3.42, and as the control group is not exposed to prior interventions, all of the WTP can be attributed to expected future behavior change in response to the additional reminders. With prior exposure to

Table 9: Moments

	Full model	Model 1	Model 2	Empirical
$P(e_{it} \leq 2)$	0.7578	0.7548	0.7570	0.7616
$P(e_{it} \leq 5)$	0.8256	0.8246	0.8161	0.8166
$P(e_{it} \leq 10)$	0.8669	0.8666	0.8538	0.8509
$P(a_{it} = 1)_C$	0.9216	0.9188	0.9251	0.9160
$P(r_{it} = 1)_C$	0.8274	0.8278	0.8161	0.8082
$P(u_{it} = 1)_C$	0	0	0	0
$P(WTP_{it} \geq 5)_C$	0.3616	0.4045	0	0.2868
$P(WTP_{it} \geq 0)_C$	0.7813	0.8070	0.8501	0.8288
$P(WTP_{it} \geq -5)_C$	0.9710	0.9754	1	0.9317
$P(a_{it} = 1)_{PR}$	0.9307	0.9287	0.9284	0.9504
$P(r_{it} = 1)_{PR}$	0.8274	0.8278	0.8161	0.8358
$P(u_{it} = 1)_{PR}$	0	0	0	0.0027
$P(WTP_{it} \geq 5)_{PR}$	0.4961	0.4045	0	0.5071
$P(WTP_{it} \geq 0)_{PR}$	0.8693	0.8070	0.8501	0.8589
$P(WTP_{it} \geq -5)_{PR}$	0.9871	0.9754	1	0.9349
$P(a_{it} = 1)_{IR}$	0.9271	0.9300	0.9284	0.9128
$P(r_{it} = 1)_{IR}$	0.8272	0.8280	0.8161	0.8408
$P(u_{it} = 1)_{IR}$	0	0	0	0.0042
$P(WTP_{it} \geq 5)_{IR}$	0.4320	0.4362	0	0.4360
$P(WTP_{it} \geq 0)_{IR}$	0.8326	0.8288	0.8500	0.8105
$P(WTP_{it} \geq -5)_{IR}$	0.9271	0.9790	1	0.9338
$P(a_{it} = 1)_{PP+IR}$	0.9272	0.9301	0.9285	0.9289
$P(r_{it} = 1)_{PP+IR}$	0.8274	0.8280	0.8161	0.8249
$P(u_{it} = 1)_{PP+IR}$	0	0	0.0038	0.0059
$P(WTP_{it} \geq 5)_{PP+IR}$	0.4318	0.4361	0	0.4565
$P(WTP_{it} \geq 0)_{PP+IR}$	0.8325	0.8288	0.8494	0.8279
$P(WTP_{it} \geq -5)_{PP+IR}$	0.9810	0.9790	1	0.9675
$P(a_{it} = 1)_{PP}$	0.9216	0.9189	0.9252	0.9345
$P(r_{it} = 1)_{PP}$	0.8274	0.8278	0.8161	0.8338
$P(u_{it} = 1)_{PP}$	0	0	0	0
$P(WTP_{it} \geq 5)_{PP}$	0.3615	0.4043	0	0.3790
$P(WTP_{it} \geq 0)_{PP}$	0.7812	0.8069	0.8495	0.8194
$P(WTP_{it} \geq -5)_{PP}$	0.9710	0.9753	1	0.9412
Q^{Opt}	0.1429	0.1951	0.9514	–

Notes: The table reports the model moments implied by the parameter estimates in Table 8. The parameters are estimated using SMM where we assume that $T = 8$, $\delta = 0.99963$, $p_t^0 = 0.019$, $p_t^R = 0.305$, $k_{T-2}6.4$, $\eta = 1$, $\gamma_0 = 90$, $\mu_0 = 0$, $\Lambda_0 = 1$, and that the price for responses is $q = 5$ in the period when outcomes are measured. Q^{Opt} is the objective function used in SMM optimization evaluated at the estimated optimum. It is a measure of the goodness of fit.

Figure 5: Baseline annoyance distribution and shift in distribution caused by learning



Notes: In the structural estimation we assume a normally distributed annoyance cost with $N(\Lambda, \sigma_\Lambda)$ where $\Lambda = 1$ and σ_Λ is given by the structural estimate in Table 8. After learning the distribution is given by $N(\Lambda + \Delta\Lambda, \sigma_\Lambda)$.

attention focusing, the average WTP is estimated to ZAR 4.95 and 30.87% of the WTP can be attributed to the prior experimental exposure. If we further decompose the WTP which can be attributed to the prior experiment, it is clear that most of the effect comes not from the change in behavior seen during the experiment but from the shift of the annoyance parameter. That is if we were to only evaluate attention focusing in terms of the behavioral impact we would be likely to underestimate the welfare effect. However, the elicited WTP estimates captures the additional effect of experiencing that reminders are less annoying and more helpful that originally anticipated. which has made the participants view reminders as less annoying and hence has led to higher adherence and lower annoyance costs.

Exposure to informational content only gives an average WTP of ZAR 2.71 which is lower than the control group WTP. We estimate that 82.8% of the WTP is due to the expected behavioral response to future reminders which is what ensures that the average estimate is positive. The prior experimental exposure has a negative effect which is almost entirely due to the change in γ as our informational content seems to have lowered and not increased the perceived net benefits of taking iron supplements. Finally, we estimate the moral suasion content to be associated with an average WTP of ZAR 3.4190 which is almost identical to the WTP in the control condition. Therefore, 99.9% of the WTP is estimated to capture the expected behavioral response to the additional reminders with a small negative effect coming from the prior experimental exposure. Again most of the experimental exposure effect comes from changes in the weighting parameters, in this case in μ. Taken together our decomposition suggests that changes in the weighting parameters in the utility function are important for understanding the WTP effect of the exposure to the experiment and mostly so for attention focusing.

Table 10: Decomposition of WTP

	Control	Attention focusing	Information provision	Moral suasion
Average WTP in ZAR	3.4204	4.9474	2.7100	3.4190
Percentage of WTP explained by:				
Expected behavioral response to future reminders	$\sim$ 100%	69.13%	82.80%	99.96%
Prior experimental exposure	$\sim$ 0%	30.87%	17.20%	0.04%
Decomposition of prior experimental exposure				
Percentage of WTP explained by:				
Indirect effect:Behavior change during experiment	-	$\sim$ 0%	$\sim$ 0%	0.004%
Direct effect: Change in parameter weights (Λ, γ, μ)	-	$\sim$ 30.87%	$\sim$ 17.20%	0.043%

Notes: The table shows the average WTP for two weeks of daily reminders in the control group and if exposed to messages with attention focusing, information provision, or moral suasion content. The averages and the decomposition are calculated using simulated data and the structural parameter estimates from the full model in Table 8. To decompose the WTP estimates, we use WTP in the control condition to measure the value of the participants expected change in behaviour when faced with additional reminders. To decompose the experiment exposure effect, we calculate the WTP holding behaviour during the experiment fixed at the control level.

7 Discussion

A wealth of evidence shows that reminders are effective in achieving a meaningful shift in behavior in many contexts. In line with this previous evidence, we also find that attention focusing reminders are effective in our setting – they increase average adherence by 2-3 percentage points. This estimate falls perfectly into the range of the vast literature of nudging studies that find similar effects (DellaVigna & Linos 2022, Milkman et al. 2021). However, this average effect tells us very little about why this type of reminder works. Our paper demonstrates that such a simple model-free analysis can miss out on important insights for welfare analysis and for learning about long-term compliance.

In addition to estimating the reduced form effect of specific types of reminders, we evaluate how our treatments affect recipients' demand for future reminders. We find that the majority of women choose to receive additional reminders. This demand for additional reminders is increased even further when the women have been exogenously exposed to prior reminders. A plausible explanation is that reminders alleviate memory costs. So even though the majority of women are capable to remembering to take the iron pills themselves, they prefer to receive reminders. Thus, they value the possibility of outsourcing the cognitive costs of remembering to an external entity (in this case, the health service).

Using our model, the structural estimation and the decomposition of the WTP we find that the main effect comes from learning about the benefits of being reminded. The moral suasion component only has a very marginal effect. The idea that individuals who do not seem to need a nudge as it does not change their behavior in a meaningful way might nevertheless derive utility from the nudge is consistent with findings in the commitment device literature that people who demand commitment devices, such as restrictive bank accounts or food deliveries without any tempting options, are the same type of people who carry out "the right behavior" even without any commitment device (Beshears et al. 2020, Sadoff et al. 2020). Neither these commitment device papers, nor our reminders study can determine whether individuals' demand for the provided technology is "optimal", since we do not observe the individual benefits of the technology.[28] Nevertheless, revealed preferences show that the vast majority of women prefers to receive reminders. We also find that those women who report struggling to remember and who self-select into receiving additional reminders report a higher adherence after two weeks than the women who do not self-select into the reminders.

Clearly, as with any empirical study, ours takes place within a specific context. However, it is arguably representative of an class of situations for which reminders may be important. Specifically, those in which the benefits of taking a particular action regularly are large relative to the costs. Whether it is wishing a friend a happy birthday, taking pills, brushing our teeth, flossing, turning off the stove, taking our keys with us or locking the door, all these small activities create cognitive load. Most of us are able to remember, but we might be better off if we didn't have to. The large amount of small tasks to remember also gives an indication why it might not be feasible or desirable to set up reminders ourselves, even if we know best when a reminder would be useful. An app that would remind us just at the right time about all these small tasks without reminding us at the wrong time, would likely be a highly valued product.

[28]In a series of lab experiments Bronchetti et al. (2021) vary the costs and benefits of being reminded and can thus determine optimality.

A related, policy-relevant question for our context is whether our results can be viewed as informative for a wider population, given that the women in our study have consented to taking part in the study. We sent our invitation to all women across South Africa who had signed-up with the mobile health service, who were over 18 and had their due date during the relevant period. Sampling from the over 60% of the pregnant population that uses the health service allows us to learn about a population, we are particularly interested in, women who make use of mobile health services. Comparing those who opt-in to our study with those who do not, we find that there are only minor differences in language preferences and phone use. The invitation message stated that we were studying health behavior during pregnancy, the actual behavior was not mentioned. Opting-in to reminders will usually require access to a mobile phone as well as consent from the women. If women are defaulted in to the reminders, unsubscription rates would most likely be higher and thus, the remaining sample would again be those women who see some benefit to receiving text message reminders. For most repeated reminder applications, whether it is Facebook birthday reminders or phone notifications, some willingness to be reminded must be given.

There are only a handful of papers that look at the willingness to be nudged/ reminded. For example, there has been some recent work on the relevance of transparency of nudges and their effectiveness. Osman et al. (2018) and Sunstein et al. (2019) show in hypothetical experiments and surveys that higher trust in institutions increases approval and acceptance of nudges. Further, Bruns et al. (2018) showed in an experiment on default nudges and contributions to a climate fund that adding a transparency statement had no effect on the effectiveness of the nudge. Thus, nudges that are transparent and in line with the interests of the decision maker might work equally well when transparent and when the person being nudged trusts the choice architect (Gold et al. 2020).

In our case, it appears that trust in the Department of Health and the MomConnect service is high and the interest between the sender and the receiver of the reminder is perfectly aligned, both in actual interest as well as perceived interest. In this, our context differs from scenarios in which nudges are used to promote behavior that benefits the public good but not the individual themselves. Our reminder nudges aim to create a direct personal benefit for the nudged individual. While not the focus of the current paper, understanding how nudges work when incentives are not perfectly aligned is an important question for future work. For example, it is valuable to understand how reaction to reminders differ when the benefits accrue to the group rather than the individual as, for example, is the case when designing reminders that aim to promote prosocial behavior or reduce environmental externalities (see Carlsson et al. (2021) for an overview of these types of nudges). Our model could easily be adapted to such a setting.[29]

[29]These considerations are especially important when nudges are used that affect utility directly through the nudge,

We find that the largest behavioral and WTP effects come from the attention focusing component of our treatment and that the information and moral suasion components have a negative or only marginally significant effect. This finding is very much in line with other studies on reminders. Antinyan & Asatryan (2019) find in a meta-analysis of tax reminders that the main effect on behavior comes from the reminder itself, while while varying the framing of the message has a minor effect (or no effect). Altmann & Traxler (2014), Gravert & Collentine (2021) and Campos-Mercade et al. (2021) all find null results when considering variations in the framing of the same reminder, despite the effect of the reminder itself being significant. Milkman et al. (2021) show that the difference in reminder content in several dozen studies is not significantly different to each other.

Similar to us, other studies have found negative effects from information in addition to reminders (Adams et al. 2021, Bettinger et al. 2020). Bettinger et al. (2020) presents a field experiment in Brazil in which the parents of school children received either messages conveying information about their children's school absence (information) or messages that only highlighted the importance of attending school (salience). They find that most of the behavior change is driven by salience, not by a change in beliefs and conclude that for several reasons pure salience interventions are better and cheaper than the popular informational interventions. Despite our information being much cheaper to produce than their detailed information on student attendance, which teachers need to report ever week, we come to the same conclusion that it would be more effective and certainly more cost-effective to send pure reminders. Bettinger et al. (2020) and our paper, despite targeting very different behaviors have in common, that we are targeting a repeated behavior (habit) that is quite obviously "the right behavior", as in taking prescribed medicine and children attending school regularly. In these cases, adding information seems to be either unnecessary or even counterproductive. Pregnant women and parents know what to do, but seem to appreciate some help in keeping the behavior top-of-mind.

More research is needed to test the conditions under which additional information could be beneficial. It seems likely that in one-off informational interventions that aim to change a one-off behavior, such as informing prospective students about the possibility of scholarships, would benefit more from information. For example, Dynarski et al. (2021) show that informing low-income students that they are guaranteed a scholarship with enrollment has significant positive effects on applications to college. However, Adams et al. (2021) find in an information intervention on credit card switching, a one-off behavior, that while information has a positive effect, the effects became

rather than the outcome of the nudge. A reminder or moral suasion makes the decision maker aware that their decision is being influenced, while a default or an order effect would usually not be noticed as a mean to influence their decision.

weaker the more information was added to the message. A successful information treatment most likely needs a major shift in beliefs on a relevant dimension.[30]

Overall, this discussion highlights the crucial importance of paying careful attention to contextual factors when considering the likely effectiveness of reminders.

8 Conclusion

While reminders and information interventions have been shown to affect behavior for a share of the targeted individuals, we are only at the beginning of understanding the mechanisms behind how reminders and information work to change beliefs and behavior. In this paper, we introduce a theoretical framework, modeling the different components through which a reminder can change behavior. We test our model-derived hypotheses in a country-wide field experiment in South Africa to disentangle the attention focusing, information providing and moral suasion components of reminders and measure their effect on continuous interaction with a mobile health program, adherence to medication prescriptions as well as the demand for additional reminders.

The paper makes several important contributions. First, our results suggest that in a setting with repeated reminders, pure reminders are more effective than reminders that include information. Given that information reminders are more expensive to create it is also more cost effective to use attention focusing reminders. Second, our experiment shows that nudges, when used as originally intended to overcome internalities and make the decision maker "better off as judged by themselves" (Thaler & Sunstein 2003), are demanded and opt-out rates are very low. In this case, nudges work even when it is transparent that individuals are being nudged. Third, in our structural estimation we show that receivers learn about the benefits of reminders in alleviating memory constraints. Lastly, nudges might be desired by the receiver even if receivers are able to overcome the internality (such as inattention) by themselves and for most individuals behavioral effects are small. This difference between the high demand for reminders and the modest behavior change means that measuring the success of nudges purely based on their behavior change could be misleading. Particularly, in situations that have high personal benefits for the decision maker.

[30]Many information provision survey experiments show a significant shift in beliefs after receiving information, however, the majority of studies only looks at intentions to change behavior or minor "behavioral" outcomes such as making a small donation or signing a petition for a cause. See Haaland et al. (2020) for a review of the literature.

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9 Appendix

9.1 Tables and Figures

Table 11: Self-Selection into the experiment

	Did not join	Joined	Total invited
Urban	0.310	0.328**	0.314
	(0.462)	(0.470)	(0.464)
Age	28.22	26.98***	27.94
	(6.309)	(5.623)	(6.180)
English	0.506	0.604***	0.528
	(0.500)	(0.489)	(0.499)
WhatsApp	0.418	0.562***	0.451
	(0.493)	(0.496)	(0.498)
Observations	14174	4226	18400

Notes: Urban is a dummy variable taking the value 1 if the participant lives in an urban area. English is a dummy variable taking the value 1 if the participants chose English as her preferred language when signing up with MomConnect. WhatsApp is a dummy variable taking the value 1 if the participant signed up to receive MomConnect messages via WhatsApp. Chi2 tests for differences between women who joined (column 2) and who did not join (column 1): * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 3 shows the average of the sample invited.

Table 12: Variable Definitions

Variable	Description
Age	2019 - Expectant mother's year of birth
English	Indicator [=1] if respondent's preferred language is English.
Urban	Indicator [=1] if respondent resides in an urban area.
Nr. Kids	Number of kids prior to current pregnancy
WhatsApp	Indicator [=1] if respondent signed up with WhatsApp vs. text message
Important for Mother	To be a healthy mom, is it important to take iron pills? How important do you think it is? (Please reply a number from 0 to 7.)
Important for Baby	To have a healthy baby, are iron pills important? How important do you think it is? (Please reply a number from 0 to 7.)
Q1. Weekly Iron Intake	How many days did you take your iron pills last week? (Please reply a number from 0 to 7)
Q2. Difficulty Remembering [=1]	Do you find it difficult to remember to take the iron pills? (Reply with yes or no.)
Q3. Pills Available [=1]	Do they always have free iron pills available in your clinic when you need to get them? (Reply with yes or no.)
Q4. Importance for Mom	How important are iron pills for a healthy mother? (Reply 0 (not at all), 1, 2, 3, 4, 5, 6, 7 (very))
Q5. Importance for Baby	How important are iron pills for a healthy baby? (Reply 0 (not at all), 1, 2, 3, 4, 5, 6, 7 (very))
Q6. Stomach feels bad [=1]	Keep going! Does your stomach feel bad if you take iron pills? (Reply yes or no.)
Q7. Weekly days tired / dizzy	How many days did you feel very tired or dizzy last week? (Please reply a number from 0 to 7.)
Q8. See Doctor [=1]	Did you see a doctor or nurse in the past 4 weeks? (Reply with yes or no.)
Q9. Low iron levels [=1]	Did your doctor or nurse tell you that you have low iron levels? (Reply 1) Yes 2) No 3) Not anymore 4) Don't know ... recoded to "yes" =1, else =0)
Q10. Years of Schooling	How many years did you go to school? Reply with number of years.

Notes: (i) The table describes the survey variables used in the main analysis.

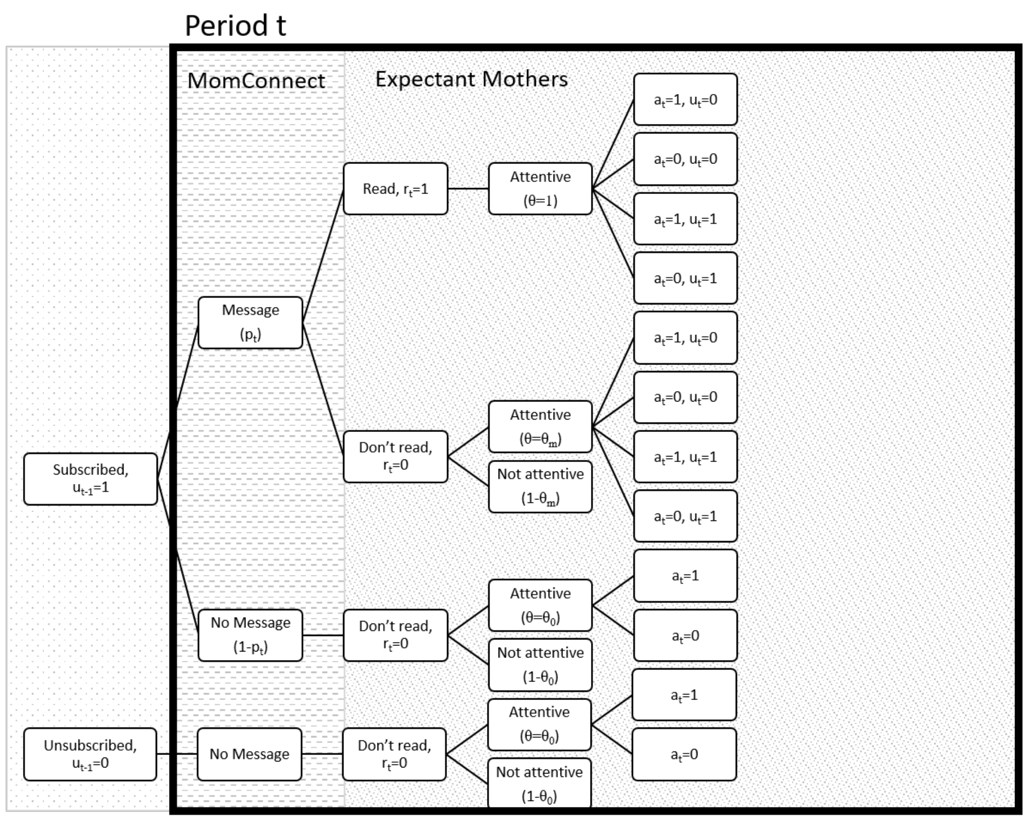
9.2 Solving the model

The model is solved by backwards induction starting from period T. The solution to the model has a within-period sequential structure. First we solve for the unsubscription and action choice in a given period and then we solve for the read choice in the same period taking the unsubscription and action choice as given. The model does not have a closed form solution but we simulate the period $T-1$ and T solution to the model. In this appendix, we characterize the solution to the last two periods, to illustrate the mechanisms of the model.

9.2.1 Solving a T=2 period model

Figure 6 illustrates the repeated decision problem of the individual. At the beginning of every period t the individual is either subscribed or not. If the individual is subscribed, MomConnect may send message about iron supplements or not. If a message arrives the expectant mother then decides whether or not to read it and be attentive to the decision problem. If the expectant mother does not read a message about iron supplements, she may still be attentive to the decision problem with some probability which depend on whether a message was sent. Conditional on being attentive, the expectant mother may then choose to take supplements and unsubscribe or not. The decision problem illustrated in Figure 6 in repeated in T periods.

Figure 6: Illustration of the period t decision problem



The model is solved by backwards induction. To illustrate the mechanisms of the model, we characterize the optimal behavior in the last two periods, periods T and $T-1$ consider a two period version of the model i.e. $T=2$. We use u_t^*, a_t^* and r_t^* to denote optimal behavior in period t. We solve the model backwards by first considering the decision problem in the last period. Conditional on being attentive in period $t=T$ the expectant mother maximizes

$$\max_{a_T u_T} \gamma b(a_T) + m(a_T) - e_T(\eta a_T + r_T + u_T) \tag{4}$$

Note that in optimum $u_T^* = 0$ because unsubscribing in the last period involves a cost with no possible utility gain as there are no future periods. It is optimal to take action in the last period (i.e. $a_T^* = 1$) if

$$e_T \leq \frac{\gamma(b(1) - b(0)) + m(1) - m(0)}{\eta} = \frac{\gamma b(1) + \mu\left(\left(\frac{k_{T-1}+1-T}{T}\right)^2 - \left(\frac{k_{T-1}-T}{T}\right)^2\right)}{\eta} \equiv e_T^{a*}(k_{T-1}).$$

Intuitively, the mothers take the supplements if the effort cost of doing so is smaller than the sum of perceived health benefits and the moral utility from taking action. Note that the threshold increases γ and μ which implies that the likelihood of taking action increases in both parameters.

Conditional on receiving a message in period $t = T$, the expectant mother then maximizes

$$\max_{r_T} \theta(r_T)(\gamma b(a_T^*) + m(a_T^*) - e_T(\eta a_T^* + r_T)) \tag{5}$$

It is optimal to read the message in the last period when

$$e_T \leq \frac{(1-\theta_m)(\gamma b(a_T^*) + m(a_T^*, k_{T-1}))}{1 + (1-\theta_m)\eta a_T^*} \equiv e_T^{r*}(a_T^*, k_{T-1}).$$

That is, if the effort cost is below the threshold e_T^{r*} reading the message is optimal. The threshold is increasing in the perceived health benefits of taking supplements, γ, and the weight on moral utility μ. An increase in the threshold means that it will be more likely that individuals read the message because it will be more likely that the effort cost realization is below the threshold. The threshold is also increasing in the size of the gain in attentiveness from reading the message, i.e. $(1-\theta_m)$ and in past adherence k_{T-1} as an increase in past adherence implies a smaller penalty from missing the target adherence rate of 1. Intuitively, individuals who did not take pills in the past are less likely to read the message in the last period because the moral utility effects are large and negative.

It is straight forward to show that $e_T^{r*}(a_T^*, k_{T-1}) < e_T^{a*}(k_{T-1})$ given that $\mu < 0$. This means that there are some values of the effort cost for which it is optimal to take action but not optimal to read the message. It also means that, if it is optimal not to take action conditional on receiving a message, then it is also optimal not to make the effort to read the message.

The expectant mother takes $u_T^* = 0$, e_T^{a*} and e_T^{r*} in to account when determining the optimal behavior in period $t = T-1$. Conditional on being attentive in period $t = T-1$ the expectant mother maximizes

$$\begin{aligned}\max_{a_{T-1},u_{T-1}} &\gamma b(a_{T-1})+m(a_{T-1})-e_{T-1}(\eta a_{T-1}+r_{T-1}+u_{T-1})\\ &+\delta E_{T-1}[((1-u_{T-1})p_T\theta(r_T^*)+(1-(1-u_{T-1})p_T)\theta_0)\\ &(\gamma b(a_T^*)+m(a_T^*)-e_T(\eta a_T^*+r_T^*))-p_T(1-u_{T-1})\Lambda]\end{aligned}$$

As the choice variables are two discrete variables this amounts to comparing the expected utility for the four choice combinations: $(a_{T-1}=1,u_{T-1}=1),(a_{T-1}=1,u_{T-1}=0),(a_{T-1}=0,u_{T-1}=1),(a_{T-1}=0,u_{T-1}=0))$. To provide some intuition for the effects we first let the action choice be given and then consider the choice to unsubscribe in period $t=T-1$ (i.e. $u_T-1^*=1$). We then do the opposite exercise and let the unsubscription choice be given and consider the choice to take action or not in period $t=T-1$.

For a given choice a_{T-1} it is optimal to unsubscribe in period $t=T-1$ if the following condition holds

$$\begin{aligned}e_{T-1}\leq&\delta p_T\big(\theta_0 E_{T-1}[\mathscr{U}(r_T^*,a_T^*,u_T^*)|u_{T-1}=1]\\ &-E_{T-1}[\theta(r_T^*)\mathscr{U}(r_T^*,a_T^*,u_T^*)-p_T\Lambda|u_{T-1}=0]\big).\end{aligned}$$

That is the expectant mother unsubscribes if the effort cost is smaller than the discounted expected gain in utility of unsubscribing. We note that if $\theta_m=\theta_0$, that is if receiving but not reading a message had the same impact on remembering, then ignoring the message in the second period would have the same effect on attention as unsubscribing but without the effort cost and hence it would never be optimal to unsubscribe in period $t=T-1$ if $\theta_m=\theta_0$. When $\theta_m>\theta_0$, staying subscribed increases the probability of being attentive regardless of whether or not the expectant mother prefers being reminded or not. The moral utility term introduces the possibility that the individual has a negative utility from being reminded.

Similarly, for a given unsubscription choice u_{T-1} it is optimal to take action (i.e. $a_{T-1}^*=1$) if the following condition holds

$$
\begin{aligned}
e_{T-1} \leq & \frac{1}{\eta}\Big(\gamma b(1)+m(1)-m(0) \\
& +\delta E_{T-1}\big[((1-u_{T-1})p_T\theta(r_T^*)+(1-(1-u_{T-1})p_T)\theta_0)\mathscr{U}(r_T^*,a_T^*,u_T^*) \\
& -p_T(1-u_{T-1})\Lambda\big|a_{T-1}=1] \\
& -\delta E_{T-1}\big[((1-u_{T-1})p_T\theta(r_T^*)+(1-(1-u_{T-1})p_T)\theta_0)\mathscr{U}(r_T^*,a_T^*,u_T^*) \\
& -p_T(1-u_{T-1})\Lambda\big|a_{T-1}=0\big]\Big).
\end{aligned} \tag{6}
$$

That is, the expectant mother takes supplement if the sum of the immediate perceived health benefits $\gamma b(1)$, the immediate gain in moral utility $m(1)-m(0)$ and the future expected utility gain (the last two terms of the expression above) is greater than the effort cost of taking the supplements. Note that if the future expected utility gain is positive then the right hand side of equation (6) is greater than the last period action threshold e_T^{a*}. Intuitively then more people would take action in period $T-1$ than in period T because of the positive spillover effects of this period's choice on next period's utility. Vice versa if the future expected utility gain is negative.

Finally, conditional on receiving a message in period $T-1$ the expectant mother takes the optimal action and unsubscription decision in period $T-1$ as given and maximizes

$$
\begin{aligned}
\max_{r_{T-1}} & \theta(r_{T-1})(\gamma b(a_{T-1}^*)+m(a_{T-1}^*)-e_{T-1}(\eta a_{T-1}^*+r_{T-1}+u_{T-1}^*) \\
& +\delta E_{T-1}\big[((1-u_{T-1}^*)p_T\theta(r_T^*)+(1-(1-u_{T-1}^*)p_T)\theta_0)(\gamma b(a_T^*)+m(a_T^*) \\
& -e_T(\eta a_T^*+r_T^*))-p_T(1-u_{T-1})\Lambda\big])
\end{aligned}
$$

The expectant mother only derives utility from the decision problem if she is attentive to it in which case she implements the optimal action and unsubscription decision in period $t=T-1$. This happens with certainty if $r_{T-1}=1$ and with probability θ_m if $r_{T-1}=0$. In contrast, she gets zero utility from the decision problem with probability $(1-\theta_m)$ if $r_{T-1}=0$ in which case she is inattentive to the decision to taking supplements. She simply does not remember to think about it.

As a result she reads the message in period $t = T-1$ if

$$\begin{aligned}e_T \leq &(1-\theta_m)(\gamma b(a_1^*) + m(a_1^*) - e_1^*(\eta a_1^* + u_1^*) \\ &+ \delta E_1\left[((1-u_{T-1}^*)p_T\theta(r_T^*) + (1-(1-u_{T-1}^*)p_T)\theta_0)\mathscr{U}(r_T^*, a_T^*, u_T^*)\right. \\ &\left.- p_T(1-u_{T-1}^*)\Lambda | a_{T-1}^*, u_{T-1}^*\right]) \\ &\equiv e_1^{r*}.\end{aligned}$$

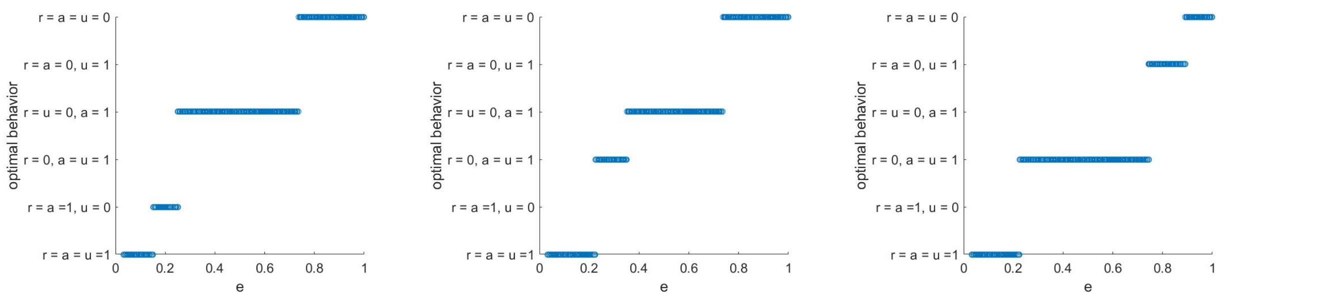
That is, the expectant mother reads the message if the effort costs of doing so are lower than the sum of the current period benefits of increasing the likelihood of being attentive and the expected benefit from increased attentiveness in this period on utility in the next period.

9.3 Model simulations

For the simulations we make some additional assumptions: We assume that F is the lognormal distribution with $N[-1, 0.5]$ i.e. the effort costs are identically and independently distributed according to the uniform distribution on the unit interval. In addition, we assume a simple linear benefit function, i.e. $b(a_t) = a_t$ and $T = 10$. In our baseline calibration, we calibrate the model parameters to $(\delta, \eta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.999943, 1, 0.01, 0.5, 0.8, -0.5, 0.5, 0.5)$ and to fix the initial level of adherence we let $k_{T-2} = 4$ and we assume $u_{T-2} = 0$. In all versions of the model, we evaluate expectations numerically using Monte Carlo Simulations with 1.000.000 simulations.

As illustrated by Figure 7, the solution has classic threshold properties: An expectant mother takes action, reads a message and unsubscribes (optimal behavior presented on the y-axis) for sufficiently low realizations of the effort cost e_{it} (presented on the x-axis). With higher effort costs, it is optimal to do less and less of the possible activities. The size of the thresholds as well as the combinations of activities that people will optimally do, depend on the parameters values. In the figure we illustrate the thresholds and the combinations of activities for different values of the annoyance cost Λ. Note that it is never optimal to read a message if one does not anticipate taking action. Reading the message will require costly effort, but if no action is taken then there will be no possibility to gain from the improved attention. In all calibrations, individuals with the lowest costs will unsubscribe, read and take action. In the baseline calibration with $\Lambda = 0.5$, individuals with slightly higher effort costs will not unsubscribe (as the costs of getting messages is small compared to the benefits), those with higher effort cost will not read the message and those with the highest effort costs will not take any action. However, with a higher $\Lambda = 0.9$, individuals with low effort costs will not read the message, with higher effort costs they will not unsubscribe, and only with high effort costs will stop taking action. In the calibration with $\Lambda = 2$, the cost of messages is large compared to the benefits, so the low effort cost individuals will not read the messages, the ones with higher costs will not take the pills and the one with the highest effort costs will not unsubscribe.

Figure 7: Illustration of threshold properties



(a) Baseline calibration (b) Baseline with $\Lambda = 0.9$ (c) Baseline with $\Lambda = 2$

Notes: Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$. In the baseline calibration, the model parameters are calibrated to $(\delta, \eta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 1, 0.01, 0.5, 0.8, -0.5, 0.5, 0.5)$ and $k_{T-2} = 4$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations. We show optimal behaviour in period $T-1$ conditional on being attentive.

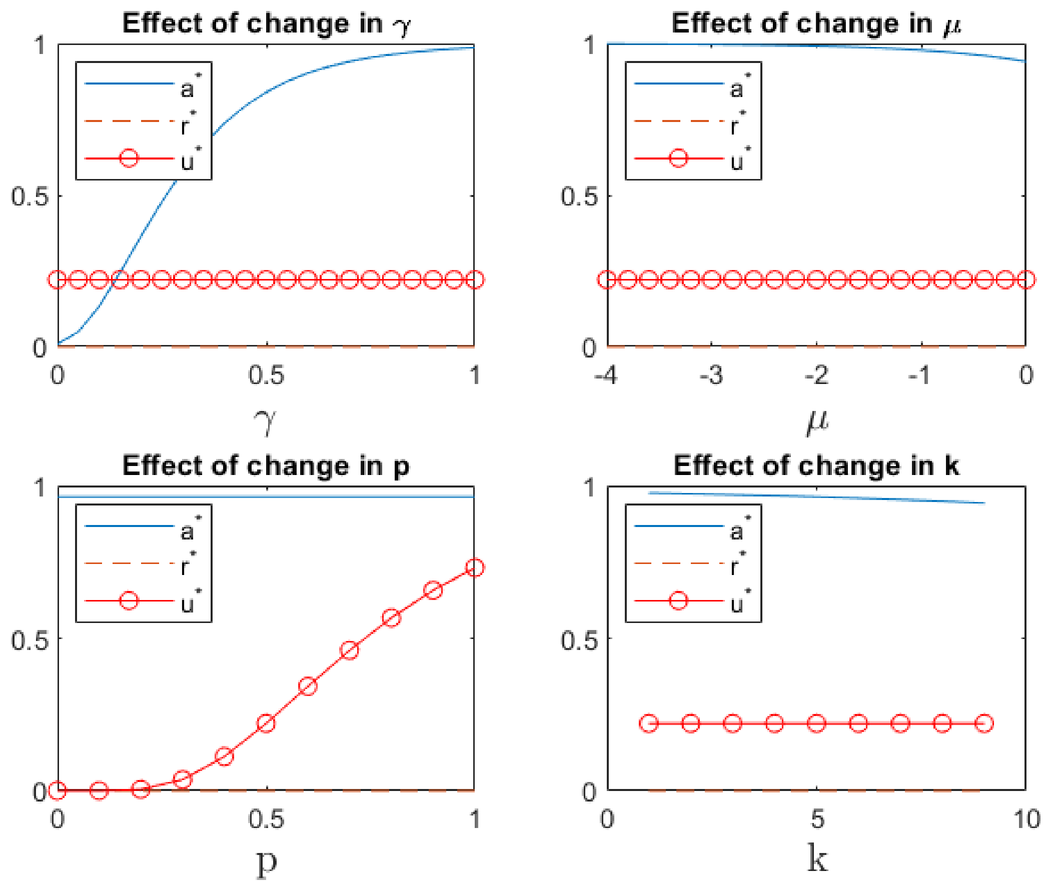
9.4 Structural Estimation Appendix

The SMM estimator, that minimizes the distance $(m(\psi) - \hat{m})'W(m(\psi) - \hat{m})$. The vector $m(\psi)$ contains the model-implied moments which depend on the estimated parameters. To calculate the model-implied moments we solve the model by backwards induction evaluating expectations numerically with a simulated population of 100.000 individuals per run. The vector $\hat{m}$ contains the corresponding observed moments. We use the identity matrix as the weighing matrix W.

We use the modified CMA-ES optimization routine by Andreasen (n.d.) to find the minimum distance. The CMA-ES routine is well suited to find the global optimum of objective functions that are potentially complex with several local optima and discontinuities. We initially use a relatively wide search with global step sizes of $\sigma^{(g)} = 1$ and in a second round narrow down step sizes to $\sigma^{(g)} = 0.05$. We bootstrap the standard errors to account for the fact that the parameters are based on moments calculated of several different subsamples of different sizes. We use 250 bootstrap draws.

We impose the following parameter restrictions for the estimated parameters $\alpha_e \in [-10; 10]$, $\sigma_e \in [0; 10]$, $\theta_0 \in [0; 10]$, $\theta_m \in [0; 10]$, $\sigma_\Lambda \in [0; 10]$, $\Delta\gamma \in [-50; 50]$, $\Delta\mu \in [-100; 0]$, and $\Delta\Lambda_R \in [-10; 10]$. The estimated parameters are not close to these bounds. Initial estimation trials suggest

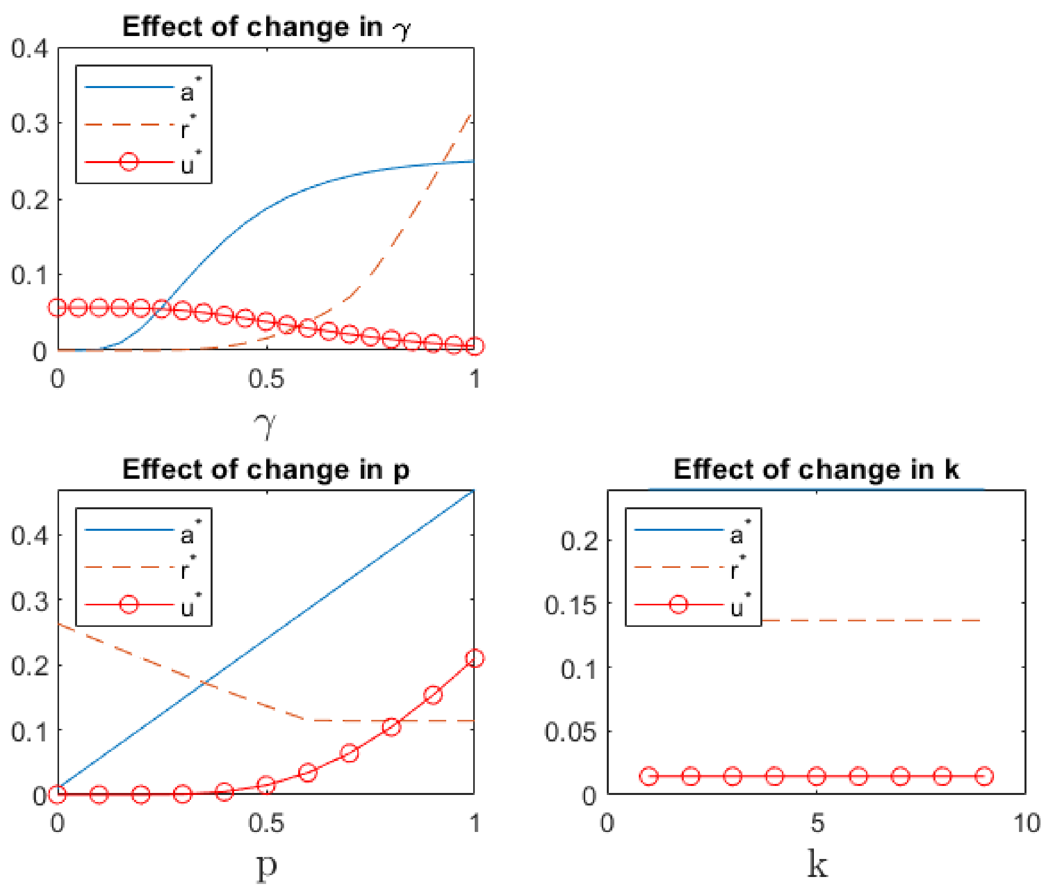
Figure 8: Sensitivity of simulated $P(a^*_{T-1} = 1), P(u^*_{T-1} = 1)$ and $P(r^*_{T-1} = 1)$ with respect to changes in γ, μ, p and k when $\theta_m = \theta_0 = 1$



Notes: Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$, the model parameters are calibrated to $(\delta, \eta\theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 1, 1, 1, 0.8, -0.5, 0.5, 0.5)$ and $k_{T-2} = 4$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations.

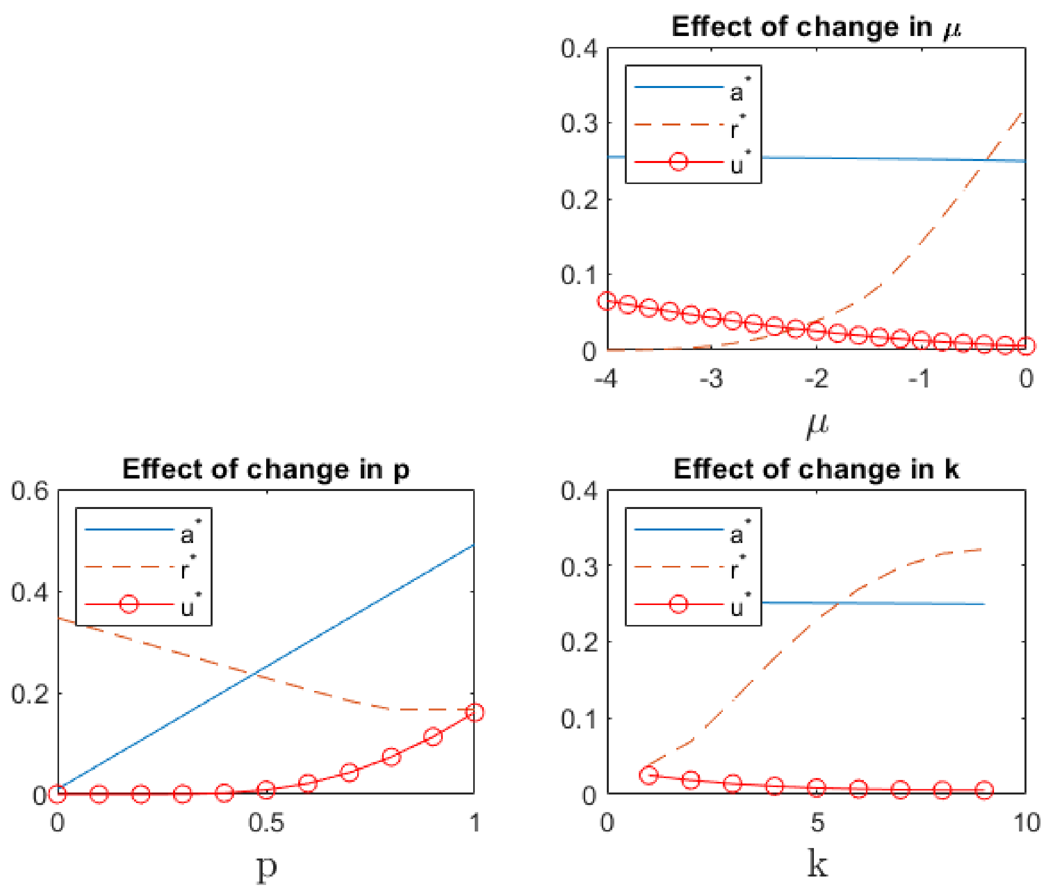
that γ_0 is not well identified above some level as changes in the size of γ_0 has almost no impact on the estimated moments and hence the objective function (see Table 13). We therefore fix γ_0 at 90 in the estimations.

Figure 9: Sensitivity of simulated $P(a^*_{T-1} = 1), P(u^*_{T-1} = 1)$ and $P(r^*_{T-1} = 1)$ with respect to changes in γ, p and k when $\mu = 0$



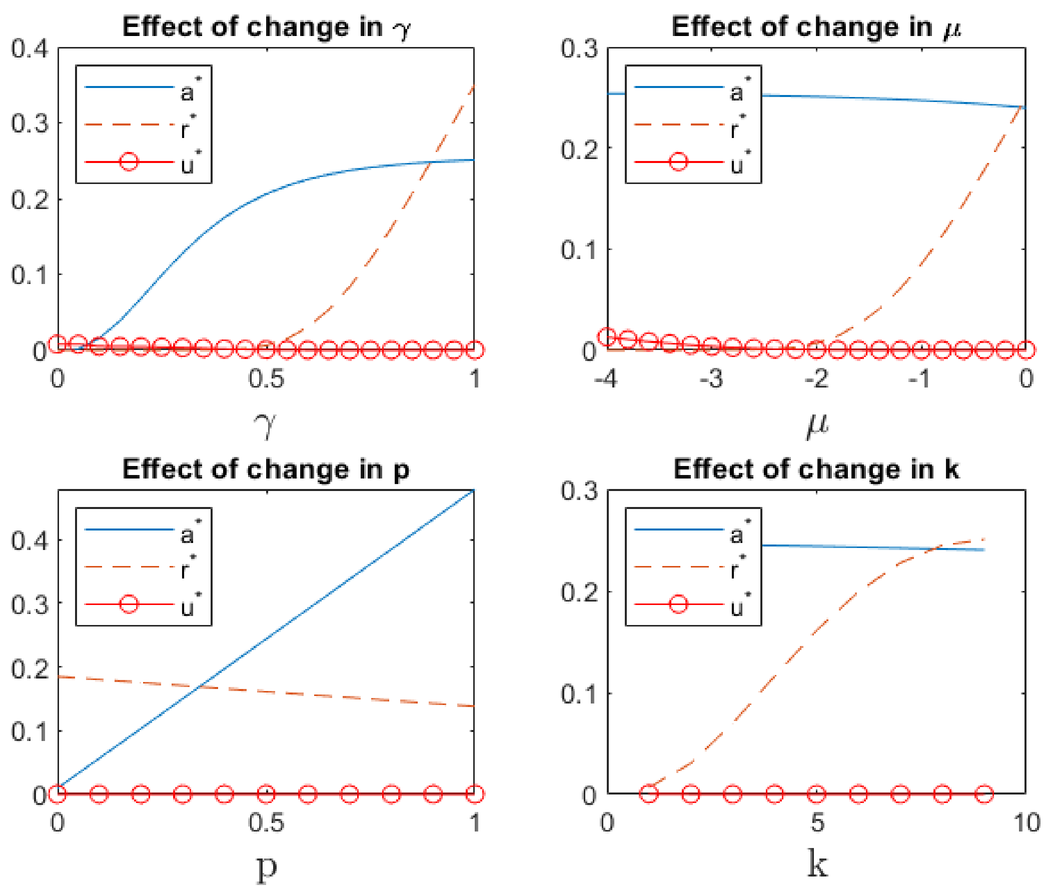
Notes: Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$, the model parameters are calibrated to $(\delta, \eta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 1, 0.01, 0.5, 0.8, 0, 0.5, 0.5)$ and $k_{T-2} = 4$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations.

Figure 10: Sensitivity of simulated $P(a^*_{T-1} = 1), P(u^*_{T-1} = 1)$ and $P(r^*_{T-1} = 1)$ with respect to changes in μ, p and k when $\gamma = 1$



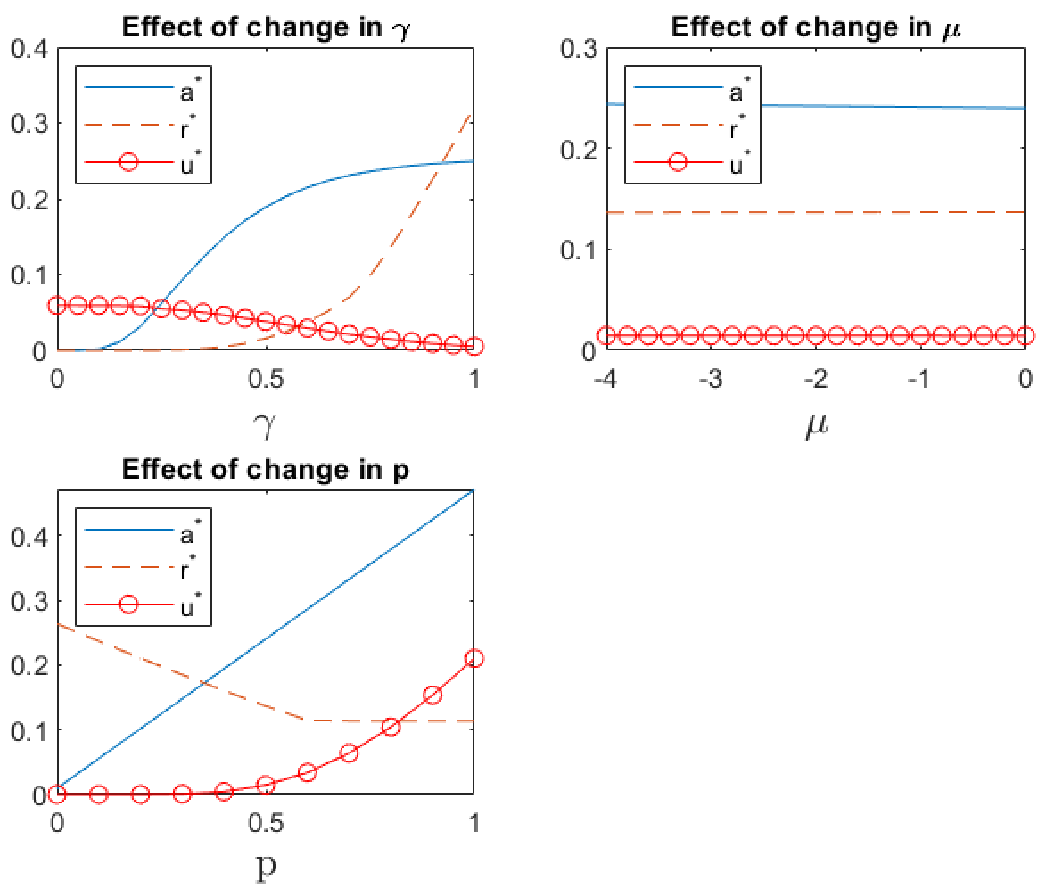
Notes: Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$, the model parameters are calibrated to $(\delta, \eta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 1, 0.01, 0.5, 1, -0.5, 0.5, 0.5)$ and $k_{T-2} = 4$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations.

Figure 11: Sensitivity of simulated $P(a^*_{T-1}=1), P(u^*_{T-1}=1)$ and $P(r^*_{T-1}=1)$ with respect to changes in γ, p, μ and k when $\Lambda = 0.2$



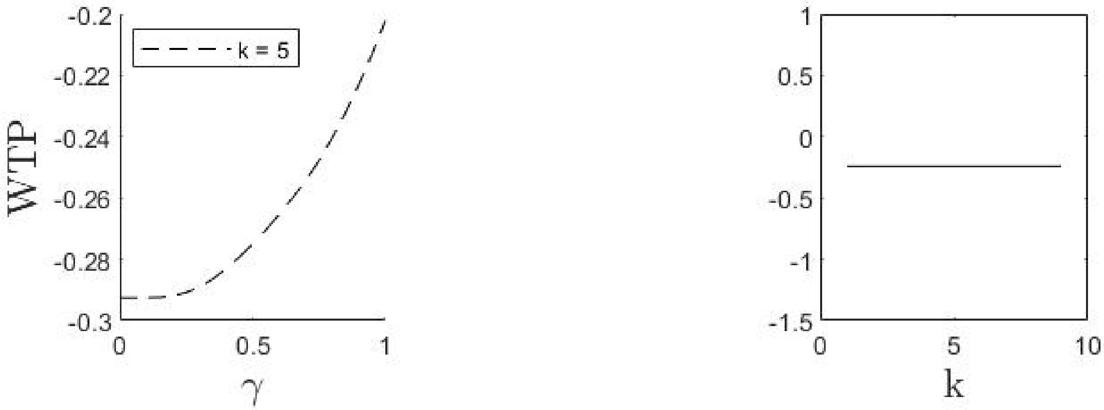
Notes: Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$, the model parameters are calibrated to $(\delta, \eta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 1, 0.01, 0.5, 0.8, -0.5, 0.5, 0.2)$ and $k_{T-2} = 4$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations.

Figure 12: Sensitivity of simulated $P(a^*_{T-1}=1), P(u^*_{T-1}=1)$ and $P(r^*_{T-1}=1)$ with respect to changes in γ, p and μ when $k_{T-2}=8$

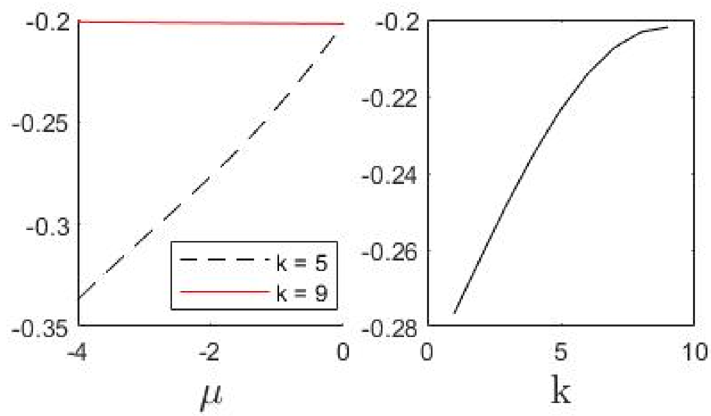


Notes: Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$, the model parameters are calibrated to $(\delta, \eta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 1, 0.01, 0.5, 0.8, -0.5, 0.5, 0.5)$ and $k_{T-2} = 8$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations.

Figure 13: Sensitivity of simulated $WTP = \Delta V_i$ with respect to γ, μ, and k with no moral costs and full information



(a) No moral costs $\mu = 0$



(b) Full information $\gamma = 1$

Notes: ΔV_i is the gain in utility when getting reminders with probability $p_{T-1} = 1$ compared to a baseline probability of $p_{t-1} < 1$. Individual level and time heterogeneity is captured by e_{ti} where $\log e_{ti} \sim N[-1, 0.5]$, $b(a_t) = a_t$, $T = 10$. In the baseline calibration, the model parameters are calibrated to $(\delta, \eta, \theta_0, \theta_m, \gamma, \mu, p, \Lambda) = (0.99963, 1, 0.01, 0.5, 0.8, -0.5, 0.5, 0.5)$ and $k_{T-2} = 4$. Expectations are evaluated numerically using Monte Carlo Simulations with 1.000.000 simulations. We show optimal behavior in period $T-1$ conditional on being attentive.

Table 13: Sensitivity of structural estimates and model fit for the full model with respect to γ_0

	$\gamma_0 = 1$	$\gamma_0 = 10$	$\gamma_0 = 20$	$\gamma_0 = 30$	$\gamma_0 = 40$	$\gamma_0 = 50$	$\gamma_0 = 60$	$\gamma_0 = 70$	$\gamma_0 = 80$	$\gamma_0 = 90$	$\gamma_0 = 100$	$\gamma_0 = 110$
α_e	-4.0418	-0.2896	-0.1554	-0.3993	-0.7438	-0.9943	-1.2971	-1.5933	-1.8344	-1.9595	-2.0075	-2.1344
σ_e	0.0005	1.4223	1.6497	1.9981	2.4239	2.7302	3.0630	3.4001	3.6685	3.8300	3.9302	4.0992
θ_0	0.8932	0.7624	0.8524	0.9000	0.9247	0.9398	0.9499	0.9570	0.9624	0.9657	0.9676	0.9696
θ_m	0.9883	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	0.9990	0.9976	0.9968
σ_Λ	6.2326	4.6335	4.4388	4.4684	4.4208	4.4280	4.4278	4.4323	4.4223	4.4286	4.4239	4.4217
$\Delta\gamma$	-12.4439	-0.6517	-2.0862	-3.4601	-4.8533	-6.1476	-7.4451	-8.6909	-11.2817	-11.4343	-11.4270	-11.3456
$\Delta\mu$	-0.1990	-0.0047	-0.4177	-7.5419	-5.0831	-5.0442	-2.7145	-1.2218	-2.4000	-2.8355	-2.8569	-2.9415
$\Delta\Lambda_R$	-3.5117	-1.4419	-0.9216	-0.8335	-0.8025	-0.7872	-0.7828	-0.7766	-0.8137	-0.7788	-0.7637	-0.7397
Q_{Opt}	1.5451	0.4993	0.2623	0.1904	0.1638	0.1527	0.1476	0.1451	0.1439	0.1429	0.1426	0.1426

Notes: The table provides structural parameter estimates of the full model for different values of γ_0 and Q_{Opt} which is the value of the objective function given the estimated parameters. All estimations in the table have been done with one run of the CMA-ES routine and a relatively wide search with global step sizes of $\sigma^{(g)} = 0.05$ and maximal step size of 1. See Andreasen (n.d.) for details on the CMA-ES routine.