Essays on Health and Development: Evidence from Indonesia and South Africa

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vorgelegt von

Anna Maria Reuter

Erstgutacher:	Prof. Dr. Sebastian Vollmer
Zweitgutacher:	Prof. Dr. Andreas Landmann
Drittprüferin:	Prof. Dr. Renate Hartwig

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1 Introduction

1.1 Background and Motivation

Apart from being a value in itself, good health can be a facilitator for economic well-being and development. It determines work productivity, prevents health care costs, and can enhance investments in physical as well as human capital (Bloom and Canning, 2000). At the same time, economic well-being can promote health, thus creating positive feedback loops between both dimensions (Bloom and Canning, 2000).

Over the past three decades, health improved substantially around the globe (Vos et al., 2020). A large share of the improvement can be traced back to a reduction of the burden of communicable, maternal, neonatal and nutritional diseases (Vos et al., 2020). At the same time, there is a countervailing trend of a rising burden of non-communicable diseases (NCDs), and an increase of zoonotic pandemics, such as the pandemics caused by HIV or coronaviruses (e.g., SARS, MERS, COVID-19) (Morse et al., 2012; Vos et al., 2020; Wang et al., 2020). This rise of NCDs and zoonotic pandemics changes the composition of the disease burden, and generates new challenges for health care systems and societies. My thesis sheds light on some of these challenges in the context of two pandemics, HIV/AIDS and COVID-19, and three NCDs, common mental disorders, diabetes, and hypertension.

One of the challenges is the need to update health beliefs and health behavior. For example, many NCDs (and HIV/AIDS) are asymptomatic at early stages. Thus, in contrast to many communicable diseases, individuals need to get tested regularly, despite feeling healthy, to be able to manage the disease early on and to prevent severe complications. However, traditional health beliefs that individuals can feel whether they are healthy, or an over-optimism on the own susceptibility of the disease, might hinder individuals to take up screening (Gong et al., 2020; Obermeyer and Osborn, 2007; Risso-Gill et al., 2015). Another very recent example is the COVID-19 pandemic. Especially in the early phase of the pandemic, individuals were confronted with a steady update of information on the disease and disease prevention, and needed to adjust their behavior rapidly and dynamically. Information and reminder interventions might support this process, but so far, the evidence on their effectiveness is mixed (Dupas, 2011). Understanding the patterns of health beliefs and health behaviors, and how they can be influenced, is crucial to address the changes in the disease burden.

Another challenge is the targeting and support of individuals and population groups that are particularly vulnerable to the changing disease burden. Sociodemographic groups are differently affected by diseases, for example due to different exposure or access to preventive measures and treatment (Green et al., 2020; Niessen et al., 2018). Also, this pattern might change over time: In Uganda, for example, there were no sociodemographic disparities in HIV incidence in the early phase of the pandemic, but over time, HIV incidence relatively increased among individuals with a lower socioeconomic status (Santelli et al., 2021). Similarly, sociodemographic groups might differ in their ability to cope with health shocks, given the double financial burden of reduced ability to work and increased health care costs (Wagstaff and Lindelow, 2014). In the context of NCDs and HIV/AIDS, this is further exacerbated by the long duration (or even chronic nature) of the disease, as individuals are less able to cope with such infrequent, but persistent shocks (Dercon, 2002). To moderate the economic consequences of health shocks, especially among the most vulnerable groups, we need to be able to identify these groups and to understand how policy interventions can support a return to economic well-being when health improves.

1.2 Chapter overview

In this doctoral thesis, I aim to contribute to the understanding of these new challenges and the scope for policy interventions. The four essays of this thesis can be categorized in two parts: The first part addresses health beliefs and preventive health behavior, and investigates how they might be affected by a text message intervention. The second part focuses on health status, its interaction with other dimensions of well-being, and how policies might mediate this relationship. In each essay, I speak to a different disease burden. In essays 1 and 4, I focus on two major pandemics of the past decades, namely the COVID-19 and the HIV/AIDS pandemic. In essays 2 and 3, I address three types of common NCDs; hypertension, diabetes, and mental distress.

1.2.1 Essay 1: Knowing Versus Doing: Protective Health Behaviour Against COVID-19 in Aceh, Indonesia

The first essay studies the knowledge on COVID-19 and preventive health behavior in an early phase of the COVID-19 pandemic in Aceh, Indonesia. The rapid emergence of COVID-19 required a fast uptake of preventive measures to protect oneself and to slow down the spread of the pandemic. Self-protection was especially important for older individuals, who were at a higher risk for a severe progression of the disease (Williamson et al., 2020).

The essay is joint work with Eliana Chavarría, Farah Diba, Maja Marcus, Marthoenis, Lisa Rogge, and Sebastian Vollmer, and was published in the Journal of Development Studies. We use data from a telephone survey among the population aged 40 to 70 in Aceh, which was conducted from March to May 2020. We use linear probability models to examine the role of individual-level determinants for COVID-19-related knowledge and behavior.

We find that knowledge was the most important determinant of preventive behavior at this time of the pandemic, similar to findings from studies on the H1N1 pandemic (Bish and Michie, 2010; Tooher et al., 2013; Yap et al., 2010). When knowledge is controlled for, sociodemographic characteristics are only minor determinants of preventive behavior. However, we find that sociodemographic characteristics are strongly associated with knowledge. This speaks to their role in the seeking and processing of health information, as it was demonstrated in other studies (Dupas, 2011; Wong and Sam, 2010). Moreover, we show that sociodemographic groups obtain their COVID-19 knowledge from different information sources. Our findings suggest that focusing policy interventions on specific information sources could help to disseminate pandemic knowledge more equally across the population.

1.2.2 Essay 2: The Effect of SMS Reminders on Health Screening Uptake: A Randomized Experiment in Indonesia

Essay 2 examines whether preventive health behavior can be influenced through text message reminders in the context of hypertension and diabetes screening in Aceh. As in many other low- and middle-income countries (LMICs), hypertension and diabetes are on the rise in Indonesia (IHME, 2021). For both conditions, early diagnosis allows an effective treatment before severe complications develop. At the same time, they are asymptomatic at early stages, thus screenings are needed to detect them early on. In Indonesia, screenings are offered for free, and additionally encouraged through monthly village visits by the health staff. Despite these efforts, a large share of people with hypertension or diabetes remains undiagnosed, a phenomenon also known from other LMICs (Geldsetzer et al., 2019; Manne-Goehler et al., 2019).

Maja Marcus, Lisa Rogge, Sebastian Vollmer and I test the potential of a text message intervention to increase the utilization of the screening offers. We target individuals between ages 40 and 70, who should be screened annually according to WHO recommendations (WHO, 2010a). We collected data on diabetes and hypertension knowledge and screening behavior from 2,006 randomly sampled individuals in Aceh. Based on this data, we designed text messages to inform individuals on the benefits of screening. We randomly assigned half of the sample to treatment, which consisted of two times three text messages right before a screening date in the village, and the other half to control, which did not receive these messages. We find that the intervention increased screening uptake by 6.6 percentage points, in comparison to a screening uptake of 33% among the control group. The effect size is comparable to similar interventions in the context of immunization and sexually transmitted diseases (Jacobson Vann et al., 2018; Mekonnen et al., 2019; Taylor et al., 2019), showing that this kind of interventions can be similarly effective in the context of preventive hypertension and diabetes screening.

Our findings indicate that the intervention works as a reminder to get screened. The treatment effect is driven by screening uptake in the month the messages were sent for the second time, and by screening in the primary health care centers rather than the village-based offers. We do not detect any impact on knowledge related to the text message content or the diseases more in general, similar to another intervention in the context of COVID-19 behavior (Banerjee et al., 2020).

We estimate that our text message intervention increases the screening uptake at costs of USD 11.18 per additionally screened person, with potentially even lower costs at scale-up. In times of a digitalization of health care systems and an expansion of mobile phone coverage in the population, text messages might serve as a low-cost, easily scalable policy measure to increase screening uptake.

1.2.3 Essay 3: Mental distress and its association with sociodemographic and economic characteristics: community-based household survey in Aceh, Indonesia

The third essay speaks to the association of sociodemographic and economic characteristics with health, specifically in the context of common mental disorders (CMD) in the general population in Aceh. CMD and economic well-being are suspected to follow a vicious cycle: Worse financial outcomes can induce CMD through stress and fears, and CMD can create a financial burden through lower productivity and increased health care costs. However, there is scarcely evidence on the patterns of CMD and its association with economic outcomes for LMICs (König et al., 2019; Lund et al., 2010).

This joint work with Sebastian Vollmer, Aiyub, Suryane S. Susanti and Marthoenis was published in BJPsych Open, and is based on data from a community-based household survey in Aceh. We interviewed 1490 individuals aged 17 or older from 620 households. Among the respondents, 14% showed symptoms of CMD according to the Self Reporting Questionnaire (SRQ-20). Female, older, lower-educated and unmarried participants were particularly affected, which is largely in line with other studies (Das et al., 2009; Kessler et al., 2010; Levinson et al., 2010). Also, CMDs tend to cluster within households, indicating a potential multiple disease burden on families. We find that CMD symptoms are associated with a higher burden of other, physical diseases, and an economic burden due to treatment costs. In addition, symptoms of CMD seem to affect the daily work of individuals negatively.

Our analyses identify the sociodemographic groups which are particularly affected by CMD symptoms in Aceh, and show that CMD symptoms go along with an economic burden. By this, we highlight which groups should be particularly targeted by mental health interventions to reduce the disease burden of CMD in Aceh. Also, this could reduce the economic burden of CMD, given the cost-effectiveness of mental health interventions when targeted at individuals in need (Barbui et al., 2020). Similarly, cash transfers to poor households, irrespective of their mental health, can improve mental and economic well-being (Haushofer et al., 2020). However, the design of such a state support can be crucial, as discussed in essay 4.

1.2.4 Essay 4: Parental Health, Children's Education and Unintended Consequences of State Support: Quasi-experimental evidence from KwaZulu-Natal, South Africa

Essay 4 investigates the interplay of a health treatment and state support, focusing on the impact of eligibility for antiretroviral therapy (ART) on children's education in KwaZulu-Natal, South Africa. ART slows down the progression of HIV/AIDS drastically, and presumably saved more than 5 million lives between 1995 and 2012 (UNAIDS, 2013). This large, positive health shock is expected to have implications beyond the health of the treated individual: Before ART was available, adult HIV/AIDS was negatively correlated with children's education. The availability of ART might weaken this link, as it enables adults to sustain their health and productivity. Therefore, it might have a protective effect on children's education.

Together with Till Bärnighausen and Sebastian Vollmer, I examine the impact of parents' eligibility for ART on children's educational attainment with clinical and household panel data from KwaZulu-Natal. We exploit a policy guideline which defined eligibility for ART based on a biomarker in the blood (CD4 cell count, a proxy for disease progression). This creates a quasi-random assignment of ART eligibility around the threshold. We find that ART eligibility improves health outcomes, but there is no overall effect on children's education. However, the impact of ART eligibility varies by the previous receipt of state support: If parents received a disability grant beforehand, there is a negative impact of ART eligibility on education. The disability grant is linked to the same biomarker as ART, and recipients can lose the grant as their health improves during ART. Indeed, we can show that ART eligibility goes along with reductions in the asset index of individuals who previously received the disability grant. In contrast, state support which is not linked with ART eligibility seems to have a protective impact on children's education.

Our results demonstrate how the impact of health improvements on other outcomes might be mediated through the economic structure of the household. This adds to the findings on the role of state support in the case of poor health: Larger state support cushioned impacts of parents' disability on children's education in Canada (Chen et al., 2015), but reduced children's education in the Netherlands, presumably by crowding out parental employment (Dahl and Gielen, 2021). Thus, state support needs to be designed carefully to channel the impact of health shocks on further dimensions of well-being.

1.3 General summary and conclusion

Globally, and in LMICs specifically, the disease burden changed substantially over the past three decades. This brought along new challenges, among others the need to update health beliefs and behavior, and to support the groups most vulnerable to these changes. This thesis sheds light on the sociodemographic patterns in these challenges and the scope for policy interventions in the context of Indonesia and South Africa.

Essay 1 demonstrates the role of information for the uptake of preventive behavior in the context of the COVID-19 outbreak in Aceh. If individuals are informed on key aspects of the disease and preventive measures, sociodemographic disparities in the adoption of these measures largely vanish. Identifying and addressing different information channels early on helps to increase access to the relevant information. Also, text message reminders can help to increase preventive behavior, as essay 2 shows in the context of hypertension and diabetes screening in Aceh. Though in the tested form, they are not sufficient to update beliefs, the raised salience is sufficient to trigger a preventive check-up visit. Given the low costs of text messages, especially when based on an existing database, this is an efficient tool for stakeholders to increase preventive health behavior in the broader population.

Similar to health beliefs and health behavior, health status can vary across sociodemographic groups. In the context of Aceh, vulnerable groups are disproportionally affected by symptoms of common mental disorders, as shown in essay 3, and these symptoms are associated with worse economic outcomes. Financial aids might help vulnerable groups to mitigate economic consequences of health shocks, and to counteract any lasting losses in economic well-being after health recovered. Essay 4 demonstrates the role of such state support in the context of HIV/AIDS treatment in KwaZulu-Natal, and highlights that these policies should assure financial support throughout the recovery process to avoid unintended negative consequences for the household.

In the face of new health challenges, it is crucial to understand the patterns of the new disease burden to target and design adequate policies. The increasing digitalization allows large-scale and cheap interventions which can be efficient tools to nudge individuals into favorable preventive health behavior. Further research can help to improve the efficacy of these interventions and to tailor them to specific target groups, as demonstrated in “mega” RCTs in the US (Milkman et al., 2021a, 2021b). However, nudges might not be sufficient in every context, due to other barriers to preventive health behavior such as present bias or information avoidance (Kremer et al., 2019).

In the case of health shocks, more intensive interventions in the form of financial support might be needed to avert long-term losses in well-being. Financial support designed to support sick individuals can dampen negative impacts on well-being (Chen et al., 2015), but can also introduce negative effects by disincentivizing employment (Dahl and Gielen, 2021), or when cutting support too soon, as discussed in this thesis. At the same time, financial support not tied to the health status, but dedicated to poor households, can increase investments in preventive health, and improve health in the short as well as the long run (Banerjee et al., 2021; Dupas and Miguel, 2017; Haushofer et al., 2020). Thus, further analyzing the role of financial support as a mediator of the impact of health shocks can help to make use of its full potential.

2 Knowing versus Doing: Protective Health Behavior against COVID-19 in Aceh, Indonesia

Joint work with Eliana Chavarría, Farah Diba, Maja E. Marcus, Marthoenis, Lisa Rogge and Sebastian Vollmer

A similar version of this chapter and its appendix has been published in the Journal of Development Studies (https://doi.org/10.1080/00220388.2021.1898594)

Abstract

The COVID-19 pandemic shapes the lives of people around the globe – at the same time, people themselves have the power to shape the pandemic. By employing protective health behavior, the population can alleviate the severity of an outbreak. This may be of particular importance whenever health systems or populations are vulnerable to shocks, as is frequently the case in low- and middle-income settings. Therefore, understanding the underlying drivers of protective action against COVID-19 is urgently needed for policy responses.

We investigate the individual-level determinants of disease knowledge and behavior in the context of the COVID-19 pandemic in Aceh, Indonesia. We use data from a representative sample of 40-70-year-olds, mainly obtained from telephone interviews between March and May 2020. We employ linear probability models that account for a comprehensive set of factors that were previously found to influence knowledge and practice during pandemics.

We find that both knowledge and uptake of protective health behavior are relatively high. Knowledge is the largest explanatory driver of protective health behavior, while socioeconomics and economic preferences are minor determinants. However, knowledge itself is strongly shaped by socioeconomic gradients. On this basis, we show that policies need to disseminate information in an equitable way.

2.1 Introduction

The current pandemic induced by the novel Coronavirus disease (COVID-19) puts immense pressure on governments, health systems, and individuals worldwide. Low- and middle-income countries may face additional challenges due to less resilient health and social protection systems. To contain the further spread of COVID-19 as well as its economic and health consequences, the adoption of protective health behavior is widely recommended and particularly relevant in such settings. Protective measures include preventive behaviors such as social distancing, hygiene, and mask wearing as well as appropriate actions in case of suspected infections. The success of such measures, however, relies heavily on the compliance of the population. Governments have to ensure that the population is informed on the disease and adopts the recommended behavior. Therefore, insights on how policy responses can be best aligned towards gaps in knowledge and behavior uptake are urgently needed.

In this paper, we explore the determinants of disease and prevention knowledge as well as uptake of protective behaviors of people aged 40 to 70 years in a middle-income setting. To shed light on these questions, we conducted a phone survey on COVID-19 with 1,113 individuals in the capital districts of the province of Aceh, Indonesia, between end of March and beginning of May 2020. Participants were asked about their knowledge of the pandemic, preventive actions, demand for care, perceived economic impact, and health behavior. The survey data is combined with socioeconomic information and data on economic preferences (risk preference, time preference, and trust) from an in-person baseline survey in 2019. We use linear probability models to assess which socioeconomic characteristics, information sources and preferences are associated with better COVID-19 related knowledge and behavior.

Our main finding is that knowledge is the strongest predictor of protective action, which itself underlies a socioeconomic gradient. Overall, disease and prevention knowledge are relatively high in our sample. The main COVID-19 symptoms, fever and cough, are known by 73% of the sample, and 89% know at least one of the two. Droplet and smear transmission are mentioned by 62% and 66% as transmission channels. Moreover, 87% and respectively 77% know that social distancing and hygiene measures can prevent the spread of the COVID-19. Disease and prevention knowledge are strongly associated with higher education, lower age, and urban location. TV, internet, and the community are the most important information channels for all types of knowledge, while public announcements are associated with knowledge on preventive measures only.

The uptake of preventive measures, on the other hand, is strongly predicted by disease and prevention knowledge, increasing the probability of adoption by up to 87 percentage points. Socioeconomic factors influence behavior only slightly, but urban location increases the adoption of preventive measures by five to seven percentage points. We find that economic preferences do not influence behavior in most cases, but more trusting individuals are four percentage points more likely to adopt social distancing, and more patient individuals are one percentage point more likely to wear masks. In contrast, economic preferences play a larger role for stated actions in the case of illness: Willingness-to-take risks and patience are positively associated with self-isolation, and patience is negatively associated with contacting medical professionals.

Our study adds to the growing body of literature on COVID-19 awareness, knowledge, attitudes, and practices. Findings from online surveys in other LMICs during the early phase of the pandemic report similarly high levels of COVID-19 awareness and symptom knowledge, albeit some studies also document wide misperceptions on the source of COVID-19 (Farhana and Mannan, 2020; Olapegba et al., 2020; Zegarra-Valdivia et al., 2020). The evidence for specific knowledge on transmission channels and prevention measures is more diverse. Droplet and smear transmission were widely known among respondents in India and Nigeria (Olapegba et al., 2020; Roy et al., 2020), while respondents in Peru knew only the latter (Zegarra-Valdivia et al., 2020). All studies report even higher knowledge levels of preventive measures than we found in our study (Olapegba et al., 2020, 2020; Roy et al., 2020; Zegarra-Valdivia et al., 2020), which might be partly explained by the different administration mode. For Indonesia, an online survey points out that even though most respondents had received basic information on COVID-19, they still report a need for more information, particularly on prevention, transmission, symptoms, and testing possibilities (Arriani et al., 2020). Finally, a global online survey showed high adherence to protective behaviors across all countries (Fetzer et al., 2020). Economic preferences might play a fundamental role in shaping compliance to those restrictive measures. Namely, trust and patience have been positively associated with compliance, while a higher risk-seeking profile has been negatively associated with uptake (Müller and Rau, 2021).

We complement the existing evidence as follows: The timing of our study allows us to assess the distribution of knowledge and protective behavior and the role of information sources in the early phase of the pandemic. As our survey is targeted at the 40-to-70-year-olds, our findings yield insights on a population group which is of particular risk to experience a severe course of COVID-19 (Nishiga et al., 2020; Williamson et al., 2020; Zhou et al., 2020) due to their higher age and consequently higher risk of cardiovascular diseases. In contrast to many other COVID-19 studies, we conducted a phone survey instead of an online survey. Samples retrieved from online surveys are likely to address younger, more educated and wealthier individuals (Boas et al., 2020). In contrast, our randomly drawn sample allows us to draw unbiased conclusions for the target population.

The remainder of the paper is structured as follows: First, we describe the study setting and the COVID-19 situation in Indonesia and Aceh. Next, we conceptualize which factors might influence knowledge and behavior and summarize the corresponding evidence. Then, we describe our study sample and the models employed for the analysis. Finally, we present the findings and discuss the results.

2.2 Background

2.2.1 The Province of Aceh

Aceh comes from a long history of autonomy and resistance against occupying forces such as the Dutch (Reid, 2004). This legacy contributed both to its prominent role in the strive for the independence of Indonesia and to its dispute with the national government over centralization when the new state was established (Reid, 2004). In the 1970s, the conflict escalated into combats between the Indonesian military and the Free Aceh Movement, which lasted until August 2005 and demanded thousands of lives (Waizenegger and Hyndman, 2010). The Indian Ocean tsunami in 2004 was perceived as a 'key to change' (Waizenegger and Hyndman, 2010) in this conflict and was followed by a peace agreement in 2005. While the massive inflow of international aid for disaster relief benefitted tsunami-affected areas and populations immensely (Heger and Neumayer, 2019; Waizenegger and Hyndman, 2010), the comparably small funds for conflict victims might have created inequalities within the population (Waizenegger and Hyndman, 2010). Until today, Aceh is one of five provinces with special regional autonomy, which allows for more localized political, economic, and religious decision-making (Fossati, 2016; Republic of Indonesia, 2006).

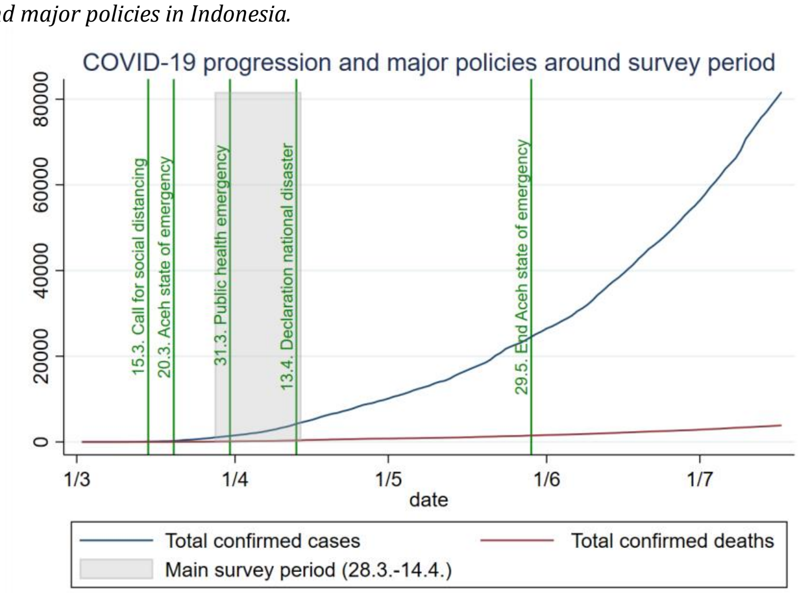
In the late 2000s, Aceh was faced with multiple challenges in the health sector (Evans, 2010). An exceptionally high share of the burden of disease fell on the poor and rural population (Evans, 2010). In 2009, the provincial government introduced a new health insurance scheme which provided free basic health care for all its citizens (Evans, 2010). This went far beyond the standards of other provincial health insurance schemes before the introduction of the national health insurance scheme in 2014 (Pisani et al., 2016). Nowadays, Aceh is facing the double burden of communicable and non-communicable diseases common in many middle-income settings in transition: While cardiovascular diseases and diabetes were the main causes of death in Aceh in 2017, communicable diseases such as TB, diarrhea, and lower respiratory diseases were still among the top ten (Institute for Health Metrics and Evaluation, 2020).

Being located in the periphery of the country, Aceh has been subject to much less research than more central Indonesian districts. Within Aceh, our study sample comprises of respondents from the provincial capital Banda Aceh and its peri-urban surrounding district Aceh Besar, which are of particular relevance for our research questions in the context of COVID-19 due to their dense population structure.

2.2.2 COVID-19 in Indonesia and Aceh

Our data collection was set at an early stage of the pandemic in Aceh and Indonesia as a whole, and was shaped by rapid policy responses as can be seen in Figure 2.1. During the first weeks of data collection, Indonesia had approximately 1,000 confirmed cases, and COVID-19 was designated a public health emergency (Hale et al., 2020; President of Indonesia, 2020a). By the end of the collection period, the pandemic was declared a national disaster (President of Indonesia, 2020b), the number of confirmed cases had tripled. Reported infection numbers in Aceh province were still below 10, but the actual spread was expected to be higher as testing capacities are low (Serambi Indonesia, 2020a). Therefore, this study's data and results reflect the level of awareness, knowledge and attitudes during the early phase of the outbreak.

Figure 2.1 Cases and major policies in Indonesia.



Policy dates are taken from official announcements and orders (Governor of Aceh, 2020; President of Indonesia, 2020a, 2020b). Cases are taken from Hale et al. (2020).

In March, the Ministry of Health launched nationwide information campaigns, which were also endorsed in Aceh, indicating recommended habits of prevention against the virus. The main messages were frequently washing hands with soap, cover mouth and nose when sneezing or coughing, keeping a distance to others in public, avoiding handshakes, and touching the face (Ministry of Health, 2020a). When having a cough, cold, and shortness of breath, the recommendation was to immediately contact a health facility (Ministry of Health, 2020b). Starting late March, the country undertook a partial lockdown, limited the daily hours of operation of airports, and dictated social distancing restrictions (Randi, 2020). By Mid-April, the widespread use of masks was encouraged and supported by free distributions campaigns in different regions across the country including Aceh (Serambi Indonesia, 2020b). Even though the first COVID-19 case in Aceh was only confirmed on March 26th, strict policies such as school closures, travel restrictions, and a province-specific state of emergency were imposed in mid-March. By late 2020, Aceh has almost surpassed 8000 infections, of which the vast majority was detected in our densely populated study districts Banda Aceh and Aceh Besar. (Ministry of Health Aceh, 2020)

2.2.3 Determinants of Knowledge and Protective Action

Research on the intersection of public health and economics has identified a multitude of factors that could influence health knowledge and behavior. Focusing on health behavior at the individual level, we describe factors derived from the literature which are expected to play a role in the context of the COVID-19 pandemic: knowledge and the role of information sources as a prerequisite to practice, socioeconomic characteristics, which shape both knowledge and practice, and lastly economic preferences as further mediators when translating knowledge into action.

2.2.3.1 Knowledge

One major determinant of the adoption of protective health measures is information (Dupas, 2011). In a pandemic, behavioral responses are shaped by knowledge on how the virus spreads and presents itself, which protective actions exist, how to utilize these, and which benefits they entail (Bish and Michie, 2010; Tooher et al., 2013; Yap et al., 2010). References from the H1N1 and SARS outbreaks consistently show that greater knowledge of virus symptoms and transmission channels is positively associated with precautionary actions, such as washing hands more frequently, using a mask, using hand sanitizer, and keeping distance from others (Aburto et al., 2010; Bish and Michie, 2010). In the same line, individuals with a greater knowledge of the meaning of a pandemic have been found to display stronger intentions to comply with quarantine restrictions during a hypothetical influenza outbreak (Eastwood et al., 2010).

At the same time, knowledge is itself determined by various factors. Access to information, the type of information provided, and the distinct information channels used can all shape knowledge formation (Dupas, 2011; Manika and Golden, 2011). Previous pandemic outbreaks have shown that the type of information channel is associated with knowledge through levels of trustworthiness, outreach, relevance, and effective delivery (Aburto et al., 2010; Wong and Sam, 2010). In turn, the preferred information channel might vary according to sociodemographic characteristics. For example, participants of a study carried out in Malaysia belonging to the lower education group indicated television as their preferred source of information, while internet and local community organizations were the most frequent answers among participants from the higher education group (Aburto et al., 2010; Wong and Sam, 2010).

However, knowledge is likely not the only factor influencing health behavioral responses (Leung et al., 2005). The mere receptiveness to information from an individual increases the likelihood that he/she will engage in prevention behaviors (Manika and Golden, 2011). Socioeconomic characteristics, as well as economic preferences and even emotionally driven factors, might also determine the level of compliance with restrictive measures (Cowling et al., 2010; Müller and Rau, 2021; Wong and Sam, 2010). Furthermore, the perceived susceptibility and perceived severity of a disease can explain the willingness to adopt precautionary actions such as handwashing, mask wearing, and isolation restrictions (Bish and Michie, 2010; Lau et al., 2010).

2.2.3.2 Socioeconomic Characteristics

Factors such as age, gender, education, and wealth have been found to predict knowledge and the adoption of protective action. With respect to knowledge, socioeconomic characteristics may affect the individual's access to information as well as their capacities to process it (Dupas, 2011; Mani et al., 2013). For instance, people with less education have been found to receive less information than people with higher education either because of a shortfall in information provision, health information seeking behavior, or other factors (Wong & Sam, 2010). Knowledge tends to be increasing with age (Tooher et al., 2013), but the relationship is not as clear, and some evidence even points towards lower knowledge in older cohorts (Lau et al., 2010).

Much of the evidence suggests higher uptake of protective measures (including hygiene, social distancing, and vaccination) with increased age, but few studies also show higher uptake in younger age cohorts or no association with age (Bish and Michie, 2010). Due to age being a risk factor for a more severe disease outcome (Nishiga et al., 2020; Williamson et al., 2020; Zhou et al., 2020), other household members' age may also potentially shape the uptake of protective measures against the coronavirus. Studies on gender differences reveal that women have a higher likelihood of adhering to preventive behavior in the context of pandemics (Bish and Michie, 2010). Similar to knowledge, more education has been found to be positively associated with preventive behaviors during pandemics (Balkhy et al., 2010; Eastwood et al., 2010; Lau et al., 2010). The evidence on the influence of wealth is more limited, but points towards more knowledge among wealthier individuals (Tooher et al., 2013). Relatedly, how living in rural or urban areas is associated with health knowledge and protective behavior has not been exhaustively exploited in the literature. However, empirical evidence from developed countries suggests that people living in rural areas are less likely to employ protective behavior, e.g. make diagnostic tests, comply with screening guidelines, or adopt healthy habits (Bennett et al., 2008); and more likely to engage in risky health behaviors, e.g. smoking, alcohol consumption, or poor dietary management (De la Cruz-Sánchez and Aguirre-Gómez, 2014).

2.2.3.3 Economic Preferences

Beyond these factors, economic preferences and beliefs such as time preferences, risk preferences, and trust can determine protective behavior. The decision to engage in preventive health measures and treatment seeking involves both a time and a risk component, which can be mediated by trust. Consequently, impatience and willingness-to-take risk are commonly expected to decrease the likelihood to invest in protective health measures[1] (Dardanoni and Wagstaff, 1990; van der Pol et al., 2017). Individuals with higher levels of trust are expected to be more likely to adopt protective health measures (Rocco et al., 2014). Moreover, to the extent that protective behavior during pandemics resembles a public good game, patient individuals are expected to be more compliant (Curry et al., 2008), while the impact of risk-preferences is more ambiguous and interlinked with trust (Bohnet and Zeckhauser, 2004).

The empirical literature supports these expected behaviors to a large extent. Patient individuals are more likely to engage in protective behavior (Goldzahl, 2017; Picone et al., 2004; Tsutsui et al., 2012, 2010) and to cooperate (Curry et al., 2008; Fehr and Leibbrandt, 2011). Risk-averse individuals are more likely to engage in protective behavior in some studies (Dohmen et al., 2011; Tsutsui et al., 2012, 2010) but not in all (Goldzahl, 2017; Picone et al., 2004). Moreover, trust in the information source can pose a necessary condition for the uptake of protective measures (Prati et al., 2011) and might even substitute the role of knowledge in this context (Sailer et al., 2020). First findings from the COVID-19 pandemic show that patient and risk-averse individuals are more likely to avoid crowds, with patient individuals also being more likely to stay at home (Müller and Rau, 2021). Trust influences compliance with restrictions in some settings (Sailer et al., 2020), but not in all (Müller and Rau, 2021).

[1] For willingness-to-take risks, this is assuming that the protective behavior is perceived as the ‘safer’ lottery.

2.3 Methods

2.3.1 Data

We conducted interviews with 1,113 individuals from Aceh, Indonesia, as part of a larger randomized control trial on health screening uptake for non-communicable diseases. The target population of the RCT was people between 40 and 70 years of age, who are not in routine health care[2] and have access to a mobile phone in their household. This sample make-up is of particular relevance in the context of the COVID-19 outbreak, as this age cohort is also at risk for a more severe disease course if infected with the coronavirus (Nishiga et al., 2020; Williamson et al., 2020; Zhou et al., 2020).

This study draws on information collected during face-to-face baseline interviews in November and December 2019 and a follow-up telephone survey in 2020 conducted between March 28th and May 2nd (90% of the interviews were completed before April 14th). The baseline sample was drawn in a two-stage stratified random design to allow a representative sample of the target population. First, we randomly drew 152 villages from a complete list of villages in the districts Aceh Besar and Banda Aceh (see appendix, Figure A 2.1), which constitute the primary sampling unit. This draw was stratified by district to have an equal number of villages from the mostly rural Aceh Besar and the mostly urban provincial capital Banda Aceh. Within villages, households were selected randomly. Most villages have lists of households that are registered in the village (through the *Kartu Keluarga*), but contain neither all the information on inclusion criteria nor exact addresses, so that the search for potential participants sampled through these lists was practically not feasible. Instead, we employed a random walk scheme that should yield a similar sample. We ensured to have a similar sample size from each village that is geographically dispersed by setting a village-specific house skip rate based on the number of households and the expected response rate. The expected response rate was determined based on a combination of insights from the frequency of households that meet our inclusion criteria in the national socioeconomic survey (SUSENAS) and interview piloting. The starting point of the walk was determined by first randomly selecting one village subdivision, within which a starting house was randomly selected

[2] Exact inclusion criteria: no previous diabetes or hypertension diagnosis, no diabetes screening during the previous year, and not in regular care for another disease at the time of the baseline interview

based on a pre-defined protocol. If several household members within one household met the inclusion criteria, one was selected at random. Please find the detailed instructions to the interviewers in the appendix (A 2.1). A disaggregation of the number of contacted, eligible and participating households can be found in Table A 2.1 in the appendix. Around half of the houses that were contacted following the random walk were empty, but in this setting, it is not possible to clearly distinguish between uninhabited houses and those where none was home. Of those who were present, 88% consented to the eligibility check, in which one third of contacted households were found to have at least one eligible member, who then completed the interview in 99.5% of cases. For the follow-up interviews, all baseline respondents who had a valid telephone number were contacted up to five times following the calling procedure in the appendix (A 2.2). This way, we were able to re-interview 70% of the baseline sample. An inspection of the geo-locations of the baseline interviews as well as the comparison of the sample characteristics with the SUSENAS data give us confidence that this sampling procedure yielded a representative sample of the population of interest. This remains largely similar in the phone interview sample (see descriptive statistics section).

The final dataset is a combination of household and individual characteristics from the baseline survey and COVID-19 specific questions from the telephone survey (refer to the appendix, A 2.5, for the questionnaire and Table A 2.2 for the variable definitions). During the baseline survey, we collected information on socioeconomic characteristics, household member characteristics, and economic preferences. We measured wealth using an asset index according to the procedure of the demographic and health survey (The DHS Program, n.d.)[3]. We measured economic preferences on risk and patience with self-reported survey questions detailing a ten-point Likert-scale, taken from and validated by the Global Preferences Survey (Falk et al., 2018, 2016). Trust was measured with a self-reported survey question ('In general, one can trust people') on a four-point agreement scale as used in the German Socioeconomic Panel (Kantar Public, 2018).

[3] The components consist of 10 assets that were found to be most influential when determining the same asset index in SUSENAS 2017 for the two sample districts: ownership of a gas cylinder, refrigerator, PC, TV, jewelry, AC, car, improved latrine, motorbike, and improved drinking water.

Questions on COVID-19 knowledge and behavior were adapted from studies on the 2009 H1N1 pandemic (Balkhy et al., 2010; Ibuka et al., 2010) and collected during the telephone interviews. Knowledge of transmission, symptoms, and prevention as well as uptake of protective behavior were measured by unaided recall questions, in order to minimize response bias and misreporting. The perceived likelihood of contracting the coronavirus was measured with a four-point Likert scale ranging from very likely to very unlikely. Perceived severity of COVID-19 was measured by ranking the perceived danger of this virus against that of tuberculosis and diarrhea, which are the two infectious diseases that cause most deaths in Indonesia (Institute for Health Metrics and Evaluation, 2020).

Our outcomes of interest, disease and prevention knowledge and protective behavior, are defined from the above survey questions as follows. We analyze disease knowledge based on knowing about the main transmission channels, symptoms, and prevention measures of COVID-19. By the time of our survey, the transmission through droplets was already confirmed, while the evidence on smear transmission was less conclusive. We measure knowledge on droplet transmission with a binary variable indicating if the respondent stated that the virus could be transmitted through droplets after coughing or sneezing. A binary variable for knowledge on smear transmission indicates whether the respondent stated that the virus could be contracted by touching an infected person (e.g. shaking hands) or touching objects used by an infected person.

Officially stated symptoms of COVID-19 changed over the course of the disease. Before our survey started, sneezing and having a cold were also mentioned as symptoms by the WHO and the Indonesian Health Ministry. However, as these were dropped from the symptom list during our survey, we focus our analysis on cough and fever, which were recognized symptoms throughout the survey period. We define symptom knowledge as mentioning both, fever and cough, as COVID-19 symptoms. We focus our analysis on the three most prominent preventive measures: Social distancing, hygiene, and mask wearing. We define social distancing as at least one mentioned measure out of avoiding group gatherings, avoiding close contact with others, and staying at home. Hygiene is defined as frequently washing hands or using hand sanitizer, clean and disinfect often, and/or cover with forearm or tissue when sneezing. Finally, we are interested in planned actions in case a respondent suspects being infected with the coronavirus. We classify possible actions into two categories: Isolation, if respondents plan to stay at home or to quarantine, and contacting a medical professional, if respondents plan to call a medical professional or visit a health facility in person.

2.3.2 Statistical Analysis

We analyze the determinants of pandemic knowledge and protective health behavior using linear probability regression models. A graphic display of all tested associations can be found in appendix Figure A 2.2. To take the complexities of the baseline sampling design into account, the standard errors in all reported statistics are adjusted for district stratification and villages as primary sampling units. To test for the robustness of these estimations and increase comparability with related studies, we also run a reduced model only including socioeconomic characteristics for each outcome and alternative estimation methods (Probit, Logit). We choose the linear probability model as main specification for ease of interpretation while the results are not altered by this choice.

2.3.2.1 Determinants of Knowledge

First, we estimate the determinants of pandemic knowledge:

$$KNOWLEDGE_i = \alpha + \beta SOCIOECON_i + \gamma INFO_i + \varepsilon_i \tag{2.1}$$

where $KNOWLEDGE_i$ is a vector of six dummy outcome variables indicating whether respondent *i* had the respective pandemic knowledge on disease transmission (droplets, smear), symptoms (fever and cough), and preventive measures (social distancing, hygiene, mask wearing). On the one hand, we are estimating a set of coefficients for socioeconomic characteristics (β) using the vector $SOCIOECON_i$, which contains seven dummy variables indicating whether the respondent is over 50 years old, female, lives in a household with above median wealth, with other household members above the age of 50, or in the city of Banda Aceh; as well as a categorical variable specifying the level of education (lower secondary, or higher secondary and above compared to primary education or less). We are further examining the role of information channels in knowledge formation (γ) via a set of regressors in the $INFO_i$ vector consisting of seven separate indicators for having received COVID-19 information through TV, newspaper, internet or social media, radio, public announcements (commonly through speakers at mosques, community halls or on cars), or the family or community. α is the constant and ε_i, the error term.

2.3.2.2 Determinants of Uptake

In the second step, we model the determinants of protective health behavior:

$$UPTAKE_i = \alpha + \beta SOCIOECON_i + \delta KNOWLEDGE_i + \theta PREF_i + \varepsilon_i \quad (2.2)$$

where $UPTAKE_i$ is the outcome vector of five dummy variables indicating whether the respondent adopted the respective preventive measure (social distancing, hygiene, wearing masks) and action in case of illness (isolation, contacting a medical professional). In addition to the association with socioeconomic characteristics that are defined as in equation (2.1), we are examining the role of pandemic knowledge (δ) and economic preferences (θ) in the adoption of protective health behavior. The elements of the disease knowledge vector $KNOWLEDGE_i$ are defined in the same way as in equation (2.1), but only the subset that is relevant for the respective protective action enters its uptake regression. The preventive action regressions always include knowing the outcome action (e.g. knowing about handwashing in the regression on handwashing practice), as well as the transmission channel that can be addressed with this action: for social distancing, both knowledge on smear and droplet transmission are likely to matter, but for hygiene the relevant driver is knowledge on smear transmission, while for wearing masks it is droplet transmission. In the regressions of determinants of actions in case of illness (isolation and contacting a medical professional), only knowledge of the main symptoms is included as a regressor as this is a prerequisite for detecting a potential infection. Finally, $PREF_i$ is a set of three covariates specifying the willingness to take risks, patience, and trust.

2.4 Results

2.4.1 Descriptive Statistics

Of the interviewed participants who responded to the COVID-19 module, 99% indicated to have heard of COVID-19 (item refusal: 11%), resulting in a sample of 1,113 respondents. The socioeconomic characteristics of our sample are depicted in Table 2.1. In our sample, 46% of the respondents are 50 years or older, and 64% are female. Moreover, 27% of the respondents have no or primary education, 22% reached lower secondary education, and 51% completed upper secondary education or higher. The sample is nearly evenly split between the city of Banda Aceh and the surrounding district

Aceh Besar. As depicted in Table A 2.3 in the appendix, our baseline sample is statistically similar to the representative district samples from SUSENAS 2017 (restricted to 40-to-70-year olds in households that own a phone), with our sample containing more women and slightly less educated individuals. Along most characteristics, the participants that responded to the Corona module are statistically similar to the whole baseline sample and are on average slightly but significantly higher educated.

Compared to the rest of Aceh province and Indonesia as a whole, our study districts have a higher overall level of education, which is likely due to covering the provincial capital and its surroundings. Furthermore, Aceh province, and thus our study sample, has had near universal coverage with health insurance for several years, which might hint that residents are generally better connected to the health system.

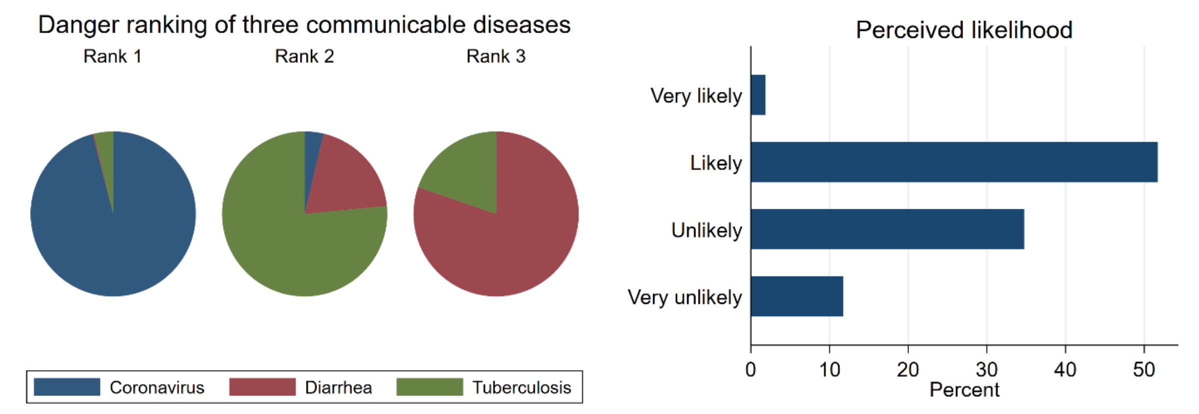
Table 2.1 Basic sample characteristics

	Mean	SD	N
Age	49.88	8.00	1,112
50 or older	0.46	0.50	1,112
Member 50 or older	0.41	0.49	1,112
Female	0.64	0.48	1,111
Education			
Up to Primary	0.27		299
Lower Secondary	0.22		246
Higher secondary or more	0.51		568
Wealth above median	0.51	0.50	1,112
Banda Aceh	0.45	0.50	1,113

COVID-19 is perceived as a serious threat by the large majority of respondents in our sample. Compared to two other common and severe communicable diseases in the area, diarrhea and tuberculosis, COVID-19 is ranked by nearly all respondents as the most dangerous disease (see Figure 2.2). Also, more than half of the respondents think it is likely they will experience COVID-19 (see Figure 2.2). There is an indication that the economic impacts of COVID-19 are immediate and severe. Within the first four days of our survey, when confirmed cases were still very low in the area, 80% of the respondents reported they experienced income decreases due to COVID-19.[4]

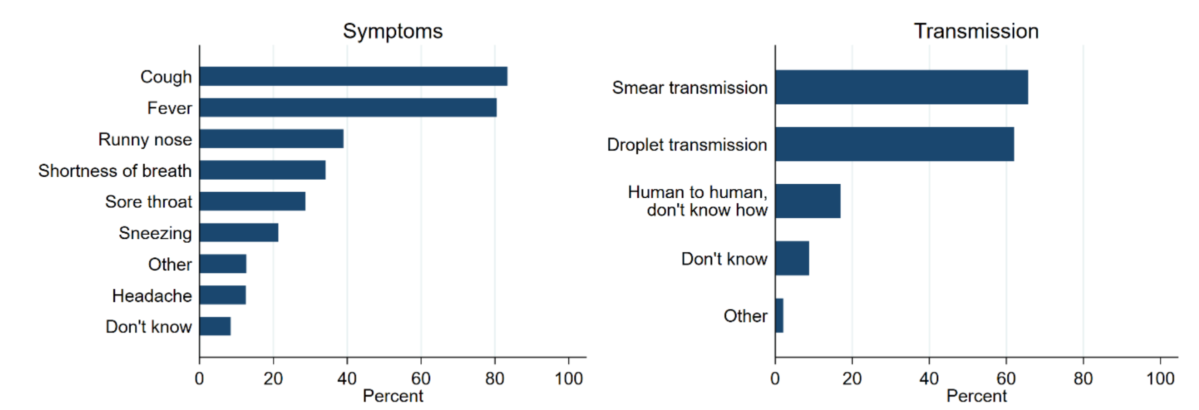
[4] Even though the question was deemed appropriate during pre-testing, four days into the data collection, enumerators reported that this question caused distress in some respondents, who had just lost their livelihood. Hence, we excluded it immediately thereafter.

Figure 2.2 Perceived severity and likelihood



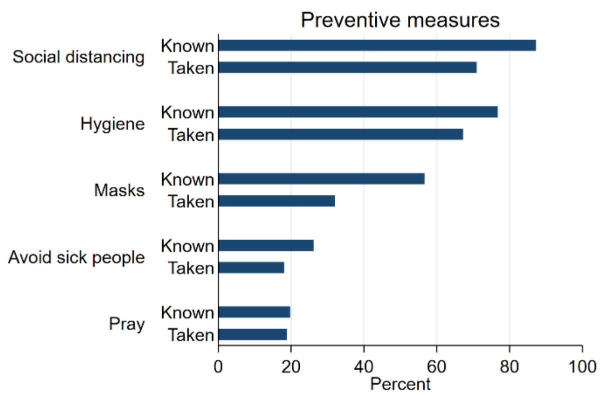
Most respondents could name at least one of the common symptoms of COVID-19. As depicted in Figure 2.3, cough and fever each are mentioned by more than 80% of the sample, followed by runny nose (39%), shortness of breath (34%), and sore throat (29%). Both, fever and cough, are named by 73% of the respondents. Two-thirds of the sample state at least one path of smear infection (touching objects used by infected persons or touching infected persons), and 62% mention that COVID-19 can be transmitted through droplets (see Figure 2.3). For both questions, about 8% of the sample report that they do not know the answer. Disaggregating these indicators by socioeconomic groups points towards higher knowledge in more wealthy, educated, and urban population groups (Table A 2.4 in the appendix).

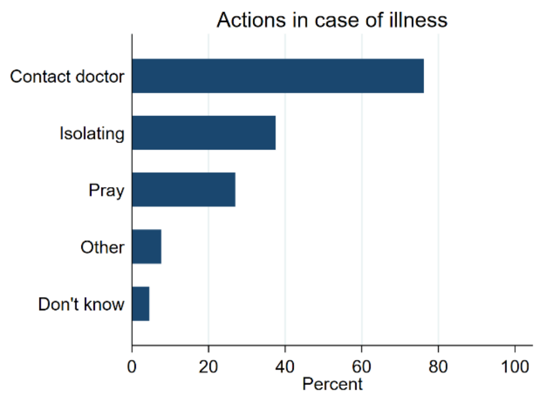
Figure 2.3 Knowledge on symptoms and transmission



Social distancing and hygiene measures are widely known to the sample (87% and 77% respectively, Figure 2.4). Yet, there appears to be a gap between knowledge and uptake of these measures. For masks, this knowledge-uptake gap is especially sizeable: While 57% of the sample state masks can help to prevent COVID-19, only 32% report to use masks. A small proportion holds misconceptions about preventive measures. For example, some respondents believe that taking antibiotics or using traditional remedies could protect against the infection of the coronavirus (less than 1% in each case). In the hypothetical case of illness, 72% of the respondents would contact a medical professional, and 35% would self-isolate. Table A 2.5 in the appendix depicts that both knowledge and practice are on average higher in the group with higher education and those living in urban areas, whereas other socioeconomic groups show less clear patterns than for disease knowledge.

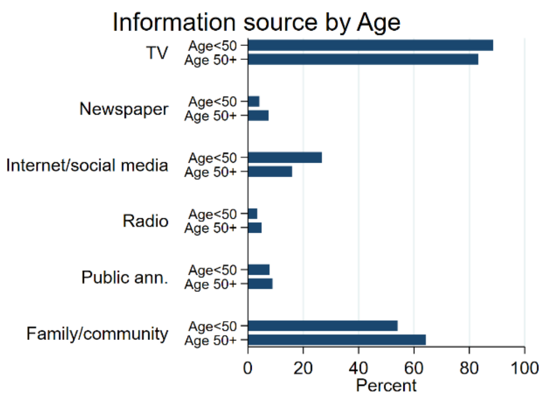
Figure 2.4 Knowledge and behavior regarding protective measures.

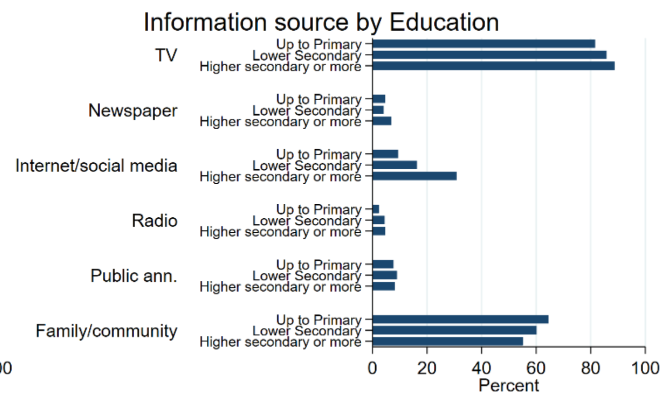




As depicted in Figure 2.5, most respondents received their COVID-19 information from the TV and the family or community. Internet and social media were used significantly more by respondents younger than 50 and those with a higher secondary education or more (Table A 2.6). Older and less educated individuals use the TV for information to a lesser extent, but to a significantly larger extent the family and the community, compared to younger and higher educated respondents.

Figure 2.5 Information sources by group





2.4.2 Determinants of Knowledge

The results of estimating equation 2.1 on the disease knowledge outcomes can be found in Table 2.2. We find that belonging to the group of respondents aged 50 years or older is significantly associated with less knowledge of transmission via droplets. We also find an education gradient that is consistent for all specifications and knowledge categories. Having a higher education is associated with a 7.8 percentage points (p.p.) increase in the probability of knowing droplets to be a transmission channel, an 8.2 p.p. increase of knowing about smear transmission, and a 10.0 p.p. increase in knowledge of the two most common symptoms. Being female or having another household member aged 50 years or older is not significantly associated with any of the disease knowledge outcomes.

Wealth is significantly and positively associated with smear transmission knowledge. Living in urban areas is positively associated with knowledge on droplet transmission and symptoms, from a 6.5 p.p. increase in the probability of knowing the main symptoms to a 13.3 p.p. increase in the probability of droplet transmission knowledge. Among the sources of information, TV, internet and/or social media, and family and community are significantly and positively associated with the three measures of knowledge, while radio seems to play a role only for smear transmission knowledge.

Table 2.2 Estimation results on disease knowledge

	(1) Knows droplet transmission	(2) Knows smear transmission	(3) Knows fever and cough
50 or older	-0.103***	-0.026	-0.032
	(0.030)	(0.032)	(0.026)
Member 50 or older	-0.020	-0.011	-0.020
	(0.031)	(0.029)	(0.028)
Female	-0.017	-0.043	0.013
	(0.029)	(0.029)	(0.027)
Lower Secondary	0.009	-0.016	0.034
	(0.040)	(0.043)	(0.041)
Higher secondary or more	0.078*	0.082**	0.100***
	(0.043)	(0.034)	(0.033)
Wealth above median	0.040	0.118***	0.009
	(0.027)	(0.030)	(0.030)
Urban	0.133***	0.031	0.065**
	(0.034)	(0.035)	(0.026)
TV	0.277***	0.170***	0.271***
	(0.043)	(0.044)	(0.042)
Newspaper	0.065	0.030	-0.014
	(0.063)	(0.063)	(0.056)
Internet/social media	0.235***	0.128***	0.089***
	(0.031)	(0.030)	(0.031)
Radio	-0.075	0.188***	0.071
	(0.076)	(0.062)	(0.053)
Public announcements	0.056	0.017	0.032
	(0.046)	(0.051)	(0.044)
Family/community	0.149***	0.140***	0.164***
	(0.029)	(0.033)	(0.028)
Obs.	1096	1096	1095
Mean	0.620	0.656	0.734
R2	0.154	0.088	0.102

Determinants of disease knowledge. Droplet transmission indicates whether the respondent states that COVID-19 might be transmitted through droplets. Smear transmission indicates whether the respondent names touching infected persons or objects used by infected persons as transmission channels. Fever and cough indicates whether the respondent names fever and cough as symptoms for a COVID-19 infection. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. Urban indicates living in the city of Banda Aceh. TV, newspaper, internet/social media, radio, public announcements, family/community are binary variables indicating from which information sources COVID-19 knowledge was obtained (multiple answers possible). Standard errors accounting for sampling design in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. A base model with socioeconomic variables only is depicted in Table A 2.8 in the appendix. Logit and probit models are depicted in Table A 2.10 in the appendix.

Table 2.3 portrays the determinants of disease prevention knowledge. Namely, we evaluate the drivers of social distancing, hygiene, and mask-wearing knowledge. The education gradient for higher secondary school or higher remains consistent for all specifications. Living in urban areas is positively associated with hygiene and masks wearing knowledge. Being 50 or older or having a family member in this age group is not associated with any of the preventive knowledge outcomes, but women are more likely to state hygiene practices as preventive measures.

Wealth is associated with a 12.2 p.p. increase in the probability of knowing masks-wearing as a preventive measure against COVID-19. TV, internet/social media, and family and community remain positively and significantly associated with all measures of prevention knowledge. In addition, public announcements are positively associated with the three knowledge measures.

Table 2.3 Determinants of disease prevention knowledge

	(1) Knows social dist.	(2) Knows hygiene	(3) Knows mask wearing
50 or older	-0.027	-0.009	-0.044
	(0.022)	(0.025)	(0.030)
Member 50 or older	0.009	-0.012	-0.017
	(0.023)	(0.030)	(0.030)
Female	0.022	0.056**	0.029
	(0.023)	(0.027)	(0.032)
Lower Secondary	0.050	0.048	0.068
	(0.034)	(0.040)	(0.044)
Higher secondary or more	0.071**	0.111***	0.091**
	(0.029)	(0.034)	(0.040)
Wealth above median	-0.007	0.028	0.122***
	(0.022)	(0.025)	(0.033)
Urban	0.005	0.048*	0.054
	(0.022)	(0.027)	(0.033)
TV	0.101***	0.238***	0.316***
	(0.037)	(0.040)	(0.042)
Newspaper	0.053	-0.010	0.088
	(0.042)	(0.058)	(0.062)
Internet/social media	0.064***	0.144***	0.126***
	(0.022)	(0.028)	(0.027)
Radio	0.030	-0.047	0.068
	(0.047)	(0.058)	(0.068)
Public announcements	0.070**	0.090**	0.141***
	(0.028)	(0.039)	(0.045)
Family/community	0.107***	0.159***	0.196***
	(0.020)	(0.024)	(0.033)
Obs.	1095	1095	1095
Mean	0.872	0.768	0.566
R2	0.051	0.114	0.131

Determinants of preventive health knowledge. Social distancing includes staying at home, avoiding close contact with others, and avoiding group gatherings. Hygiene measures include washing or disinfecting hands, sneezing or coughing in forearm or tissue, and cleaning and disinfecting often. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. Urban indicates living in the city of Banda Aceh. TV, newspaper, internet/social media, radio, public announcements, family/community are binary variables indicating from which information sources COVID-19 knowledge was obtained (multiple answers possible). Standard errors accounting for sampling design in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01. A base model with socioeconomic variables only is depicted in Table A 2.8 in the appendix. Logit and probit models are depicted in Table A 2.11 in the appendix.

2.4.3 Determinants of Protective Behavior

Table 2.4 shows the determinants of preventive health behavior uptake, where the dependent variables are social distancing uptake, hygiene uptake, and mask-wearing uptake. Being 50 or older is associated with a 3.2 decrease in the probability of adopting hygiene measures, significant at the 10 percent level. Individuals living in households with above-median wealth are more likely to wear masks, whereas having a household member that belongs to the older cohort is negatively associated. Living in urban areas is positively associated with adopting the three distinct behavior measures and is significant at the 1 (and 5) percent level for social distancing and wearing masks (and hygiene).

Specific knowledge of the preventive measure is associated with a higher probability of adoption of the preventive practices. Social distancing knowledge is associated with a 74.0 p.p. increase in the probability of social distancing uptake, hygiene knowledge is associated with a 86.6 p.p. increase in the probability of adopting hygiene behavior, and knowledge on wearing masks is associated with 53.3 p.p. increase in the probability of wearing masks. Lastly, the probability of wearing masks is positively associated with patience, whereas the probability of complying with social distancing recommendations is positively associated with trust and willingness to take risks.

Table 2.4 Determinants of preventive behavior

	(1) Does social dist.	(2) Does hygiene	(3) Wears masks
50 or older	-0.015	-0.032*	-0.011
	(0.024)	(0.018)	(0.027)
Member 50 or older	0.014	0.011	-0.054**
	(0.025)	(0.018)	(0.025)
Female	-0.004	-0.014	0.040*
	(0.023)	(0.019)	(0.023)
Lower Secondary	-0.035	-0.027	0.015
	(0.032)	(0.027)	(0.033)
Higher secondary or more	0.013	-0.019	0.037
	(0.028)	(0.021)	(0.031)
Wealth above median	0.007	-0.005	0.054**
	(0.024)	(0.017)	(0.023)
Urban	0.070***	0.046**	0.073***
	(0.023)	(0.019)	(0.025)
Knows droplet transmission	0.030		0.039*
	(0.026)		(0.022)
Knows smear transmission	0.056**	0.001	
	(0.026)	(0.019)	
Knows social dist.	0.740***		
	(0.022)		
Knows hygiene		0.866***	
		(0.015)	
Knows mask wearing			0.533***
			(0.025)
Willingness to take risks	0.008*	0.002	-0.004
	(0.005)	(0.004)	(0.005)
Patience	-0.004	-0.003	0.009**
	(0.004)	(0.004)	(0.004)
Trust	0.039*	-0.021	-0.001
	(0.021)	(0.016)	(0.019)
Obs.	1077	1077	1077
Mean	0.713	0.676	0.322
R2	0.342	0.615	0.382

Determinants of preventive health behavior. Social distancing includes staying at home, avoiding close contact with others, and avoiding group gatherings. Hygiene measures include washing or disinfecting hands, sneezing or coughing in forearm or tissue, and cleaning and disinfecting often. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. Urban indicates living in the city of Banda Aceh. Willingness-to-take-risk and patience are elicitated on a scale from 0 to 10 using the module from the Global Preference Survey. Trust is measured as general trust in people using a four-point Likert scale. Standard errors accounting for sampling design in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. A base model with socioeconomic variables only is depicted in Table A 2.9 in the appendix. Logit and probit models are depicted in Table A 2.12 in the appendix.

Finally, Table 2.5 displays the estimation results for actions in case of a suspected COVID-19 infection. Respondents aged 50 or older in our sample are 7.2 p.p. less likely to isolate in case of contracting the novel Coronavirus. Having a family member in the household aged 50 or older is positively associated with contacting a medical professional in case of illness and with isolating in the full specification. People with wealth above the median are more likely to contact a medical professional if they suspect they have the disease.

People living in urban areas have a higher likelihood of isolating in case of illness, but a lower likelihood of contacting a medical professional. Specific knowledge of COVID-19 symptoms is positively associated with isolating and contacting a medical professional in case of illness. Lastly, willingness to take risks is positively associated with isolation, whereas patience is positively associated with isolating but negatively associated with contacting a medical professional. Trust is not found to be a significant driver for action.

Table 2.5 Determinants of action in case of a suspected infection

	(1) Would isolate	(2) Would contact medical professional
50 or older	-0.072**	0.033
	(0.031)	(0.029)
Member 50 or older	0.049*	0.073**
	(0.029)	(0.030)
Female	-0.035	-0.042
	(0.030)	(0.029)
Lower Secondary	-0.040	0.055
	(0.041)	(0.041)
Higher secondary or more	0.015	0.047
	(0.032)	(0.030)
Wealth above median	-0.009	0.078**
	(0.033)	(0.031)
Urban	0.147***	-0.064**
	(0.032)	(0.029)
Knows fever and cough	0.191***	0.180***
	(0.030)	(0.032)
Willingness to take risks	0.014**	0.008
	(0.007)	(0.006)
Patience	0.013*	-0.013**
	(0.007)	(0.005)
Trust	0.005	-0.029
	(0.024)	(0.019)
Obs.	1083	1083
Mean	0.359	0.735
R2	0.081	0.062

Determinants of action in case of illness. Isolating includes quarantining or staying at home in case of illness. Would contact medical professional includes calling health professionals or visiting health facilities. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. Urban indicates living in the city of Banda Aceh. Knows fever and cough indicates whether the respondent names fever and cough as symptoms for a COVID-19 infection. Willingness-to-take-risk and patience are elicitated on a scale from 0 to 10 using the module from the Global Preference Survey. Trust is measured as general trust in people using a four-point Likert scale. Standard errors accounting for sampling design in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. A base model with socioeconomic variables only is depicted in Table A 2.9 in the appendix. Logit and probit models are depicted in Table A 2.13 in the appendix.

2.5 Discussion

The aforementioned results show several important determinants of pandemic knowledge and protective health behavior. Awareness of and knowledge on the transmission channels, symptoms, and preventive mechanisms of the coronavirus were very high, even though the study was set in an early phase of the COVID-19 outbreak in Aceh. Our respondents' knowledge on transmission channels appears to be comparable to several studies on the H1N1 pandemic and to be generally higher for preventive mechanisms (Tooher et al., 2013). Preliminary findings on the COVID-19 pandemic show that also in other geographical regions prevention knowledge was very high, while evidence on transmission modes and symptoms was more varied (Olapegba et al., 2020; Roy et al., 2020; Zegarra-Valdivia et al., 2020).

We find that knowledge underlies strong socioeconomic gradients in a direct and an indirect way: On the one hand, higher education, living in urban areas, and to a lesser extent higher wealth and younger age are all associated with significantly higher knowledge across several outcomes. These findings are consistent with evidence on the H1N1 pandemic, showing that higher education and employment are associated with higher knowledge (Tooher et al., 2013). On the other hand, knowledge is significantly associated with several information sources, which themselves underlie differential usage along socioeconomic characteristics. We find that individuals with higher age and lower education rely relatively more often on their social networks, such as family and community, whereas younger and more educated individuals utilize the internet to a greater extent – as found in other studies and settings (Aburto et al., 2010; Wang et al., 2013; Wong and Sam, 2010). At the same time, not all information sources contribute to knowledge formation to the same extent. For instance, receiving information through the social network is less strongly associated with various knowledge outcomes as compared to other information channels (see Table A 2.7 in the appendix).

This is in line with previous work showing that socioeconomic gradients in knowledge may be explained by challenges in accessing information and/or in the understanding of the information provided (Dupas, 2011; Mani et al., 2013). While both are likely to matter in this study setting, some of our results point specifically towards the importance of the access channel. Firstly, we find that the type of information provided may vary across sources: Public announcements, which typically provide listeners with hands-on advice on how to protect oneself against the coronavirus, are only associated with the knowledge of preventive health behaviors, but not with more general knowledge on transmission channels or symptoms. Secondly, the speediness of information dissemination may vary across socioeconomic groups: While mask wearing was initially not known to be protective against the coronavirus, this changed as the pandemic progressed (Aceh Info COVID-19, 2020). As our findings show that higher wealth is significantly associated with the knowledge that masks protect against COVID-19, this may point towards wealthier individuals having faster access to information.

In turn, knowledge is found to be the strongest predictor of preventive. Concrete knowledge on how to protect oneself against the coronavirus is the main channel through which behavioral responses are determined. This is also reflected in our descriptive results, where we see that the knowledge-uptake gap for preventive mechanisms does exist, but is usually rather small. It is noteworthy that the knowledge-uptake gap is largest in the case of wearing masks, which is also reflected in a somewhat different pattern of regression results. One explanation might be that recommendations regarding mask wearing were less clear in the beginning of the pandemic and did not call for general adoption (Aceh Info COVID-19, 2020). From a policy perspective, this may reflect that focusing on conveying hands-on knowledge is an effective way of getting the population to adopt preventive measures.

While the education gradient is significant for knowledge formation on preventive health measures, it completely disappears for the uptake of these. One potential explanation for this could be that education determines whether a person has access to, understands, and accepts the information that a health measure may prevent COVID-19 as valid. Once this has occurred – as captured by the association between education and knowledge – education may matter less for the actual uptake of such measures, especially in cases where measures are functionally relatively easy to implement – such as washing one's hands. Education could furthermore plausibly affect whether a measure is carried out correctly (e.g. wash hands for at least 30 seconds with soap), but this would not be captured by the self-reported measure of uptake.

Previous literature, however, frequently found education to be a significant predictor for uptake of preventive health behavior against pandemic diseases. Yet, these studies do not always include knowledge as an explanatory variable (Bish and Michie, 2010). As education is strongly associated with knowledge, it might have served as a proxy for knowledge in other studies, thereby explaining the diverging results.

Similar to the determinants of preventive action, knowledge is a strong predictor for protective actions in case of illness – stressing again the need for knowledge-driven policy strategies. Moreover, age is negatively and significantly associated with isolating. One potential reason for this may be that older respondents – a high-risk group (Williamson et al., 2020; Zhou et al., 2020) – choose to not simply stay at home, waiting to see how severe the virus presents itself. Furthermore, the positive and significant relationship between wealth and contacting a medical professional might stem from wealth translating into better access to the health care system. Despite far-reaching efforts to make health care access more equitable through national health insurance, these pro-rich health care access patterns have been found to prevail in Indonesia (Johar et al., 2018). Living in urban areas is positively associated with isolating, similar to the pattern that we observed for the uptake of social distancing, hygiene, and wearing masks. However, it is negatively and significantly associated with contacting a medical professional. When applying a lower level of outcome disaggregation, we find that this appears to be driven by the urban population being more likely to contact a medical professional by telephone, whereas the rural population is more likely to mention that they would go to a health facility in-person. There are several potential explanations for this pattern. First, there was a change in recommended behavior regarding how to contact a medical professional, which may have been communicated differently in urban and rural areas (Liputan 6, 2020; Ministry of Health, 2020b). Another potential explanation could be that urbanites live closer to health care facilities, allowing them to isolate at first and then visit a health care facility only on short-notice once the disease outcome progresses – whereas people living in rural areas are not as flexible due to the greater distance to a facility.

The role of economic preferences is very mixed. Only two outcome measures are correlated with willingness to take risk, namely social distancing and isolating, which might reflect their potential to incur high costs. Furthermore, we would expect that for measures whose success depends on others, such as social distancing, hygiene, and mask wearing, trust should affect the uptake of these measures. However, we only observe this for social distancing (at the 10% significance level). Finally, self-regarding and other-regarding preferences might play a role: Social distancing, hygiene, and contacting a medical professional serve the own health, as might mask wearing, depending on the respondent's perception. At the same time, all measures except for contacting a medical professional can also protect the health of others. As we do not control for altruism, we cannot always disentangle to which extent self- or other-regarding preferences drive the respective behavior. However, we observe that other-regarding preferences matter at least for some decisions: More patient and less risk-averse respondents are more likely to plan to isolate, a measure which serves mainly to protect others. Patience matters for the willingness to concede some of one's current utility to protect others' future utility (Curry et al., 2008), while the willingness to take risk might reflect the risk of these costs, or proxy occupational groups which can afford to stay at home (Hill et al., 2019).

Our study underlies several limitations. First of all, while phone surveys encompass several advantages and in-person interviews are not possible during times of a pandemic, there are also potential drawbacks to be considered. For instance, it may be more difficult to re-contact respondents via phone than via home visits. We do see sample attrition from baseline to endline. However, with a response rate of 70%, we compare well with the upper ranges of response rates achieved in other phone interviews (Himelein et al., 2020), and attrition is not found to be systematic. A further potential drawback of remote interviews is that respondents may be less trusting of enumerators when they speak to them on the phone than when talking to them in person. This may affect their willingness to respond or the content of their answer. In order to minimize this, the same enumerator who had visited the respondent during the baseline survey was deployed to interview them over the phone whenever feasible.

A second limitation to be considered is that our analysis is built on self-reported measures, which may be prone to response or recall bias, especially when surveying behavior. We tried to minimize the response bias as much as possible, by asking unaided questions, rather than listing answer categories for individuals. Further, the recall bias may not be as pronounced in this setting, as the pandemic-related knowledge and behavior was likely a very prominent topic for the respondents even outside of our study. Relatedly, respondents may define reported knowledge and behavior differently. For instance, while we measure whether respondents adopted regular hand washing as a protective mechanism, we do not know whether in doing so, they follow the recommended guidelines on duration and the use of soap.

Third, while we analyze a very comprehensive set of explanatory factors, we were not able to include all relevant variables identified in the literature. More specifically, evidence shows that individuals' perceptions play a role in pandemic health behavior, since beliefs on the severity of a virus, as well as how susceptible one is to contract it, will likely affect the motivation to protect oneself against it (Cowling et al., 2010; Yap et al., 2010). In our sample, the perceived severity of COVID-19 is very high for practically all respondents and therefore yields no variation. While this does not impact our analysis, it should be considered as an important contextual factor. Furthermore, perceived susceptibility of the disease is not included in the analysis due to high selective item non-response. 21% of our sample refused to answer the question on how likely they think it is that they will contract the coronavirus, a refusal rate unmatched by any other variable in our survey. This is likely due to a cultural perception, in which respondents fear this question to be self-deterministic, i.e., stating a high likelihood of contracting the coronavirus may actually cause a high likelihood. The high refusal rate in this question may therefore actually further underline the finding of a high perceived severity of the disease in our sample. Lastly, due to the study design we are unable to show causal inferences; therefore, results should not be interpreted as such.

Finally, we would like to stress that even though our study area and population are specific, the implications are relevant beyond this context. Taking both age and preconditions into account, an estimated 24-34% of the global population has at least one of the risk factors for a complicated COVID-19 infection (Clark et al., 2020). As health system capacities are always limited, but particularly so in LMICs and in response to COVID-19 (Walker et al., 2020), this group underlies similar uncertainties regarding their treatment in case of an infection, which is in turn likely to affect their protective behavior.

2.6 Conclusion

In this study, we examine the socioeconomic, behavioral economic, and informational determinants of protective health behavior against the coronavirus in an at-risk population in Aceh, Indonesia. Our study was carried out via home visits and phone interviews, allowing for a more complete and representative population segment than the frequently used online studies on pandemic behavior. We identify several important determinants of pandemic knowledge and protective health actions, allowing for a guided policy response. We find knowledge to be the driving factor in protective behavioral responses against the coronavirus. Knowledge itself is underlying several socioeconomic patterns, which need to be taken into consideration for equitable policy strategies.

More research needs to be carried out in order to better understand and alleviate the underlying mechanisms of the socioeconomic gradient in knowledge formation. Particularly, the strong and consistent rural-urban gap both in knowledge and uptake needs to be further explored. Lastly, even though curative health behavior is likely to be driven by health system factors, we show individual-level determinants to matter as well in our analysis on actions in case of illness. However, most literature focuses only on preventive health behavior. As the COVID-19 outbreak progresses and more individuals will be faced with such a scenario, more evidence is urgently needed in order to develop effective population-level strategies on how to maneuver all stages of a pandemic.

3 The Effect of SMS Reminders on Health Screening Uptake: A Randomized Experiment in Indonesia

Joint work with Maja Marcus, Lisa Rogge and Sebastian Vollmer

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Abstract

While the burden of non-communicable diseases is rising in low- and middle-income countries, the uptake of screening for these diseases remains low. We conducted a community-based RCT in Indonesia to assess whether personalized and targeted text messages can increase the demand for existing public screening services for diabetes and hypertension in the at-risk population. Our intervention increased screening uptake by approximately 6.6 percentage points compared to the pure control group. Among those, who received and read the messages, the effect size is 17 percentage points. The intervention appears to work through a reminder rather than a knowledge effect. We conclude that text messages can be a cheap and easily scalable tool to reduce testing gaps in a middle-income country setting.

3.1 Introduction

The ongoing epidemiological transition in low- and middle-income countries (LMICs) raises new challenges for their health systems. While the burden of infectious diseases remains high, non-communicable diseases (NCDs) are on the rise. Many of these diseases require a care very different from infectious diseases: They can be tackled effectively many years before individuals notice symptoms, and before severe complications develop. At the same time, individuals must be aware of this "invisibility" and take up preventive health behavior early on.

Diabetes and hypertension screening can be seen as a special case of preventive health behavior, for which it is not the aim to avoid an illness altogether but to detect a prevalent condition early enough to avoid or postpone complications. Screening is possible at very low costs, and at very early stages, behavioral changes can be sufficient to control these conditions. Yet, screening for diabetes and hypertension is underutilized in many LMICs (Geldsetzer et al., 2019; Manne-Goehler et al., 2019), even in settings with a free and easily accessible screening infrastructure, such as Indonesia.

In this study, we test whether a low-cost, low-touch text message intervention can increase the uptake of hypertension and diabetes screening in Indonesia. To understand the potential effect better, we explicitly test whether the intervention can transport new information, and whether risk aversion and patience are mediating the effect. Lastly, we examine household spillover effects to see whether the intervention can be effective beyond the direct message recipient.

We assessed these research questions via a randomized controlled trial in the general at-risk population, in which half of the participants received the full intervention and half is the pure control group. The treatment group received two sets of three text messages, with each set sent before one of the monthly village screening dates between January and March 2020. The messages called upon the recipients to attend screening at the specified time and place and gave short information on their elevated risk, the necessity, and the benefit of screening. The intervention was targeted at individuals over the age of 40, who are at increased risk to develop diabetes or hypertension and should be screened once a year in accordance with WHO PEN screening guidelines (WHO, 2010a). We randomly sampled 2,006 participants from two districts in Aceh province in a two-stage stratified design. Baseline data was collected in November and December 2019 and endline data was collected approximately one month after the last screening date via telephone surveys as the COVID-19 outbreak did not allow for in-person interviews.

We find that the intervention increased the uptake of screening services from 33% to 40%, which is a 6.6 percentage point or a 20% increase compared to the control group. For respondents who received at least one full set of messages and could remember any message content, the effect size increases to 17 percentage points. The text messages seem to work as a reminder for screening: While there is an overall increase in the uptake of screening, there is no impact on knowledge related to the text message or general disease knowledge. Respondents primarily remembered the content on the logistics and the advice to get screened. The only new information, which is remembered by a quarter of the respondents who recall any content is the fact that their age group implies a higher risk for hypertension and diabetes. In addition, the treatment effect is driven by attending screening at the community health center (Puskesmas) rather than the specific village screening meeting (Posbindu) that was mentioned in the messages. The treatment effect does not seem to differ across time and risk preferences. We cannot detect any spillovers to other household members.

In a standard model, investment in preventive health care such as screening would be the result of the monetary and non-monetary costs and benefits of each health option, as well as the time horizon over which they occur (Dupas and Miguel, 2017). In such a world, the individual's investment in preventive health care is optimal for the individual, and the societal optimum could be reached by changing the cost structures. However, in reality, an underinvestment in preventive health care is observed (Kremer et al., 2019). This underinvestment can be the result of various factors, such as inaccurate or motivated beliefs, trust, present bias, or limited attention.

Previous studies showed that preventive health behavior can be improved by both new information and reminders conveyed via text messages. Our work builds on and contributes to this literature in the following ways. First, previous literature showed that text messages can be effective in targeting complex and sustained behavior changes for preventive health, such as smoking cessation or increased physical activity (Cole-Lewis and Kershaw, 2010). These studies usually use text messages with high frequency and over long durations, or in combination with other more intensive treatments. Complementing this, we employ a low-touch intervention, where only 6 messages were sent out over the course of two months, and examine one specific health action, which needs to be carried out only once over long time periods. This health action further differs from the aforementioned, as NCD screening not only aims at preventing the disease altogether, but also serves as detection for already existing cases – introducing additional factors into the individual's cost-benefit analysis in comparison to purely preventive behaviors. Second, other low-touch interventions for one-time health actions showed that text messages can be an effective tool for the scheduling or reminding of health care appointments, including health check-ups or the adherence to vaccination schedules (Jacobson Vann et al., 2018; McLean et al., 2014). Our study goes beyond such settings by addressing community-wide NCD screening outside of the direct health practitioner-patient relationship and by targeting a population that is less connected to NCD care. Third, studies focusing on NCD screening services were primarily conducted in high-income countries, which typically have a longer history of NCDs as the leading health burden and of NCD care structures (McLean et al., 2014; Sallis et al., 2019). We complement this evidence by studying Indonesia – a middle-income country setting, in which screening for NCDs might be less habitual, as they have caused the majority of deaths only since the 1990s (IHME, 2018). To our knowledge, the only studies examining NCD screening in LMICs targeted cervical cancer screening (Zhang et al., 2020), which exclusively occurs in female population groups and is a separate noncommunicable disease class from diabetes and hypertension. Apart from text messages, other interventions to increase screening demand specifically for diabetes and hypertension in LMICS are also rare; the only other study we know of uses again a more intensive treatment, namely in-person scripts and pharmacy vouchers (de Walque et al., 2020; Gong et al., 2020). Lastly, beyond the main treatment effect, we contribute to the scarce evidence base of spillover effects, particularly within the household, of preventive health interventions (Dupas & Miguel, 2017).

In the following chapter, we summarize the current prevalence of and screening for diabetes and hypertension in Indonesia. Then, we describe the experiment in detail by deriving the hypotheses from previous evidence and our own pre-studies, presenting the intervention design, estimation strategy, data collection and outcome definitions. The fourth chapter displays the experiment's results as well as implications for a potential scale-up. Finally, we conclude and give an outlook for further research.

3.2 Context

Similar to other LMICs, the burden of NCDs is rising in Indonesia. From 1990 to 2017, the share of NCDs in causes of death rose from 48% to 75% (IHME, 2018). In 2017, hypertension and diabetes were among the top three risk factors for morbidity (IHME, 2018). The most recent national health survey from the Ministry of Health revealed that diabetes prevalence has risen to 11% and hypertension to 34% (Riskesdas, 2018), both above the global average. To battle this trend, the national government has started implementing targeted prevention programs. In the last decade, nationwide programs were established to integrate a division responsible for NCD needs in every community health center (*Puskesmas*) (Mahendradhata et al., 2017).

One main effort is the village screening program *Posbindu (Pos binaan terpadu*). Once per month, trained nurses from the local *Puskesmas* offer information as well as screening and monitoring services for various NCDs to the general population at a central place within each village. This basic service is free of charge for the user and financed through a combination of the *Puskesmas* and village budget. At the village level, community health workers (*kader*) are responsible for organizing and advertising the meetings. In addition to *Posbindu*, it is possible to get free screening at the district's *Puskesmas* at all times, and for a charge of approximately 50,000 IDR[5] at private practices. However, the national health survey shows that the general population has rarely used the NCD screening services so far. About one third of those aged above 45 report that they never had their blood pressure checked, and around 70% never had their blood sugar level checked (Riskesdas, 2018).

This pattern of high diabetes and hypertension prevalence and low screening uptake is also observed in our study region in Aceh province: the diabetes and hypertension prevalence is slightly above the national mean, and reported screening rates were below the national average in 2018 (Riskesdas, 2018). A focus group discussion with 12 *kaders* from our study area revealed that *Posbindu* tends to be visited by elderly women and those who were already diagnosed[6]. The *kaders* perceive it as more difficult to motivate the general population to attend the meetings even though sufficient time and equipment

[5] 3.56 USD at an exchange rate of 14032.02 IDR/USD, this charge includes blood pressure, blood glucose and additionally cholesterol and uric acid measurement.

[6] The focus group discussion was part of our pre-study to gather information on the supply-side perspective.

would be available. In addition, the province has close to universal health insurance coverage for over a decade, which makes it a suitable setting to study the demand-side barriers to screening uptake.

3.3 Method

3.3.1 The Intervention

Our intervention is a repeated set of SMS text messages on the necessity and logistics of diabetes and hypertension screening. It was designed to address disease misperceptions as well as behavioral barriers to screening uptake. The intervention was piloted in mid-January 2020 (see appendix A 3.5) and fielded from late January until March 2020.

3.3.1.1 Targeted mechanisms

As a high prevalence of NCDs is a rather new phenomenon in LMICs, individuals might not yet be aware of the role of screening as preventive health behavior, or might not have internalized regular check-ups. Text messages on screening dates might tackle several of these barriers: They might convey new information, thus update beliefs, make the screening decision more salient to the individual, thus serving as a reminder, or introduce a deadline to be screened.

To find out which factors keep at-risk individuals from taking up screening in the Acehnese context, we conducted a qualitative and a quantitative pre-study[7] (see A 3.5 for the detailed study timeline). For the qualitative arm, twelve in-depth semi-structured interviews with individuals from the target population were conducted in November 2019. These findings were quantified and extended in the quantitative baseline data collection from late November until December 2019 (see chapter 3.3.3 for data collection details).

These pre-studies showed that the majority of our respondents were informed about the main characteristics of hypertension and diabetes, as well as the possibility to screen free of charge. There are some perceived non-monetary costs such as fear of diagnosis and the notion that preventive health programs are designed for the elderly or women, but no strong stigmatization. On the other hand, respondents are aware that early treatment

[7] The detailed design and findings will be made available in a separate paper.

initiation can help and that especially diabetes likely leads to high treatment costs. However, to most respondents it was not salient that their age implied a higher risk for both conditions, and most did not know that one could have them without feeling any symptoms. Studies from other parts of Indonesia confirm that even if individuals could identify risk factors, the own susceptibility was underestimated (Pujilestari et al., 2014), and even diagnosed respondents did not yet internalize that the need for screening does not depend on feeling ill (Rahmawati and Bajorek, 2018). Informing individuals about the need for screening independent of symptoms and their age-based risk might thus increase screening uptake.

Furthermore, forgetfulness and limited attention might prevent screening uptake. Reminders and fixed dates might simply make the decision for screening more salient and induce planning (Milkman et al., 2013), or increase the perceived urgency of screening. Similarly, evidence from other LMICs suggests that present bias can be a substantial barrier to screening uptake, as individuals postpone the health investment infinitely (Kremer et al., 2019). Deadlines can be efficient countermeasures as they signal that on the deadline, individuals cannot decide between now or later, but only between now or never (Kremer et al., 2019). Hence, individuals might not procrastinate the health investment any longer, but might be inclined to take up screening at the deadline. While the screening date is a non-binding deadline, the mere notion that missing the date implies a waiting period of one month might be effective to reduce naïve procrastination (O'Donoghue and Rabin, 2015).

Previous studies showed that impatient individuals are less likely to seek screening (Picone et al., 2004), resulting in a higher risk of underdiagnoses (Kim and Radoias, 2016). Increasing the salience of the time dimension might reinforce this heterogeneity, while deadline setting might help especially impatient individuals to take up screening. Similarly, more risk-averse individuals invest more in preventive health in some cases (Tsaneva, 2013), but not in all (Goldzahl, 2017; Picone et al., 2004), depending on how uncertain the outcomes of screening and treatment are perceived (Selden, 1993). Thus, the information conveyed in text messages might impact screening demand differently for relatively more and relatively less risk-averse individuals.

Finally, text messages could impact individuals beyond the targeted respondents due to information sharing, social learning, or mere convenience when respondents are accompanied to the screening facility. Spillovers of health interventions are rarely examined (Dupas and Miguel, 2017), but are of interest when analyzing the overall impact of an intervention. In the case of text messages, this might be particularly relevant, as they can be shared easily.

Thus, to assess the effectiveness of the intervention, we test the following hypotheses:

H1: The intervention increases screening uptake of the message recipient.

H2: The intervention increases screening and disease knowledge.

H3: There is a heterogeneous treatment effect along risk and time preferences.

H4: The intervention increases screening uptake of other household members.

3.3.1.2 Content & Personalization

The messages' content included the village-level *Posbindu*[8] screening date and location as well as selected information about hypertension and diabetes. We opted to emphasize the benefits of early screening uptake, in order to positively frame the messages, rectify respondents' misconceptions, and confirm their correct beliefs. Furthermore, as very few respondents were aware of age being a significant risk factor for diabetes and hypertension, we included this information to increase relevance and urgency for the recipients. Also, we included a note that the community health worker (*kader*) or the community health center (*Puskesmas*, abbreviated to PKM) can be contacted for further information. This aimed at increasing the trustworthiness and legitimacy of the messages, while at the same time providing respondents with contacts should any questions arise. To maximize their potential impact (e.g. Head et al. (2013)), the messages were personalized by providing village-level information, addressing the age of the recipient, as well as including the recipient's name in the greeting.

Based on these considerations, we formulated the following messages (see A 3.1 in the appendix for the translation of each message):

[8] 17 out of 146 villages did not have a *Posbindu* screening during our study period. In these cases, participants were invited to the *Posbindu* in a neighboring village as participation is not restricted to village residents.

Message 1: Greetings [Mr/Ms name], do you know that [diabetes|hypertension| does not always show symptoms but can be treated better if detected earlier. Check for FREE at POSBINDU [date].

Message 2: Greetings [Mr/Ms name], do you know that people over 40 years old have a high risk of diabetes & hypertension? Ask kader / PKM & check for FREE at POSBINDU [date].

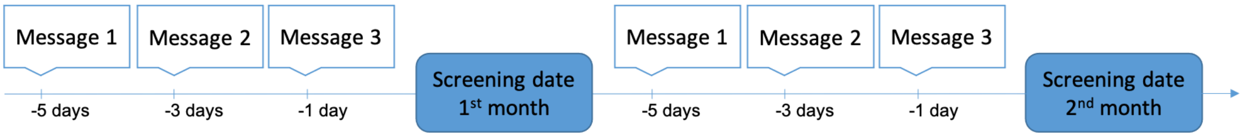
Message 3: Greetings [Mr/Ms name], remember to benefit from a FREE diabetes and hypertension CHECK in POSBINDU tomorrow morning at [place within the village]. Contact nearest kader or PKM.

3.3.1.3 Implementation

Each individual in the treatment group received six SMS messages to the telephone number that s/he chose to be his/her contact number at baseline. The respondent did not have to be the owner of the phone, but s/he needed to be accessible through the phone number. As depicted in Figure 3.1, three messages were sent before the first village screening date and three were sent before the second date one month later. In the first cycle, the first message addressed diabetes, while in the second cycle, it addressed hypertension. In both screening cycles, messages were sent five days, three days and one day before the screening date. For 12 respondents in the treatment group, the first screening date took place end of January 2020, whereas for everyone else in the treatment group it took place in February.[9] The screening dates were enquired by our local research assistants from the respective *Puskesmas* up to two weeks before the start of the intervention to ensure their accuracy. As the *Puskesmas* only coordinates the screening services for all the villages in their catchment area, and the organization at the village level is done by the village health worker, we do not expect this enquiry to have any supply side effects. Most of the intervention period was not affected by the COVID-19 pandemic as *Posbindu* typically takes place in the beginning of a month and the second treatment cycle was therefore finished for most participants in early March. Puskesnas records show that at this time, Posbindu still took place regularly and attendance did not drop compared to the previous months.

[9] To not interfere with newly implemented recommendations of social distancing, SMS were no longer sent after March 24, 2020, such that 10 people did not receive the full second cycle of the text messages. In early Marchcase numbers were still very low in Indonesia (and none in Aceh) and there were no restrictions in place.

Figure 3.1. Intervention timeline



The messages were sent out by the research team using the bulk SMS gateway provider *bulkgate*. We received delivery reports from the portal stating which messages failed to be delivered.

Treatment assignment was done in a random draw after baseline data collection in Stata 14 using the procedure proposed in DIME (2019). Half of the phone numbers were randomly allocated to the treatment group, which received the full intervention, while the control group received no intervention. Interviewers were fully blinded to treatment assignment, and could only infer treatment status from the answers the respondents gave at endline (in which the reception of messages was assessed after the screening behavior). Respondents were not aware of the existence of a control and treatment group throughout the study.

3.3.2 Estimation Strategy

We assess the impact of our intervention using intention-to-treat and local-average-treatment-effect estimates. Our regression specifications include the following outcome, treatment, and control variables, all of which were specified in the pre-analysis plan and implemented accordingly (Marcus et al., 2020).

3.3.2.1 Outcome Variables

Our primary outcome is screening uptake, which is measured in two ways. First, we use self-reported data at endline on whether respondents went to any diabetes or hypertension screening within the intervention period.[10] Secondly, we measure whether respondents went to at least one of the two *Posbindu* dates specified in our text message intervention.

Secondary outcomes are SMS-related knowledge, broader diabetes and hypertension knowledge, and household spillovers. SMS-related knowledge aims to capture the direct

[10] We further pre-specified the aim to measure screening uptake across all villages in the sample districts using *Posbindu* attendance rates from administrative data, but full access could not yet be granted.

effect of the information that is transmitted in the messages. This is measured by a count index from 0 to 7, which increases by one for each correctly answered question that relates to the message content. All dimensions are measured by separate survey items that are part of the larger block of knowledge and screening questions (refer to appendix Table A 3.4 for the list of questions). We assess broader diabetes and hypertension knowledge to evaluate any knowledge impacts beyond the pure message content, for example through information obtained from the health staff during screening, or through information seeking. We measure broader diabetes and hypertension knowledge with an index derived from a model of the determinants of health seeking behavior (Becker, 1974; Janz and Becker, 1984). The index includes items that can be influenced by information into a clear direction. An increase in the index therefore reflects both an increase in knowledge and should, as the model hypothesizes, increase the propensity to take up screening services. We measure the individual dimensions using the survey items displayed in appendix Table A 3.5. For the main results, we use a count index that increases by one with each correctly answered knowledge question. To test the sensitivity of this result, we employ principal component analysis to reduce the dimensions to one variable, weighted by their explanatory power. This index gives a holistic picture of health knowledge with a focus on diabetes and hypertension.

We measure household spillovers through a binary variable indicating whether any other household members went for diabetes or hypertension screening within the intervention period.

3.3.2.2 Treatment Status

Treatment is defined in two ways. First, we categorize respondents into treatment and control group according to their randomized status. Secondly, we define a "treatment exposure" variable, which indicates whether the respondent received all three messages in one month and can recall the content of at least one message. The former is measured using delivery reports from the bulk SMS provider. The latter is a self-reported measure collected at endline. It is based on listing at least one of the elements of our text messages when asked about the content of the NCD/ screening related message in an unaided recall question, if the respondent claims to have received such a message.

3.3.2.3 Variables for heterogeneous treatment effects

We measure risk and time preferences with one self-reported baseline survey question each, taken from and validated by the Global Preferences Survey (Falk et al., 2018, 2016). Patience is elicited by asking respondents to indicate how generally willing they are to give up something today in order to benefit from it in the future (on a scale from 0 to 10). Willingness-to-take risks is elicited by asking respondents to indicate on a scale from 0 to 10 how generally willing they are to take risks.

3.3.2.4 Control Variables

We measure age, sex, education, and phone ownership using self-reported survey questions. Furthermore, we construct a wealth index based on self-reported asset ownership using the standard DHS approach. All control variables were elicited at baseline.

3.3.2.5 Regression Specifications

We estimate treatment effects on primary and secondary outcomes in the following framework:

a) Intention-to-treat (ITT)

$$Y_i = \alpha + \beta Treat_i + \delta Control_i + \varepsilon_i \tag{3.1}$$

where Y is our outcome variable (screening uptake in the main specifications and household spillover effects, SMS-related knowledge, and broader hypertension and diabetes knowledge in secondary analyses), *Treat* is an indicator variable for treatment status, and *Control* denotes the variables age (continuous), sex (indicator for female), education (none as base category, indicators for primary, lower secondary, upper secondary, tertiary education), wealth (in quintiles, with lowest as base category), and phone ownership[11].

[11] Due to a technical problem, phone ownership was not elicited for 7 individuals. We created a separate indicator for missing phone ownership information to keep them in the estimation sample. Neither phone ownership nor the indicator are significantly different from zero in the regressions.

b) Local Average Treatment Effect (LATE)

Additionally, we estimate the local average treatment effect using an instrumental variable approach (Imbens and Angrist, 1994). Specifically, we use assigned treatment status to instrument the treatment exposure variable.

$$Exposed_i = \eta + \theta Treat_i \ + \pi \ Control_i + \upsilon_i \tag{3.2}$$

$$Y_i = \alpha + \beta \widehat{Exposed}_i \ + \delta \ Control_i + \varepsilon_i \tag{3.3}$$

We explore potential heterogeneities in treatment uptake along time and risk preferences using the following specification:

$$Y_i = \alpha + \beta Treat_i + \gamma Trait_i + \theta Trait_i * Treat_i + \delta \ Control_i \ + \varepsilon_i \tag{3.4}$$

Where $Trait$ is the respective continuous indicator of baseline risk or time preference.

Standard errors are clustered by phone number. For all main hypothesis, p-values will be adjusted for multiple hypothesis testing following the Benjamini-and-Hochberg method (Benjamini and Hochberg, 1995) as a robustness check.

3.3.3 Data and Sample Characteristics

The baseline sample was drawn in a two-stage stratified random sampling procedure. First, we randomly drew 147 villages from a complete list of villages in the districts Aceh Besar and Banda Aceh. This draw was stratified by district to have an equal number of villages from the mostly rural Aceh Besar and the mostly urban provincial capital Banda Aceh (refer to appendix Figure A 3.1 for a map of the sampled villages). Within the villages, we selected households using a random walk following the procedure described in appendix A 3.2. Around half of the identified houses were found to be occupied, out of which 85% agreed to undergo the short eligibility check. The eligibility criteria ensured that the respondent would be recommended to be screened on a yearly basis (being over the age of 40[12]), and is neither diagnosed with diabetes or hypertension nor adheres to the recommended screening schedules. Out of those who did the eligibility check, one third of households was eligible[13]. If several household members met the inclusion

[12] We set the upper age limit of 70 to ensure that the respondent is able to complete the interview. Refer to appendix A 3.2 for a detailed list and reasoning for each in- and exclusion criterion.

[13] Out of those ineligible, 36% did not have a member between the ages of 40 and 70, 28% had a member with a prior diabetes or hypertension diagnosis, 15% went for regular screening, in 8% of households eligible members were not at home and only 6% of households had to be excluded because they did not have any mobile phone (Table A 2.1).

criteria, one was randomly chosen as respondent. This yielded a sample of 2,006 individuals[14]. The survey was introduced as a research study on the health of people over 40 in Aceh province, and respondents were asked to give a phone number through which they can be reached over the next months.

The endline survey was conducted from end of March until beginning of May 2020 and was shifted to phone interviews due to the outbreak of the COVID-19 pandemic (call pattern described in appendix Figure A 3.2). The analysis sample comprises of 1,386 individuals, 704 of the control and 682 of the treatment group. This implies a re-contact rate of slightly more than 70%[15], which is high for a telephone survey, but lower than we expected from the planned in-person endline data collection. The endline sample is hence slightly smaller than was deemed necessary in the power calculation (see appendix A 3.3).

We depict endline sample characteristics across treatment and control group in Table 3.1. The average age of the respondents is 50 years, slightly more than 60% of the sample population is female, and 73% have at least lower secondary education. Literacy in Bahasa Indonesia is over 90%. About two thirds of the respondents owned the phone which was used to contact them, the remainder were reachable through a phone owned by a family member or someone else. Compared to the same age group living in households with a mobile phone in the representative national socio-economic survey (SUSENAS 2017), our respondents are to a higher proportion female and slightly less educated, but generally similar across basic sociodemographic characteristics (see appendix Table A 3.7).

[14] An additional 94 baseline respondents were excluded before randomization as they had not supplied us with a valid telephone number until the end of data collection. This also led to the drop-out of one village in the final sample.

[15] 1,412 respondents could be re-interviewed. Due to missing information on whether screening happened after the start of the intervention (the month of screening was not reported) for 23 respondents, and missing information on age, gender and wealth quintile for one respondent each, the final analyses sample consists of 1,386 respondents.

Table 3.1 Endline sample characteristics across treatment and control group

	Control group			Treatment group			
	Mean	Standard deviation	N	Mean	Standard deviation	N	p-value
Age	50.26	8.22	704	49.52	7.85	682	0.088
Female	0.64	0.48	704	0.61	0.49	682	0.285
Highest level of schooling							0.850
None	0.04	0.19	704	0.03	0.18	682	
Primary	0.23	0.42	704	0.24	0.42	682	
Junior Secondary	0.23	0.42	704	0.21	0.41	682	
Senior Secondary	0.35	0.48	704	0.36	0.48	682	
Tertiary	0.15	0.36	704	0.17	0.37	682	
Literacy	0.91	0.29	568	0.93	0.26	555	0.160
Wealth quintile							0.389
1	0.22	0.41	704	0.19	0.39	682	
2	0.19	0.39	704	0.18	0.38	682	
3	0.19	0.39	704	0.22	0.41	682	
4	0.20	0.40	704	0.19	0.39	682	
5	0.20	0.40	704	0.22	0.42	682	
Own phone	0.64	0.48	700	0.68	0.47	679	0.101
Joint F-test							0.277

Means, standard deviation and number of observations of main respondent characteristics by treatment group; p-values based on t-tests of difference in mean between treatment and control group, except in the case of education, wealth quintile, and the total, where we used F- tests on joint significance of the different levels respectively variables.

Treatment and control group were balanced across all key variables of interest at baseline, except for phone ownership, which was slightly higher in the treatment group (see appendix Table A 3.6). At endline, respondent age is slightly lower in the treatment group and the share of phone owners remains slightly higher. As displayed in appendix Table A 3.8 to Table A 3.10, there was no differential attrition between treatment and control group. There are no statistical differences in the demographics between the individuals of the treatment and control group lost to follow-up, except for a lower baseline disease knowledge in the treatment group at 10% significance. However, independent of treatment status, respondents who were lost to follow-up seem to be to a higher proportion female, less educated and knowledgeable about NCDs, less wealthy, and to a lesser proportion phone owners. These differences likely occur due to the need to shift the administration of the survey to the phone: Additional analyses reveal that phone ownership is more likely across younger, male and better educated individuals from households in the fifth wealth quintile. If controlling for all base characteristics simultaneously, having no educational degree and not being the phone owner are the only significant drivers of attrition (appendix Table A 3.11).

According to the delivery reports, at least one full cycle of intervention messages was delivered in 97% of cases before one of the Posbindu dates. For 84% of our sample, we have also self-reported measures of exposure[16]: Out of those who received at least one full cycle, 30% could correctly recall at least one item of the message content, indicating that the messages were not only delivered, but also received, read, and understood. Consequently, around 28% of the treatment group constitute the exposed group in the LATE estimation.

3.4 Results

3.4.1 Screening uptake

We find that our intervention had a positive effect on screening uptake of the message recipient (Figure 3.2). In the intention-to-treat analysis, treatment increased screening uptake from 33% in the control to 40% in the treatment group. This is an increase by around 6.6 percentage points (p.p.) or 20% at a statistical significance level of less than 1%. This effect is robust in all pre-specified model specifications (Table A 3.12), adjustments for multiple hypothesis testing (Table A 3.13) or alternative estimation strategies (Table A 3.15).

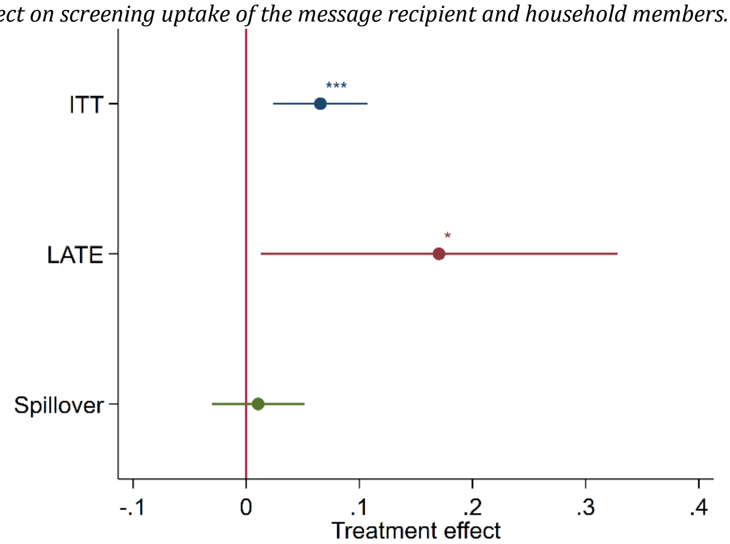
When treatment exposure (having received the full cycle of text messages and being able to recall message content) is instrumented by treatment status, the effect is more than twice as high (17 p.p.), which indicates the potential for a higher treatment effect if barriers to message reception are reduced. In section 3.4.4, we explore the main barriers from sending up to acting upon the messages in detail. It needs to be mentioned that the precision of the LATE estimate is lower than for the ITT due to the above-mentioned reduction in the sample and hence a loss in statistical power.

The effect on screening uptake of the message recipient did not lead to within-household spillover effects. We do not find evidence for other household members taking up screening more often, neither in the aggregate as displayed in Figure 3.2, nor when restricting the sample to household members in the same age group as our respondents

[16] As the questions about message content were asked only in the very end of the interview, the estimation sample for the LATE excludes 204 respondents who terminated the interview before this question. Respondents in this subsample are to a higher proportion male, to a lesser proportion phone owner, but otherwise similar.

(between the age of 40 and 70). Receiving the messages through another household member's phone or a family phone could have increased other household member's attention to the messages, but even if accounting for phone ownership, we do not find evidence for substantial spillover effects (Table A 3.20).

Figure 3.2 Treatment effect on screening uptake of the message recipient and household members.

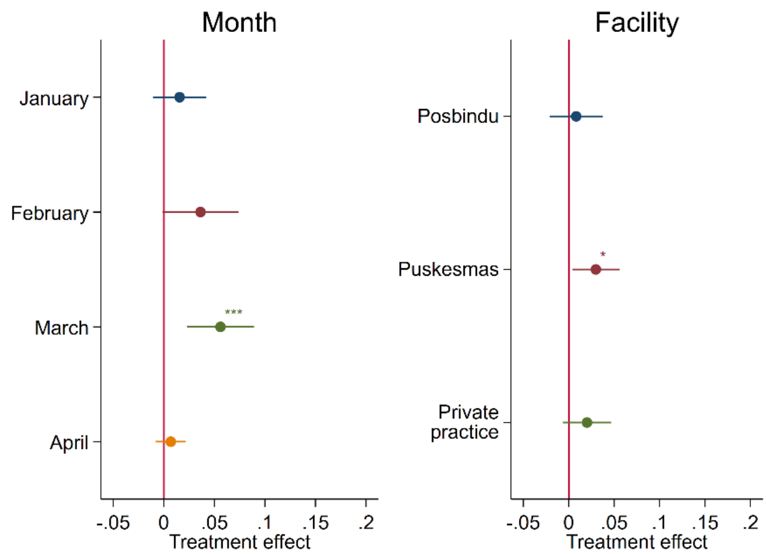


Point estimates of the treatment coefficient from equation 1 (ITT), the instrumented treatment coefficient from equation 3 (LATE) for the message recipient and other household members (ITT), controlling for age, gender, wealth and phone ownership; see Table A 3.12 for tabular display with and without covariates; displayed with 90% confidence intervals; * p < 0.1, ** p < 0.05, *** p < 0.01

To understand the treatment effect of the message recipient better, we further examine the timing and location of screening (Figure 3.3). For all respondents, we see low screening uptake in November and December, and increasing visits to testing facilities from January on. Even though treatment is positively correlated with screening uptake in all months, it is only statistically significantly different from zero in March and is comparable to the size of the aggregate treatment effect. This suggests a concentration of the treatment effect after having received the second set of text messages. When disaggregating the treatment effect according to screening provider, we see that the effect is not driven by treatment group respondents going to the specific *Posbindu* meeting that was mentioned in the messages, but rather by going for screening at the *Puskesmas*. Even though the focus of the messages was on the *Posbindu* meeting, the *Puskesmas* was always mentioned as a point of contact, and might have posed a suitable alternative for some respondents.

Apart from merely going for screening, we see that this uptake translated in significantly higher blood pressure testing rates and checks of the medical history in the treatment group. Blood glucose testing, physical measurements, and other blood checks are also positively correlated with treatment, but not statistically significantly different from zero (Table A 3.23).

Figure 3.3 Treatment effect on message recipient screening uptake by month and facility



Point estimates of treatment coefficient from equation 1 with different binary screening uptake indicators as outcomes (coded as 1 if the individual indicated to have gone to screening in the respective month/ facility and 0 otherwise); controlling for age, gender, wealth and phone ownership; see Table A 3.21 and Table A 3.22 for tabular display; displayed with 90% confidence intervals; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.4.2 Channels

We find that the intervention did not increase knowledge, as shown in Table 3.2. We can neither detect a treatment effect for the specific knowledge items mentioned in the text messages, nor for general diabetes and hypertension knowledge. These patterns hold when defining the indices via PCA rather than as a count index (Table A 3.16), and for each element of the respective index (Table A 3.17, Table A 3.18, Table A 3.19). In addition, the point estimates are small with rather precise confidence bounds, so that these results can be interpreted as a null effect. It is hence likely that the intervention increased screening uptake of the message recipient purely via a channel that does not imply an updating of beliefs through new information.

Table 3.2 Treatment effect on knowledge outcomes

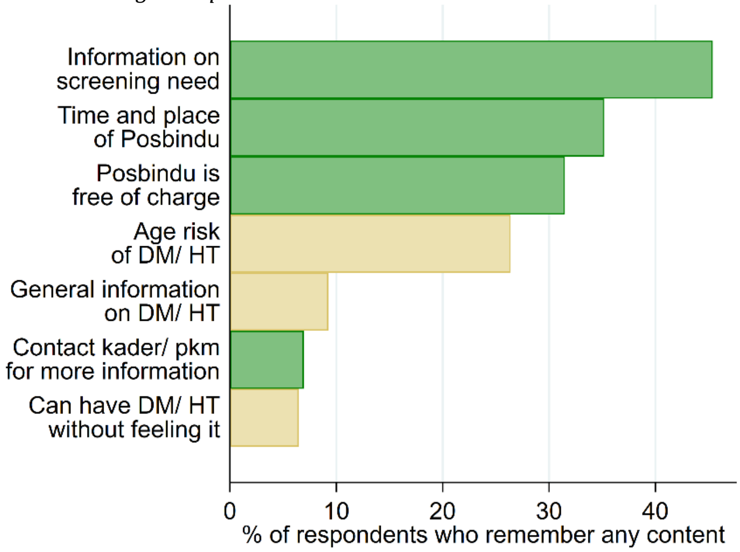
	(1) SMS knowledge	(2) SMS knowledge	(3) General disease knowledge	(4) General disease knowledge
Treated	-0.0009	-0.0029	-0.0365	-0.0570
	(0.0609)	(0.0610)	(0.0616)	(0.0597)
Covariates	No	Yes	No	Yes
Observations	1088	1088	1042	1042

ITT estimates on SMS-related and general disease knowledge indices following equation 1. Both indices are standardized to a sample mean of 0 and a standard deviation of 1. Covariates are age, gender, wealth and phone ownership. Standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3.4 displays which information the respondents who report to have received any text message on *Posbindu* are able to recall. We see that these respondents tend to remember the actionable elements of the messages (green), rather than the disease information components (yellow). More precisely, the principal directive that the respondent should be tested for diabetes and hypertension is remembered most frequently – namely by 45% of all respondents, who self-reported being exposed to the treatment. This is followed by logistical components, as 35% and 31% of these respondents remember that the messages contained information on when and where *Posbindu* takes place as well as that it offers free NCD check-ups. We interpret this as evidence for making existing information more salient to the message recipients, as even in the control group almost all of the 44% of respondents, who knew of the Posbindu program at endline, were aware that it is free of charge and where it takes place.

Similarly, the reported reasons for no screening indicate that our intervention works through increased salience rather than shifts in beliefs: Nearly all respondents who did not attend any screening since the baseline visit reported they did not attend any screening because they were not ill (93%), and only few mentioned time constraints (15%). This pattern is similar to the reasons at baseline and fits the null effect on disease-related knowledge. Hence, more intensive interventions might be needed to alter the beliefs which prevent a large share of the population from regular screening.

Figure 3.4 Ability to Recall Text Message Components



3.4.3 Heterogeneous treatment effects

We cannot detect any heterogeneous effects across time and risk preferences (Table 3.3). In most cases, the standard errors are also too large to retain the original treatment effect. One reason for not detecting any heterogeneous treatment effects might be that these self-reported measures are not strongly correlated with the screening decision in the intervention period. At baseline, we observed a significant correlation between patience and hypertension screening within the last year, but no correlation for willingness to take risk. Another reason might be that the endline sample is too small to detect any heterogeneity.

Table 3.3 Analysis of Heterogeneous Effects

	(1) Screened	(2) Screened	(3) Screened	(4) Screened
Treated	0.055	0.082	0.090	0.118**
	(0.051)	(0.051)	(0.057)	(0.057)
Willingness to take risk	0.001	0.007		
	(0.007)	(0.007)		
Treated x Willingness to take risk	0.001	-0.004		
	(0.010)	(0.010)		
Patience			0.005	0.008
			(0.006)	(0.006)
Treated x Patience			-0.006	-0.009
			(0.009)	(0.009)
Covariates	No	Yes	No	Yes
Obs.	1386	1386	1386	1386
Control group mean	0.3310	0.3310	0.3310	0.3310

Results of regressing the binary screening indicator on the binary treatment indicator, the respective time or risk preference as well as their interaction following equation 4; controlling for message recipient age, gender, wealth, and phone ownership; Standard errors clustered at the phone number in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.4.4 Implications for scale-up

In the following explorative analyses, we further investigate the scale-up potential and limits to the effectiveness of the intervention. We first focus on what hinders message recipients from reading the messages and hence being exposed to the treatment to shed more light on the potential to reduce the discrepancy between ITT and LATE. Then, we explore differences in screening experience between the three main facility types to assess the role of accessing a specific screening service. Finally, we provide a cost estimate of this intervention.

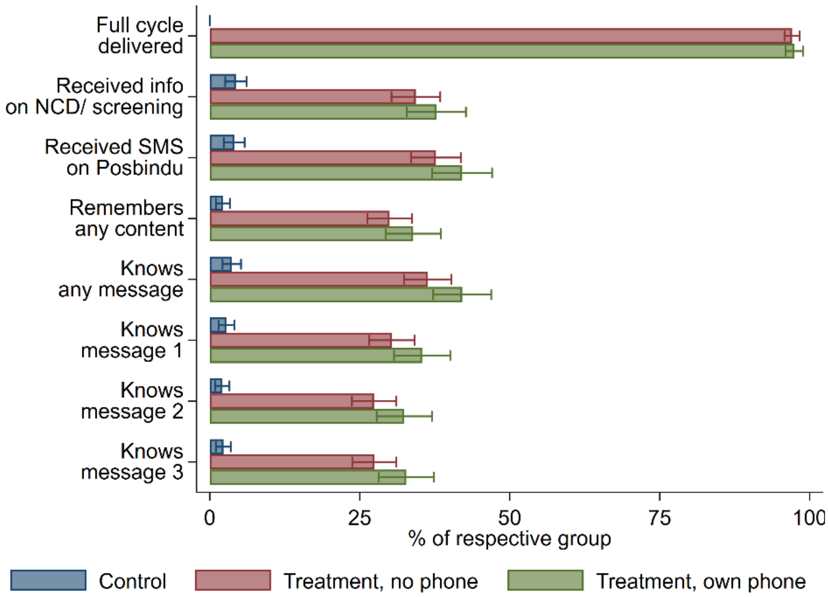
3.4.4.1 Treatment exposure

For an allocated message recipient to be exposed to the treatment, s/he needs to receive, become aware of, read, understand, and trust the messages. As stated above, message delivery by the provider does not pose a barrier. Rather, being aware or remembering to have received any information on screening appears to be the major barrier (Figure 3.5). Phone ownership appears to ease this barrier substantially: While 26% of the treated individuals without a phone remember to have received any information, the share increases to 37% among the treated phone owners. A main issue might be the transfer of the information from the owner to the respondent: 51% of the phone owners who were assigned by the respondents as contact person admitted they transmit messages only sometimes, rarely, or never (response rate: 40%). Once this barrier of becoming aware of the information is overcome, most respondents are able to remember some message content or remember to have received the messages after reading them out. Hence, with an increase in phone ownership over time, the exposure to the intervention can be expected to rise.

We do not find that illiteracy is a binding constraint to reading the messages as only 5% of the sample population reports to be illiterate and 80% face never or only rarely problems when reading Bahasa Indonesia. Alternatively, our messages might be ignored if there is already an overload of information via SMS. We find that around half of the sample receives any text message on a daily basis and on average around four messages per day. Even though this does not seem overly high, phone owners report to receive more messages. We also see that 90% of the respondents who receive SMS in general receive advertisements and 60% would like to receive less advertisement. However, our messages are rather perceived as an official announcement and not an advertisement, thus it is unlikely that our messages are perceived as a burden. This is strengthened by the statement that 68% of respondents, who recall receiving the text messages, report they found the information very relevant to them, and 30% report they found it somewhat relevant. Thus, associating the text messages with the health services might mitigate any information overload.

Taken together, any scale-up needs to consider that even though targeted more broadly, population groups who are more likely to be telephone owners (younger, male and more educated) will be more likely to be exposed to the intervention. See Table A 3.24 for a detailed list of socio-demographic and other baseline characteristics by different exposure measures.

Figure 3.5 Exposure to Treatment



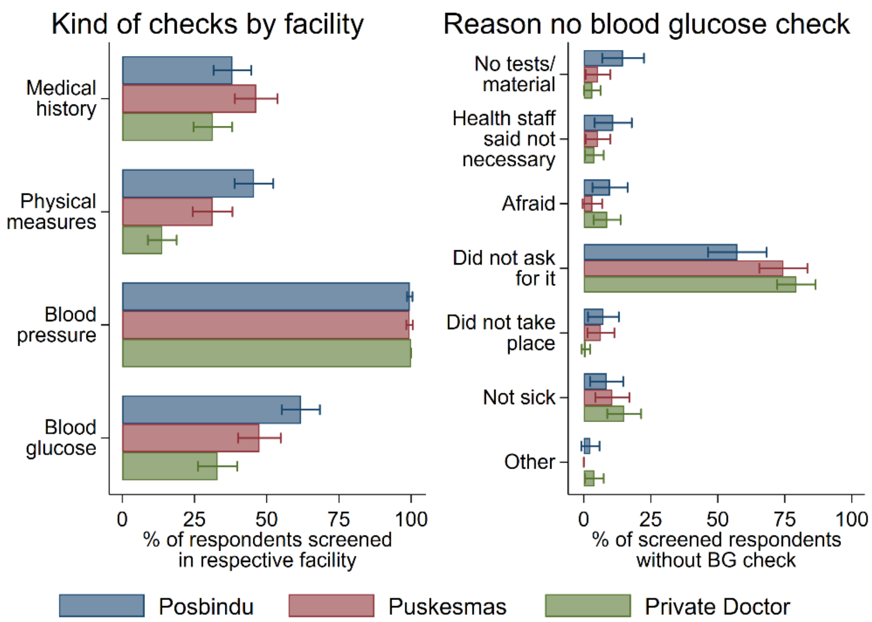
"Full cycle delivered" is based on the provider delivery reports, the remaining indicators are based on the respondent's self report at endline;"Knows any content" indicates whether the respondent could name any message content when asked in an open-ended question (compare Figure 3.4); "Knows any message" until "Knows message 3" is based on whether the respondent remembered the respective message when the enumerator read it out.

3.4.4.2 Screening services across facilities

Increased screening uptake can translate into improved control of the NCD burden the better the screening service. Our treatment effect is driven by respondents screened at the Puskesmas, but their recall of which services and recommendations for future screening were provided to them suggest that currently Posbindu offers the more comprehensive package. As depicted in Figure 3.6, nearly all respondents who reported to have undergone a screening report a blood pressure reading. However, which further checks were performed varied across facilities. While 62% of the Posbindu visitors had a blood glucose measurement, this only applies to 47% of the Puskesmas visitors and 33% of the visitors of private practices. In these two facility types, more than two thirds of the visitors who did not get a blood glucose check missed it, because they did not ask for this specifically. This might be caused by different reasons for visiting the respective facility type, but we cannot disentangle this further with our data.

Posbindu visitors were also more likely to report that they were asked to return for blood pressure screening another time, especially compared to visitors of private practices. As our treatment effect is mainly driven by increased use of the Puskesmas services, any potential scale-up might thus consider either increasing awareness towards blood glucose screening to ensure it is actively asked for at the Puskesmas, or stressing the benefits of Posbindu to nudge participants into the more specialized Posbindu.

Figure 3.6. Medical checks performed by facilities



3.4.4.3 Cost estimation

To improve the comparability of our text message reminders with other demand-enhancing interventions, we estimate the costs of our intervention per targeted person and per additionally screened person (Table 3.4). In the first column, we consider costs directly related to the intervention, i.e., costs of sending out the text messages and of inquiring the village-specific Posbindu details, assuming that any implementer would be able to target recipients using a register, such as a health insurance database. We base this estimate on the complete treatment group, rather than only the endline sample for a conservative estimate that assumes no treatment effect on the individuals lost to follow-up. In the second column, we additionally provide estimates on the screening costs occurring to the health system in the form of medical staff and material. We assume that a person presenting at a facility would take up 15 minutes of time with a medical practitioner, and price this using wage data from the National Statistical Office (Badan Pusat Statistik, 2021). In addition, we calculate the costs for blood glucose tests with a point-of-care machine, assuming that 47% of the individuals accessing the service are screened for diabetes (as observed in our sample). As every health worker has an own blood pressure monitor, no additional costs are borne for a blood pressure reading. For the scale-up, we assume that Posbindu dates can be transmitted directly to the implementer at a fix cost, such that these costs are not included in the scale-up calculation. On this basis, we estimate that a scale-up would cost IDR 5,277 or USD 0.38 per targeted person, and IDR 129,293 or USD 9.21 per additionally screened person.

Table 3.4. Cost estimates

	Intervention costs	Total costs	Scale-up (per Person)
SMS	4,651,101	4,651,101	4,500
Request for Posbindu dates	1,000,000	1,000,000	
Medical staff		640,313	638
Blood glucose test		140,121	140
Per targeted person	5,629	6,406	5,277
Per additionally screened person	137,899	156,943	129,293
Per targeted person (USD)	0.40	0.46	0.38
Per additionally screened person (USD)	9.83	11.18	9.21

All prices denoted in IDR, unless noted differently. Costs are calculated based on the targeted 1,004 respondents of the treatment group after the baseline. SMS costs were EUR 300 and are converted with an exchange rate of 15503.67 IDR/EUR. Costs for medical staff were taken from the National Statistical Office (BPS) as monthly net wages for employees in the health sector with university degree and doubled to receive an upper bound of gross wages to the health system (Badan Pusat Statistik, 2021). It was assumed that medical staff would spend about 15 minutes on each examination. It was assumed that point-of-care machines were used for the blood glucose check, as they are used at the Posbindu, such that one test would cost IDR 7,275, including lancet, stick, gloves, and disinfect. Costs for medical staff were calculated for the share of respondents who went to a screening facility due to the intervention (6%) times the share of treatment group respondents who were reached for the endline interview and for whom screening data was non-missing (68%). Costs for blood glucose tests were calculated for the share of respondents who went to a facility due to the intervention (6%) and conducted a blood glucose check (47% of the visitors) times the share of treatment group respondents who were reached for the endline interview and for whom screening data was non-missing (68%). USD were calculated using an exchange rate of 14032.02 IDR/USD. All costs were assessed between November 2019 and February 2020. If the targeted respondents who were not reached for the endline interview or for whom screening data is missing had the same treatment effect as the observed respondents, costs would reduce to USD 6.69 for the intervention costs, USD 8.04 for the total costs, and USD 6.70 for the scale-up costs per additionally screened person.

3.5 Discussion and conclusion

Like many other LMICs, Indonesia suffers from a high and increasing burden of diabetes and hypertension. Despite providing opportunities for easily accessible and free screening, uptake remains limited. Diabetes and hypertension screening are specific cases of preventive health behavior that can avoid or postpone complications rather than the disease itself, and are a relatively new component in the Indonesian health system. Thus, it is unclear whether light-touch policy measures proven effective in high-income countries, or for different preventive health behavior work in this context. We conducted an RCT to test whether the uptake of screening programs can be increased with a low-touch text messaging intervention targeted at at-risk individuals.

We find that sending two sets of three text messages before two village-based screening meetings increased screening rates by approximately 6.6 percentage points from 33% in the control group. For participants who received at least one full treatment cycle and remembered any message content, this translates into an increase by approximately 17 percentage points. We do not find a significant difference in the SMS-conveyed or general disease knowledge between treatment and control group. Also, we cannot detect any spillover effects within households, or heterogeneous effects along levels of patience or willingness-to-take-risks.

The intervention appears to work as a reminder rather than conveying new information. Even though our pre-studies revealed gaps in disease knowledge, neither the information that was mentioned in the message nor a larger set of facts and beliefs about diabetes and hypertension changed as a result of the intervention. We find several hints that the intervention might have increased the salience of the decision to take up screening and hence rather works through addressing behavioral barriers related to procrastination or limited attention. First, the elements that respondents remember most from the messages are the general need for screening and its logistics, which were both widely known at baseline already. Secondly, message recipients react more strongly after receiving the second set of text messages and opt to get screened at the Puskesmas rather than the explicitly mentioned Posbindu meeting. Nevertheless, the awareness of a concrete date for screening might have been perceived as a deadline and pushed the recipient to no longer postpone asking for a preventive check-up at the Puskesmas at their convenience.

Possibly, the personalization of the text messages was effective in increasing the relevance for the recipients but did not give them the notion to share this information, such that no spillovers occurred within households. Alternatively, spillovers might exist but be too small to be detectable in our sample. Similarly, we cannot detect heterogeneous treatment effects based on risk or time preferences. One reason might be the lack of a meaningful update of beliefs on disease risk and treatment efficacy. On the other hand, the countervailing forces of the lotteries of becoming ill and being effectively treated might cancel out any heterogeneous effects. For patience, however, we would have expected that the reminder channel alone would impact respondents with different degrees of patience differently.

The size of our treatment effect is comparable to other SMS interventions on preventive behavior in LMICs: With a risk ratio of 1.174, our findings lie between the results from the systematic reviews on immunization rates by Mekkonen et al. (2019) (RR: 1.11) and Jacobson Vann et al. (2018) (RR: 1.29). With an odds ratio of 1.284, the effect size is slightly lower than the average effect size of studies on STD detection as reported by Taylor et al. (2019) (OR: 1.73). Thus, even though the uptake of immunization or STD screening might underlie very different barriers compared to hypertension or diabetes screening, the impact of text messages can be similar. In addition to finding increased screening attendance after adding SMS reminders to routine invitations in the UK, Sallis et al. (2019) found that adding the prompt to screen in a specific month increased the effectiveness, suggesting that mentioning a concrete deadline might counteract procrastination in this high-income setting. Similar to our results on knowledge transmission, recent evidence on broadcasting SMS to increase COIVD-19 preventive behavior found changes in behavior despite no updates in knowledge (Banerjee et al., 2020).

An advantage of text message interventions is their comparatively low cost. We estimate that our intervention costs USD 11.18 per additionally screened person, incorporating the costs of the screening service. A scale-up might decrease these costs even further, especially if screening dates can be centrally collected. Thus, such interventions can be used to reach out to wide parts of the population, such as the population over the age of 40. For people at higher risk due to preconditions, more intensive interventions might be a good addition to push screening rates even more, albeit at higher costs: Using personally delivered invitation letters and pharmacy voucher, de Walque et al. (2020)

measure an increase in screening rates by even 15 to 30 percentage points at about 60 USD per screened person. Hence, combining large-scale low-touch interventions as ours with intensive interventions in more selected higher risk groups might be a route to reach the population while keeping the costs balanced.

We conclude that our intervention is cost-effective and has the potential to be scaled up in the Indonesian setting, keeping in mind the limitations that are inherent to SMS interventions. First, being targeted and exposed to the intervention highly depends on owning and regularly using a mobile phone. This implies people who are more likely to own a phone, such as younger, male and more educated individuals are more likely to be reached, and not necessarily the most vulnerable. As mobile phone ownership, network coverage as well as familiarity in usage increases, so does the potential to reach a broader set of the population. As of now, we do not see evidence that our messages induced an overflow of information, but during implementation this needs to be monitored closely and implementers need to bear in mind to target carefully and keep messages to the necessary minimum. Secondly, who is reached by the intervention strongly depends on how the target population is sampled. At scale-up, collecting numbers by visiting households is likely not feasible and would increase the costs substantially. At the same time, previous literature established that personalization matters, such that mere broadcasting might not be advisable. Instead, drawing numbers from an existing register would be ideal. With the expansion of public health insurance in many middle-income countries, health insurances might be suitable implementers. In Indonesia, for example, the recently established, centrally administered health insurance JKN covers the majority of the Indonesian population and could likely target its members based on age and potentially even previous diagnosis.

This study comes with some limitations regarding the recruitment of participants and the telephonic endline data collection. Apart from being unfeasible for scale-up, we cannot rule out that our in-person baseline survey already worked as a reminder to take up screening 2-3 months prior to the intervention. Both treatment and control group saw higher propensities to be screened from January onwards, so that the high control group uptake might in part be driven by our baseline visit. However, we can still detect a systematic difference between treatment and control group, especially as time to the baseline interview increased. Secondly, measuring the main outcome as self-report is subject to the concern of misreporting and social desirability. To minimize this concern, we added detailed follow-up questions on what happened at the screening visit and the consistency of the answers gives us confidence in the main result. Similarly, part of the reason that we do not find an update of beliefs could be that many knowledge questions were posed in a strict way, like asking for the risk factors in an unaided recall question. It might be that more nuanced updates of beliefs happened, but these are unlikely to explain the main treatment effect.

Switching the endline data collection to the telephone was the only possibility after the outbreak of the COVID-19 pandemic, but poses additional limitations. First, we could only re-interview 70% of the sample, with significant attrition across several socioeconomic characteristics. Though we do not expect that the attrition was selective due to factors other than the mode of contact, the true size of the treatment effect might be slightly different when taking the full initial sample into account. To the extent that phone ownership is correlated with both, a higher rate of recall receiving the message and a lower probability to be lost to follow-up, it is likely that our treatment effect would be slightly smaller in this case. Secondly, respondents may be less trusting over a telephone call in comparison to face to face interviews conducted in the privacy of their own home. As our study team visited the respondents during baseline, we think this problem might be less severe compared to phone surveys when the call is the first point of contact. To minimize this concern further, we assigned the enumerator who visited the respondent at baseline whenever possible and re-introduced our team and the survey in the beginning of the interview.

Our study opens several areas of complementing research. First, a scale-up study without baseline contact would be needed to validate the effectiveness of our study. Fielding the intervention in a larger sample would also offer the opportunity to test for the discussed mechanisms and heterogeneities more clearly. A second important extension would be to include longer-term outcomes such as regular or repeated screening. Beyond the intervention itself, our results showed that substantial misconceptions on who should be screened and when prevail despite including this information in the messages, calling for designing and testing more intensive interventions to address this gap.

With the expansion of mobile phone coverage around the globe, policy makers gain access to a new toolbox of low-cost and low-touch interventions at scale. We show that text messages can induce preventive health behavior and reduce the screening gap for fairly new, yet severe contributors to the health burden of middle-income countries. As universal health coverage expands and is digitized, such text messages can become cost-effective and easily customizable measures to remind a target population of preventive health behavior and stimulate new health care habits.

4 Mental distress and its association with sociodemographic and economic characteristics in Aceh, Indonesia

Joint work with Marthoenis, Aiyub, Suryane Sulistiana Susanti, Sebastian Vollmer

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Abstract

The role of sociodemographic and economic characteristics in mental distress has been rarely investigated in Indonesia. In this study, we investigate the prevalence of common mental disorders (CMD) and identify associations between mental distress and sociodemographic and economic characteristics among communities living in urban and rural (peri-urban) areas.

We conducted a community-based household survey in the province of Aceh, Indonesia, in 2018. The 20-item Self Reporting Questionnaire (SRQ-20) screening tool was used to measure symptoms of CMD. Information on sociodemographic characteristics, family functioning, labor market outcomes and healthcare costs was collected. Multivariate regressions were conducted to analyze the relationships between the measures of mental distress and sociodemographic and economic characteristics.

We found that 14% of the respondents had CMD symptoms. SRQ-20 scores were higher for female, older and lower-educated individuals. CMD prevalence was higher among non-married participants and clustered within families. Participants with CMD perceive their families as performing significantly better in the dimensions of affective involvement and behavior control compared with their counterparts. Their work was more often affected by negative feelings; they were also twice as likely to report a recent physical or mental health complaint and faced twice the treatment costs compared with their non-affected counterparts.

The prevalence of mental disorders is especially high in disadvantaged population groups. Moreover, mental distress is associated with a lower perceived productivity and a higher physical health burden.

4.1 Background

Depressive and anxiety disorders belong to the ten largest global contributors to Years Lived with Disability (YLD) (Vos et al., 2017). In 2016, both causes had a worldwide prevalence of 250 million cases each (Vos et al., 2017). Despite this large disease burden, substantial treatment gaps exist, especially within low- and middle-income countries (LMICs); population-based studies revealed that less than 10% of all people with depression and less than 3% of all people with anxiety disorders receive adequate care in LMICs (Alonso et al., 2018; Thornicroft et al., 2017).

This treatment gap is particularly worrisome as depressive and anxiety disorders, also referred to as common mental disorders (CMD), can have detrimental impacts on further facets of well-being. CMD are associated with poor physical health and predict the onset of chronic physical conditions (Kessler, 2012; Scott et al., 2016). People with CMD have worse role functioning, and their families show poorer family functioning (Du et al., 2014; Friedmann et al., 1997; Keitner, 1990; Kessler, 2012). Finally, the financial burden of CMD can be substantial: a recent review found that adults with depression face on average the 2.6 times direct health care costs and 2.3 times indirect costs of their non-depressed counterparts (König et al., 2019). However, all included studies were conducted in high-income countries; comparable data for LMIC is widely missing or focuses on poverty proxies rather than costs (Lund et al., 2010). One exception are the World Mental Health Surveys, which show a negative correlation for serious mental illnesses with unemployment and earnings (Kessler, 2012; Levinson et al., 2010).

This data gap also exists in Indonesia. While some studies investigated which sociodemographic groups are affected by CMD, the evidence on costs associated with mental disorders is thin (Das et al., 2009; Hanandita and Tampubolon, 2014; Tampubolon and Hanandita, 2014; Peltzer and Pengpid, 2018). Two studies found a significant correlation between unemployment and poor mental health (Hanandita and Tampubolon, 2014; Peltzer and Pengpid, 2018); another two found a negative association between expenditure levels and mental health (Hanandita and Tampubolon, 2014; Tampubolon and Hanandita, 2014), while yet another found no significant association for expenditure (Das et al., 2009). A detailed analysis of the possible cost structure of mental illnesses is missing in all of these studies.

This study focusses on the province of Aceh, where the past fifteen years have seen efforts to improve the situation of people with mental disorders. The mental health care system was shifted towards community mental health services (Marthoenis et al., 2016b; Prasetiyawan et al., 2006) and policies were initiated to end traditional practices of physical restraint and confinement ("Pasung") (Puteh et al., 2011). While the prevalence of CMD in Aceh has historically been high (Kementerian Kesehatan, 2007, 2013), in 2018 it lowered to 9% (close to the national average) (Kementerian Kesehatan, 2018). Still, previous research suggests that stigmatization and traditional perceptions of mental illness might lead to a low rate of case detection and thus to undertreatment (Marthoenis et al., 2016a).

This study aims to draw a comprehensive picture of CMD in Aceh, Indonesia. First, the overall prevalence and the affected populations are identified. Second, the association of CMD with health and economic factors is analyzed to evaluate the potential triple burden of CMD, poor health, and worse financial outcomes.

4.2 Methods

4.2.1 Data collection

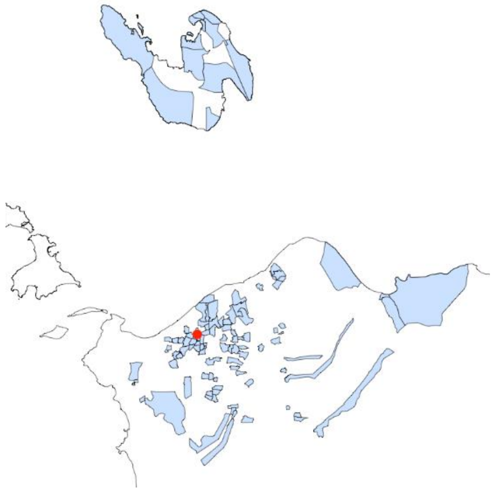
From February to April 2018, we conducted a cross-sectional household survey in the district of Aceh Besar[17] and the cities of Sabang and Banda Aceh in Aceh province, Indonesia. Within each district or city, subdistricts were randomly sampled using population weights based on population data from the regency's statistical office (BPS Kabupaten Aceh Besar, 2015; BPS Kota Banda Aceh, 2015). Within the subdistricts, villages were randomly sampled. The approached villages are depicted in Figure 4.1. Within the villages, households were sampled using a random walk scheme; if a sampled household was absent, it was visited again at another date and time. Within each household, all members[18] aged 17 years and older were asked to participate in the individual interview. Additionally, one member (preferably the household head/spouse) was interviewed for the general household questionnaire. Written informed consent was

[17] Due to feasibility, the following districts of Aceh Besar were excluded: Pulo Aceh, Lhoong, Lembah Seulawah, Leupung and Kota Jantho.

[18] Members are those identified by the key informant of the household as members.

obtained from each participant; refusal was possible for the complete survey as well as for each single item. The interviews were conducted by nursing students from Syiah Kuala University and the Nursing Academy Sabang, who undertook a two-day training prior to data collection. Ethical approval was obtained from Syiah Kuala University and the University of Göttingen.

Figure 4.1. Villages in the study sample



Administrative areas of the villages included in the study sample (universal transverse Mercator (UTM) projection zone 46) are depicted in light blue. The location of the Baiturrahman Grand Mosque in the city center of Banda Aceh is marked in red.

4.2.2 Measure of CMD

To measure CMD, we use the Self-Reported Questionnaire (SRQ-20) (Beusenberg et al., 1994; Harding et al., 1980). The SRQ-20 has been introduced by the WHO to screen for non-psychotic disorders in low- and middle income countries and has since been widely implemented (Ali et al., 2016; Beusenberg et al., 1994; Harding et al., 1980; van der Westhuizen et al., 2016) including in the study region (Irmansyah et al., 2010). The original instrument consists of 20 questions regarding the prevalence of somatic, cognitive and emotional symptoms over the past 30 days, measured on a 0-1 scale (No – Yes), thus adding up to a 0-20 scale. To adjust the SRQ-20 to local norms, we dropped the question on suicidal thoughts. An earlier study in Indonesia validated the full SRQ-20 for the cutoff 5/6 (SRQ-20≥6) to indicate the prevalence of CMD (Positive Predictive Value 60%, Negative Predictive Value 92%) (Ganihartono, 1996); this cut-off is also applied by the health surveys from the Indonesian Ministry of Health (MoH). We follow this cut-off despite removing the last item, thus obtaining a rather conservative estimate. The Cronbach alpha of the SRQ-20 in the present study was 0.813 which suggests a good internal consistency. The single items are depicted in Table A 4.1 in the appendix.

4.2.3 Further household and individual characteristics

The household and individual characteristics used for the analyses are shown in Table A 4.2 in the appendix. Gender, age and years of education serve as controls in the main analyses, and we use information on marital status, occupation, district, and reception of any state support to assess possible differences in the prevalence of mental distress across these groups. Reception of any state support is a variable collected at the household level and indicates whether any member of the household was a beneficiary of one of six public social support programs (Raskin, KIS, JKA, BSM, PKH and KKS).

Family functioning is measured using a shortened version of the McMaster Family Assessment Device (FAD) (Epstein et al., 1983). The items are grouped into six categories adapted from the McMaster Model of Family Functioning: problem solving, communication, roles, affective responsiveness, affective involvement, and behavior control, plus an extra category for general functioning. Each item asks for the level of agreement to a statement regarding one of these dimensions, ranging from “strongly disagree” (1) to “strongly agree” (4).

We assess associated costs by analyzing potential indirect costs (labor force participation, absenteeism, presenteeism) and potential direct costs (costs of treatment seeking), similar to König et al. (2019). Labor-related characteristics include data on employment status, weekly working hours and days as well as monthly payment. Moreover, we assess the subjective impact of mental distress on work productivity: we specifically asked whether participants’ work in the past 30 days had been affected by negative feelings, how many days of work had been affected, whether physical problems had been the reason for the negative feelings and whether the individual had sought treatment due to these feelings.

For the assessment of health care costs, we use self-reported information on the occurrence of any health complaints (physical or mental) over the past 30 days; whether treatment was sought and at which type of facility (multiple answers possible); how much time was spent on travelling, waiting and the treatment; and how much money was spent on travelling, treatment and medication.

4.2.4 Statistical analysis

We regress the scores of the SRQ-20 on age, gender and education to analyze the association of mental distress with these base characteristics using an F-test for joint significance. In the subsequent steps, we use these base characteristics as controls.

To identify which socioeconomic groups are affected, we employ a linear probability model regressing the indicator for CMD (SRQ-20≥6) on the respective socioeconomic characteristics controlling for age, gender and education and then predicting the prevalence of CMD over the groups of interest. To assess the association of family functioning with CMD, we use an ordered logistic model regressing each FAD item on the CMD indicator, controlling for age, gender and education. Finally, to analyze the costs associated with CMD, we regress the outcome of interest on the CMD indicator, controlling for age, gender and education, and then predict the outcome by CMD status. All models cluster standard errors at the household level. All statistical analyses were conducted with Stata SE 15.1 on MacOS.

4.3 Results

4.3.1 Participation rates

Overall, 821 households were approached; 640 (78%) agreed to participate, 132 were absent or busy, and the remainder refused or did not participate for other reasons. An average of 2.47 interviews were conducted per household. In total, the participating households consisted of 2107 adults, of whom 1490 (71%) were present and agreed to participate. In eight cases, the household questionnaire (but no individual interview) was completed; these cases were excluded in the following analysis.

4.3.2 Descriptive statistics

Table 4.1 depicts socio-demographic characteristics as well as the SRQ-20 and the SSS-8 measure of the respondents. Our sample consists of 62% women. 40% of the participants report current employment. Interestingly, 92% report having health insurance, indicating that universal health care coverage, as planned by the Indonesian government, is in feasible reach in the study region. Nearly half of the respondents (43%) report that they experienced some type of health complaint during the past 30 days, and 78% of them sought treatment. Using the cut-off as described above, we found a prevalence of 14% CMD. Even considering the reduction of the SRQ-20 to 19 items, the prevalence of CMD is much higher than found in the Ministry of Health's 2018 report (Kementerian Kesehatan, 2018).

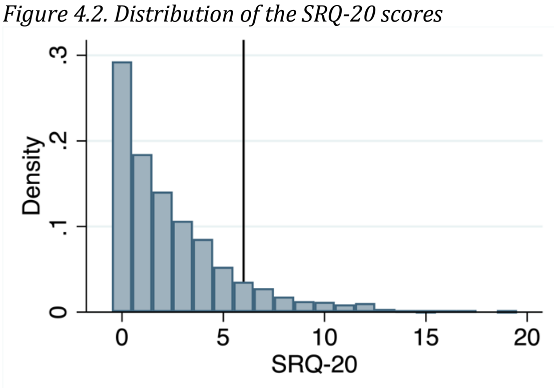
Table 4.1. Summary statistics for the sample population

	Mean/ Frequency	SD	N
Female	61.74%	0.4862	1490
Age	39.93	16.5041	1490
Highest grade completed (in years)	9.99	3.0966	1489
Is working	40.00%	0.4901	1480
Any health complaints	43.30%	0.4957	1485
Sought treatment	78.28%	0.4127	640
SRQ20	2.56	2.9601	1321
SRQ>=6	13.63%	0.3432	1321

SQR-20, 20-item Self Reporting Questionnaire. All self-reported incidence of any health complaints over the past 30 days. Only participants with health complaints were asked whether they sought treatment.

Figure 4.2 depicts the distribution of the SRQ-20 scores: they are quite smoothly distributed and have a high internal consistency (Cronbach's alpha: 0.813).

Figure 4.2. Distribution of the SRQ-20 scores



The vertical line marks the cutoff for CMD used in this study (SRQ-20≥6).

We found significant differences in the measure of mental distress across gender, age and education (Table 4.2). Female, older and less educated individuals experienced higher scores than did other population groups. These results were similar to previous findings in Indonesia (Das et al., 2009; Hanandita and Tampubolon, 2014; Tampubolon and Hanandita, 2014). As these three characteristics were presumably unaffected by mental distress in the past 30 days, we use them as controls in our subsequent analyses.

Table 4.2. Scores on the SRQ-20 by gender, age and education

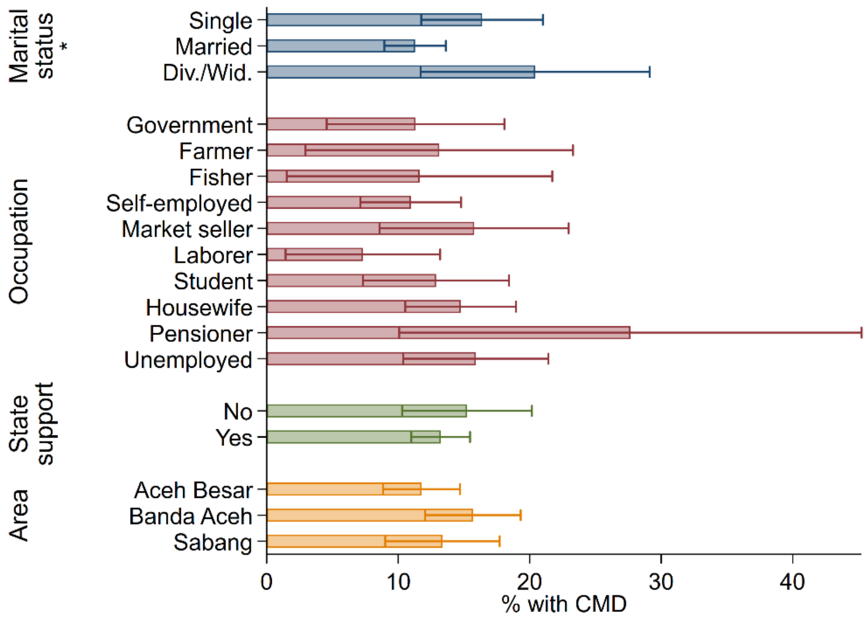
	Mean	SD	N	p-value
Total	2.559	2.960	1321	
Gender				<0.001
Male	1.757	2.429	511	
Female	3.064	3.149	810	
Age, years				<0.001
17-25	1.954	2.467	304	
26-45	2.163	2.690	534	
46-65	3.016	3.149	380	
65+	4.709	3.648	103	
Education				<0.001
None	4.310	3.873	42	
Primary	3.471	3.474	189	
Lower secondary	2.675	2.964	249	
Upper secondary	2.370	2.708	560	
Tertiary	1.961	2.672	280	

P-values were obtained from an F-test of joint significance when regressing the instrument on the respective categories, clustering standard errors at the household level.

4.3.3 Sociodemographic groups affected by CMD

We predict the probability for CMD (SRQ-20≥6) using a linear probability model controlling for age, gender, and educational level. Figure 4.3 compares the predicted probabilities by marital status, occupation, study area, and presence in households receiving state support. We found a significant difference in predicted probabilities of CMD by marital status. On average, widowed and divorced participants had a 1.8 times higher predicted probability for CMD compared to married participants. While there were significant differences between single occupation groups, these differences were not jointly significant over all occupation groups; there were also no significant differences by reception of state support or study area.

Figure 4.3. Predicted probabilities of CMD by marital status, occupation, state support and study area



Predicted probabilities were obtained by employing a linear probability model regressing the indicator of CMD (i.e. SRQ-20≥6) on the characteristic of interest controlling for gender, age and education. The model was then used to predict probabilities over each category of the characteristic of interest. Standard errors were clustered at the household level. 95% confidence intervals are displayed. Stars indicate significant differences between categories, with * p<0.05, ** p<0.01. Div., divorced; Wid., widowed. Numerical results are shown in Table A 4.3 in the appendix.

4.3.4 Family functioning and CMD

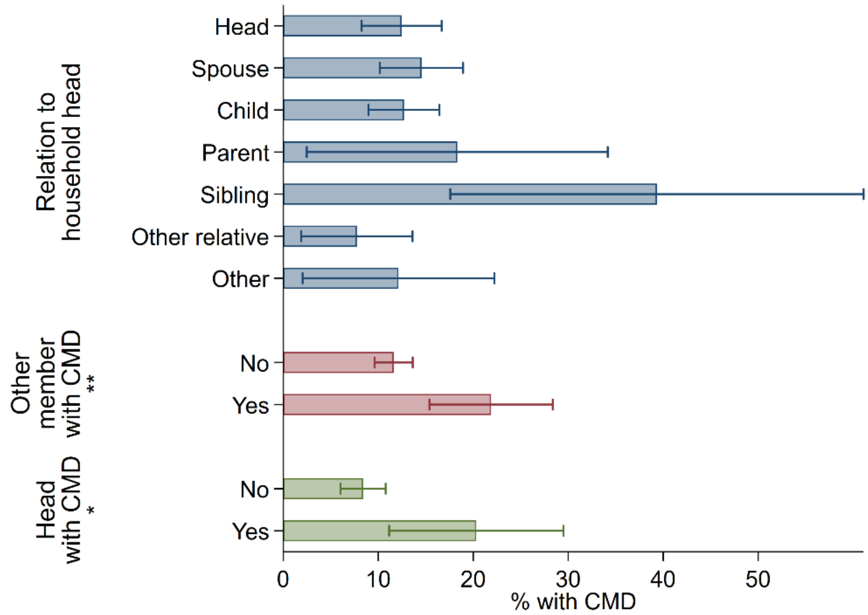
We took a closer look into the role of families and CMD. Table 4.3 displays summary statistics by households. In 26% of all households, at least one of the interviewed members showed symptoms of CMD: moreover, 15% of all interviewed household heads had symptoms of CMD.

Table 4.3. Family characteristics of the study sample by household

	Mean/Frequency	SD	N
Number of household members	4.56	1.92	632
Number of conducted interviews	2.36	1.47	632
Any members with CMD	25.64%	0.44	589
Number of members with CMD	0.31	0.58	589
Head was interviewed	65.51%	0.48	632
Head with CMD	14.68%	0.35	361

As displayed in Figure 4.4, there was a significantly higher share of CMD among siblings of household heads as compared with the spouses, children, other relatives of the head, or the heads themselves. Overall, the differences were not jointly significant. Respondents were about twice as likely to show symptoms of CMD if any other household member had CMD or if the household head had CMD.

Figure 4.4. Predicted probabilities of CMD by family characteristics

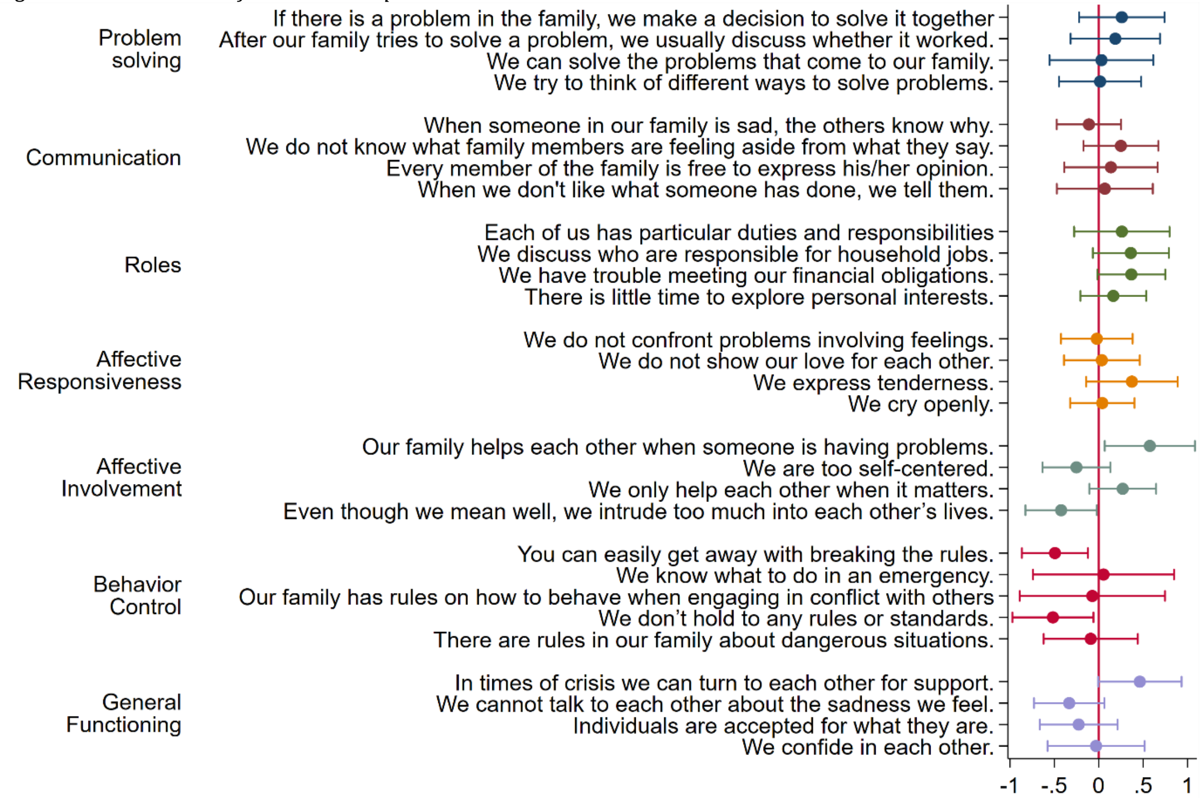


Predicted probabilities were obtained by employing a linear probability model regressing the indicator of CMD (i.e. SRQ-20≥6) on the characteristic of interest controlling for gender, age and education. The model was then used to predict probabilities over each category of the characteristic of interest. Standard errors were clustered at the household level. 95% confidence intervals displayed. Stars indicate significant differences between categories, with * p<0.05, ** p<0.01. Numerical results are depicted in Table A 4.4 in the appendix.

We used an ordered logistic regression model to analyze the association of mental distress with family functioning as measured by the FAD. Figure 4.5 displays the coefficient estimates, with positive coefficients indicating a higher propensity to agree to the specific statement. Marginal effects are reported in Table A 4.5 in the appendix.

People with CMD were significantly more likely to perceive their families as performing well regarding several aspects in the dimensions of affective involvement and behavior control. This is somewhat surprising, considering findings from the wider literature which indicate mental disorders are negatively correlated with family functioning (Friedmann et al., 1997).

Figure 4.5. Correlation of CMD with responses to FAD items



Coefficient estimates from an ordered logistic model regressing FAD items on the CMD indicator (i.e. SRQ-20≥6) controlling for gender, age and education. Standard errors are clustered at the household level. The answer scale ranges from 1 – Strongly disagree to 4 – Strongly agree. Positive coefficients indicate a higher likelihood to agree to a statement, and vice versa. 95% confidence intervals displayed. Numerical results and marginal effects are depicted in Table A 4.5 in the appendix.

4.3.5 Costs associated with CMD

We now turn to the possible financial burden of mental distress by investigating its association with working status, working hours, working days, monthly pay and disturbance of daily tasks. To estimate the association of mental distress, we regress the outcomes of interest on the binary indicator for CMD and predict the outcome of interest by CMD status. Associations with work characteristics were plotted in Table 4.4. Working status, working days, working hours and earnings were not significantly associated with CMD.

Mental distress in the form of negative feelings can substantially affect work productivity. Participants with elevated mental distress were four times more likely to report any impact of negative feelings on their work than did their counterparts ($p<0.01$). Over the past 30 days, an average of 1.5 more days were affected than was the case for their counterparts ($p<0.01$). They were nearly four times more likely to seek treatment due to these feelings ($p<0.01$); however, they also more often reported that physical problems were the main cause of these feelings ($p<0.01$).

Table 4.4. Differences in work characteristics

	SRQ-20≥6			
	No	**Yes**	**p-value**	**N**
Is working	0.42	0.35	0.061	1,313
	(0.01)	(0.03)		
Working days/week	5.87	5.69	0.422	519
	(0.05)	(0.21)		
Working hours/week	32.13	35.04	0.419	504
	(1.09)	(3.50)		
Log of earnings	14.29	13.99	0.068	520
	(0.04)	(0.16)		
Daily tasks affected	0.07	0.29	<0.001**	1,308
	(0.01)	(0.04)		
Affected days	0.28	1.78	<0.001**	1,311
	(0.05)	(0.32)		
Sought treatment due to feelings	0.07	0.26	<0.001**	1,316
	(0.01)	(0.04)		
Feelings caused by physical problems	0.02	0.24	<0.001**	1,314
	(0.00)	(0.03)		

Predicted outcomes for each characteristic of interest are obtained by regressing the characteristic of interest on the CMD indicator controlling for gender, age and education. Then, the model is used to predict outcomes by CMD status. Standard errors are clustered at the household level. Stars indicate significant differences between categories, with * $p<0.05$, ** $p<0.01$.

Finally, we examine the differences in health complaints and treatments sought for individuals with CMD; the results are depicted in Table 4.5. Individuals with mental distress were twice as likely to have had a health complaint during the past 30 days ($p<0.01$), and 1.8 times ($p<0.05$) more likely to attend private practices than did their counterparts. There were no economically meaningful differences in time spent for treatment seeking, but people with CMD ($p<0.05$) paid on average twice the treatment costs of their counterparts.

Table 4.5. Differences in health care seeking

	SRQ-20≥6			
	No	**Yes**	**p-value**	**N**
Any health complaint	0.349	0.681	<0.001**	1,317
	(0.015)	(0.031)		
Sought treatment	0.757	0.823	0.095	517
	(0.023)	(0.033)		
No. of facilities	1.119	1.190	0.147	398
	(0.022)	(0.043)		
Primary health center	0.455	0.487	0.580	398
	(0.034)	(0.047)		
Government clinic	0.142	0.162	0.646	398
	(0.023)	(0.037)		
Private clinic	0.027	0.020	0.634	398
	(0.012)	(0.012)		
Private practice	0.141	0.248	0.020*	398
	(0.024)	(0.041)		
Joint clinic/practice	0.247	0.211	0.441	398
	(0.028)	(0.040)		
Traditional healer	0.049	0.020	0.212	398
	(0.014)	(0.016)		
Travel time [min]	15.926	16.623	0.720	376
	(0.907)	(1.793)		
Waiting time [min]	29.370	29.654	0.970	374
	(4.478)	(5.782)		
Treatment time [min]	10.696	13.471	0.101	375
	(0.755)	(1.473)		
Travel costs [k IDR]	17.125	28.936	0.157	377
	(2.827)	(7.601)		
Treatment costs [k IDR]	23.702	49.500	0.024*	373
	(4.640)	(11.435)		
Medication costs [k IDR]	52.390	63.792	0.623	377
	(14.341)	(17.172)		

Predicted outcomes for each characteristic of interest were obtained by regressing the characteristic of interest on the CMD indicator controlling for gender, age and education. Then, the model is used to predict outcomes by CMD status. Standard errors are clustered at the household level. Stars indicate significant differences between categories, with * p<0.05, ** p<0.01.

4.4 Discussion

Common mental disorders constitute a substantial share of the global burden of disease. Previous evidence from LMICs suggests that disadvantaged socio-economic groups might be especially vulnerable to CMD. Moreover, studies from high-income countries show that people with CMD can face considerably higher direct and indirect costs than their non-affected counterparts. Though there is evidence of a correlation between CMD and poverty proxies in LMICs, analyses of associated costs are still rare (Lund et al., 2010).

In our study, we use a population-based household survey to identify the affected groups and the associated financial and health care costs in Aceh, Indonesia. Using the SRQ-20, we find a prevalence of common mental disorders of 14% in our study sample, with higher scores among female, older and less educated participants. Widowed and divorced respondents are twice as likely as married respondents to have CMD. The association of CMD with gender, education and marital status confirms findings from other low- and middle-income settings and in Indonesia (Arvind et al., 2019; Das et al., 2009; Hanandita and Tampubolon, 2014; Levinson et al., 2010; Tampubolon and Hanandita, 2014). However, evidence on the gradient of age is very mixed in other studies from Indonesia (Das et al., 2007; Peltzer and Pengpid, 2018): our results match the findings from Das et al. (2007) but contradict findings by Peltzer and Pengpid (2018) that showed higher CMD in younger respondents. In India, respondents below 30 were at significantly lower risk for depressive disorders, but differences between older age cohorts were not significant (Arvind et al., 2019). The World Mental Health Surveys did not find any age gradient for LMICs (Kessler et al., 2010).

We also find that the probability of CMD nearly doubles when another household member shows symptoms of CMD, which is in line with the literature (Das et al., 2007). Surprisingly, our results show that individuals with CMD report better family functioning regarding affective involvement and behavior control compared to others. This contradicts findings from studies in other countries (Chavan et al., 2018; Du et al., 2014; Friedmann et al., 1997; Keitner, 1990); it is unclear whether this difference stems from the fact that our study is population-based, while all other studies compare clinical and non-clinical samples or only consider the affected population. Further studies on a similar topic might consider comparing the condition of the subjects in clinical and community settings.

In line with the literature, our study indicates that people with CMD are affected in their productivity and physical well-being (Chavan et al., 2018; Das et al., 2009; Kessler, 2012; König et al., 2019; Koopmans et al., 2005; Levinson et al., 2010; Lund et al., 2010; Scott et al., 2016). Their daily activities are more severely disturbed by negative emotions, but this is attributed to physical problems; in addition, they are twice as likely to have health complaints. Compared to other people who sought treatment, participants with CMD face twice the treatment costs. Independent of the direction of causality, this signals a vulnerability of people with mental distress to poverty; indeed, a correlation between poverty and CMD is very common in LMICs (Lund et al., 2010). Although disentangling the causal directions is challenging, longitudinal evidence suggests that both might interact in a vicious cycle (Lund and Cois, 2018). This would exacerbate any excess costs found from cost-of-illness studies. These costs also transform to the societal level: the societal costs of mental distress were estimated in 2010 to be 1.5% of the annual global GDP (Bloom, D.E. et al., 2011). Nevertheless, treatment possibilities can be comparatively cheap: cost-effective interventions for mental, neurological and substance abuse disorders are estimated to cost 3-4 USD per capita per year in LMICs (Patel et al., 2016). Moreover, previous studies showed that mental health interventions can effectively break the vicious cycle of poverty and mental illnesses (Lund et al., 2011). Policies to combat the burden of mental disorders are thus economically feasible, and policy stakeholders should react to decrease the individual and societal economic burden of mental distress.

4.4.1 Limitations

A few limitations are noteworthy: our analyses focus on associations instead of causalities. For example, it is unclear whether CMD cause lower productivity, or whether lower productivity gives rise to CMD, or both. Moreover, elevated mental distress also coincides with the occurrence of general health problems, and negative emotions are reported to be caused by physical problems. This raises the question of whether the SRQ-20 proxies physical health rather than mental health. This is difficult to disentangle, as several of the items ask for symptoms which could also have physical causes. On the other hand, the association of physical with mental conditions has been shown frequently in clinical settings and population wide (Scott et al., 2016). Again, the direction of causality is not always clear.

Our data is additionally constrained in several dimensions: first, despite the random sampling, female and unemployed participants are over-represented in our sample. We partly adjust for this by controlling for gender, age, and education, but household members who did not participate (mostly due to absence) might show a systematically different burden of mental distress. Still, as on average more than 70% of all adult household members participated in the survey, we are confident that the loss of representativeness in the targeted study sample is not too large. Second, our study took place in an urban and peri-urban setting; treatment costs might be higher and labor market options less diverse in more remote areas, potentially changing the cost pattern of mental distress.

Finally, the province of Aceh might not be representative for all Indonesian regencies. It is one of five provinces with special autonomy rights and the only regency in Indonesia where Sharia law is in place. The region was the setting of a long conflict between autonomous groups and the central government in Jakarta, and it was devastated by the Indian Ocean tsunami in 2004. Though Indonesia is frequently hit by natural disasters, this tsunami stood out in terms of not only casualties and destruction, but also inflow of international aid. This context might have caused a higher prevalence of mental distress compared to other regions but might also have created more opportunities to cope with the shock compared to other disasters.

4.5 Conclusions

We find that people from disadvantaged groups are significantly more likely to have common mental disorders, stressing the importance of low-threshold and affordable mental health care. Despite different policy efforts in Aceh in the past years, the prevalence of mental distress is substantial. In the light of a double burden of physical and psychological conditions, accessible, adequate and financially feasible health care is important, independent of the direction of causality. Although Indonesia is on its way to establishing universal health care, the difference in treatment costs for people with mental distress is still considerable; more efforts to decrease out-of-pocket payments are needed. Also, to the extent that mental illness affects work productivity, early detection and treatment are important to prevent financial strains during the progression of the disorder. Although the causality might run both ways, this vicious cycle can be broken through mental health interventions. Putting mental health on the policy agenda can thus yield improvements in the dimensions of mental, physical, and financial well-being.

5 Parental Health, Children's Education and Unintended Consequences of State Support: Quasi-experimental evidence from KwaZulu-Natal, South Africa

Joint work with Till Bärnighausen and Sebastian Vollmer

A similar version of this chapter and its appendix was published in the Discussion Paper Series of the Courant Research Centre Poverty, Equity and Growth (http://www2.vwl.wiso.uni-goettingen.de/courant-papers/CRC-PEG_DP_291.pdf)

Abstract

This study investigates whether eligibility for antiretroviral therapy (ART) of HIV positive parents improved their children's educational attainment in KwaZulu-Natal, South Africa, employing a regression discontinuity design. We find that there is a positive impact of ART eligibility on paternal health, but this does not translate into general improvements of children's education. Instead, impacts differ by the previous reception of state support. Previous recipients of health-contingent state support can lose the state support after initiation of ART, as their health improves after ART is initiated. For these parents, we see a negative impact of ART eligibility on children's education, potentially driven by the negative impact on the household's wealth. In contrast, there is a positive impact of ART eligibility on children's education for fathers who previously received non-health-contingent state support.

5.1 Introduction

Parental health can be a key determinant of the next generation's well-being. It affects the parent's ability to earn income and take care of their children, and might impact children's physical or mental health, the household's health expenditure, as well as investments in children's human capital (Alam and Mahal, 2014; Sherr et al., 2014). This study investigates the impact of a potentially positive health shock, parental eligibility for HIV/AIDS treatment, on children's educational attainment in KwaZulu-Natal, South Africa.

Over the past decades, the HIV/AIDS epidemic has been a large contributor to the burden of disease in sub-Saharan Africa. South Africa was particularly affected, with AIDS-related deaths peaking at 270,000 in 2006 (UNAIDS, 2021). Six years later, this number had halved, and by 2020, it had reduced to 83,000 (UNAIDS, 2021). One large driver of the fall in AIDS-related deaths is the rapid expansion and improvement of antiretroviral therapy (ART) in South Africa and worldwide. ART slows down the progression of HIV, and is presumed to have averted 5.5 million deaths globally between 1995 and 2012 (UNAIDS, 2013). It immensely reduces the risk of HIV transmission and improves the patients' ability to cope with the disease, thus enhancing overall health and productivity (UNAIDS, 2013).

While ART enables patients to return to a nearly normal life, the wider impact on the patients' families is not yet comprehensively studied. Our study investigates the role of ART for children's education. For this, we combine clinical and household panel data from KwaZulu-Natal, South Africa, between 2000 and 2017. We make use of a natural experiment to develop a quasi-experimental study design: In the past, WHO clinical guidelines defined ART eligibility based on the CD4 cell count, a biomarker in the blood. The CD4 cell count decreases over the course of HIV/AIDS, and a low CD4 cell count was used as indicator for a late stage of the disease. WHO guidelines recommended that only patients below a certain CD4 cell count should be eligible for ART. This setting allows us to compare children of parents with CD4 cell counts slightly below the threshold with children of parents who just missed the threshold, using a regression discontinuity design.

We find that eligible parents just below the CD4 threshold initiate ART much faster, and eligible fathers are less likely to report a clinic visit in the past 12 months than their ineligible counterparts just above the CD4 threshold. However, the transmission into gains in children's education is mediated by the role of state support: There is no overall significant impact of ART eligibility, but we find a negative impact on children's education when parents received a disability grant prior to the ART eligibility assessment. This goes along with reductions in the household's asset index for these parents, an effect which is especially strong when fathers are affected. This negative impact is due to the linkage of the disability grant to the CD4 cell count: When the CD4 cell count improved, as it happens under ART, patients could lose the disability grant. The negative impact on the asset index underlines this mechanism, which could in turn lead to the negative impact on children's education. This is not the case for other state grants, which are not linked to the CD4 cell count.

Our study contributes to the understanding of the role of parental health for household well-being in general, and for children's education in particular. Panel surveys show that children's educational outcomes often worsen after a parent became ill, with a varying role of children's and parents' gender across studies (Alam, 2015; Bratti and Mendola, 2014; Luca and Bloom, 2018; Sun and Yao, 2010). The economic implications of health shocks might play a major role in this relationship, as improved access to health insurance reduces child labor (Landmann and Frölich, 2015) and moderates the negative impact of health shocks on education (Woode, 2017). Our findings demonstrate the role of financial support as a mediator of the impact of health shocks.

Furthermore, the access to ART poses a special case in this literature, as it provides a positive instead of a negative health shock. The impacts of health shocks might not be symmetrical, for example if labor market frictions prevent the transmission of health improvements into employment and economic well-being. Yet, a causal identification is difficult, as ART initiation is not exogenous. The existing studies compare adults initiating ART at different points in time (Zivin et al., 2009), or analyze the local roll-out of ART using a difference-in-differences design (Baranov and Kohler, 2018; Lucas et al., 2019). We make two contributions to this evidence: Firstly, we focus our analysis on the time ART was offered directly to the individual, to estimate the impact in the absence of any indirect effects of ART availability. Secondly, our identification strategy allows us to causally estimate the impact on children's education with the comparatively weak assumptions of a regression discontinuity design (Bärnighausen et al., 2017).

The remainder of the paper is structured as follows: First, we shed more light on HIV/AIDS and the roll-out of ART, the situation in South Africa, and the potential impacts on children's education. Next, we describe our data and empirical approach. Then, we present our findings, potential mechanism and robustness checks. Finally, we conclude with a summary and discussion.

5.2 Background

5.2.1 HIV/AIDS and ART

Antiretroviral therapy slows down the progression of HIV infection to AIDS (Hammer et al., 1997) and reduces the occurrence of opportunistic infections (Detels et al., 2001). After initiation of ART, patients rapidly gain weight (Coetzee et al., 2004). Compared to pre-ART patients, their physical and emotional well-being improves (Booysen et al., 2007; Louwagie et al., 2007; Rosen et al., 2010), with the largest increases in well-being observed shortly after treatment initiation (Booysen et al., 2007; Jelsma et al., 2005). Also, ART reduces the risk of HIV transmission during sexual intercourse (Detels et al., 2001) and pregnancy (WHO, 2010b).

CD4 cell counts decrease during the onset of HIV (Fahey et al., 1990) and were established as a proxy to measure the progression of AIDS. Analogously, they rapidly improve within the first weeks of ART (Hammer et al., 1997; Wools-Kaloustian et al., 2006). Also, the CD4 cell count at initiation strongly influences the success of ART: Patients with initially lower CD4 cell counts are at higher risk of detrimental side-effects of ART, further progression of AIDS, or even death (Coetzee et al., 2004; Egger et al., 2002; Murphy et al., 2001).

5.2.2 HIV/AIDS and ART in KwaZulu-Natal

In 2003, the prevalence of HIV/AIDS among the adult population in South Africa was 21.5%, with a substantial variation across regions and sociodemographic groups (WHO, 2005). One of the most affected regions was KwaZulu-Natal, where the prevalence was highest among women aged 25-29 years (51%) and men aged 30-34 years (44%) (Welz et al., 2007). Individuals with a lower education and in the middle of the wealth distribution were at especially high risk of contracting HIV (Bärnighausen et al., 2007).

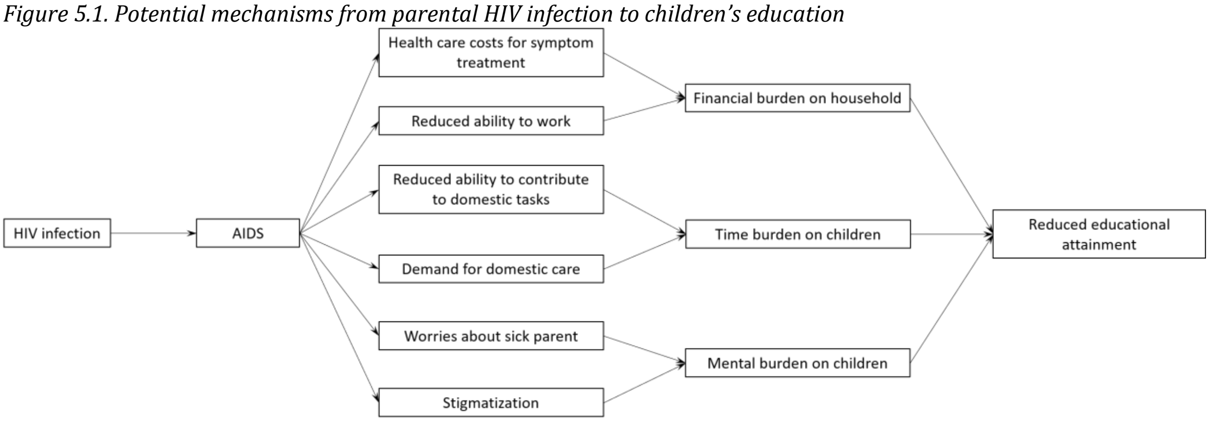
In 2004, the nationwide roll-out of ART started and ART became available in KwaZulu-Natal (Houlihan et al., 2011). National treatment guidelines followed the WHO recommendations and were mostly based on the patient's CD4 cell count. The first guidelines defined patients with a CD4 cell count ≤200 or WHO stage IV (independent of CD4 cell count) as eligible for ART (Plazy et al., 2015). The eligibility rules were updated in 2010, 2011 and 2015, and finally discarded in 2016, when all people living with HIV became eligible for ART irrespective of their CD4 cell count (Meyer-Rath et al., 2017).

Longitudinal analyses show that after eight years, about 82% of the individuals living with HIV in our study population had learned their HIV status (Haber et al., 2017). Only 45% accessed an HIV clinic, 39% became eligible for ART, and 35% initiated ART (Haber et al., 2017). The median time from HIV infection to the first CD4 test are nearly five years, with faster transition times for women than for men and for individuals with higher education levels (Maheu-Giroux et al., 2017). After the CD4 test, less than half of the individuals who were not eligible return for the recommended retest within one year, with a larger loss among men and younger individuals (Lessells et al., 2011). Among eligible patients, only 61% are still in care after five years, with the highest loss due to mortality (Mutevedzi et al., 2013). Disengagement from care takes place mainly within the first three months of ART initiation and increased over time (Mutevedzi et al., 2013). However, overall the retention in care between the first positive HIV test and the virologic suppression improved over time (Haber et al., 2017).

5.2.3 The role of adult HIV/AIDS and ART for children's education

To conceptualize how parental ART might affect children's education, we take one step back and discuss how parental HIV/AIDS can affect children's education in the absence of treatment, as depicted in Figure 5.1 (for a review, see Sherr et al., 2014): As adults get sicker over time, they are less able to earn income (Levinsohn et al., 2011) and to contribute to domestic tasks and caregiving. The co-infections caused by a suppressed immune system require medical care. With further progression, adults might get so sick that they require constant care at home. The household's financial burden increases (Alam and Mahal, 2014), and children might need to take over new responsibilities to step in for the sick adult or to take care of them (Robson et al., 2006; Skovdal and Ogutu, 2009). This also implies less monetary and time resources to invest in children's education. In addition, children might face a substantial mental burden due to worries about their sick parent (Cluver et al., 2012; Skovdal and Ogutu, 2009), stigmatization of HIV/AIDS-affected families (Cluver et al., 2012; Skovdal, 2012; Hosegood et al., 2007), and new responsibilities such as care-taking or income earning (Cluver et al., 2012; Skovdal and Ogutu, 2009; Robson et al., 2006).

Figure 5.1. Potential mechanisms from parental HIV infection to children's education



Most studies on the relationship between adult HIV/AIDS and children's education are purely observational (Goldberg and Short, 2016; Guo et al., 2012), but there is an indication for a negative effects of adult HIV/AIDS on children's school participation (Cluver et al., 2012), attendance (Cluver et al., 2012; Robson et al., 2006) and progress (Mitchell et al., 2016). Similarly, in the case of parental deaths, drops in children's school attendance and participation occur already before HIV-infected adults decease, with mixed evidence whether the rates recover after the death or not (Evans and Miguel, 2007; Ainsworth et al., 2005; Yamano and Jayne, 2005).

To which extent ART can leverage this burden is still under examination. As discussed above, the patient's health improves rapidly after ART initiation. Similarly, studies show that productivity, working hours and employment rates increase after ART initiation (Larson et al., 2013; Linnemayr et al., 2013; Rosen et al., 2010; Thirumurthy and Zivin, 2012). Yet, longitudinal data from South Africa demonstrate that a full recovery of employment might take several years, given a drop in employment prior to ART initiation and high unemployment rates in general (Bor et al., 2012). This might explain the different impacts on households across settings: In Kenya, for example, nutritional outcomes improve and children's time devoted to domestic and market-related activities reduces after an adult introduced ART (D'Adda et al., 2009; Thirumurthy and Zivin, 2012; Zivin et al., 2009). In South Africa, however, there is indication for increased food insecurity within the first year on ART (Patenaude et al., 2018). In addition, although ART is provided for free, the direct and indirect costs associated with treatment uptake can be quite substantial and result in financial distress (Chimbindi et al., 2015).

Evidence on the effect of adult ART initiation on children's education is scarce. An early study by Zivin et al. (2009) analyzes trends of households with a member initiating ART in Kenya. They find that children from these households increased their school attendance relative to later-stage ART households, and that improvements in adult health were associated with these results. Two further studies focus on the impact of ART arrival by using a difference-in-differences design, comparing changes for households close to ART clinics with changes for households further away: Baranov and Kohler (2018) find that in Malawi, households closer to ART clinics increase spending on education after ART becomes available, an effect particularly driven by HIV-positive households. However, also HIV-negative households are affected: their grade completion rates increase after ART roll-out, what the authors trace back to updated beliefs on mortality risks. In Zambia, Lucas et al. (2019) estimate the HIV status of households based on socioeconomic characteristics. Using the same identification strategy as Baranov and Kohler (2018), they find that ART roll-out does not affect school enrollment, but increases the likelihood to be grade-for-age for children from (likely) HIV-affected households. We extent this literature by going beyond the introduction of ART as a new treatment possibility, and investigate the impact of individual access to ART directly. Moreover, all existing studies rely on some form of parallel trends assumptions. By employing a regression discontinuity design, we exchange these comparatively strong assumptions for the weaker assumption of continuity of expected outcomes across the threshold.

5.2.4 The role of state support

In our setting, many families rely on state support in form of state grants to meet their daily needs (Booysen, 2004). These state grants might help to surpass the period between ART initiation, with non-trivial indirect costs of accessing treatment, and a recovery in employment. One of the grants that the South African government offers is the disability grant, which considers the inability to work due to HIV/AIDS. Disability grants are mostly temporary, with a re-assessment of the eligibility criteria after six months (de Paoli et al., 2012).

During our study period, there were no detailed national guidelines for grant eligibility. However, qualitative evidence suggests that many health practitioners took into account the same CD4 threshold as for the ART eligibility, namely 200 cells/µl (de Paoli et al., 2012; Hardy and Richter, 2006). This created a conflict between maintaining ART and receiving the disability grant: As patients take up treatment, their CD4 cell count and their health improve, putting them at risk of losing the disability grant. Qualitative evidence suggests that individuals might therefore adopt excessive drinking or interrupt ART, trying to decrease their CD4 cell count before the next assessment (Peltzer, 2012). Indeed, it has been found that patients who ever received a disability grant have a 20% slower CD4 recovery rate than patients who never received this grant (Haber et al., 2018).

In 2008, the government emphasized that the ability to work, not the CD4 count, should be the determining factor for eligibility (Knight et al., 2013). Still, as health improves rapidly after the initiation of ART, individuals will be at risk of losing the disability grant soon after the initiation of ART. For patients who already received a disability grant before the CD4 assessment, this might be particularly burdensome, as they might have financially depended on this grant beforehand. Hence, for previous recipients of the disability grant, there might be a negative link between parental ART eligibility and children's education, by impeding health improvements or by cutting an important income source during the time of recovery.

5.3 Method

5.3.1 Data

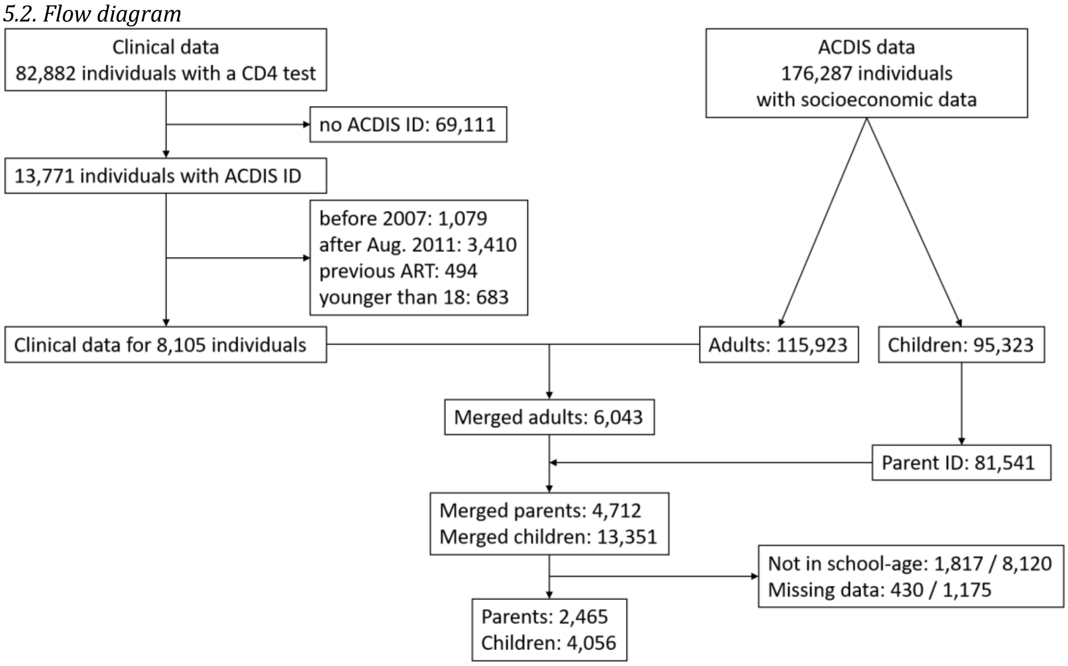
Since 2000, the Africa Health Research Institute (former: Africa Centre for Population Health) has collected longitudinal socio-economic, demographic, clinical and laboratory data from the northern area of KwaZulu-Natal, South Africa (Muhwava et al., 2008; Tanser et al., 2008). The area is predominantly rural, but also includes some peri-urban settlements and an urban township (Tanser et al., 2008). Circulatory migration to urban areas is common (Muhwava et al., 2008), and main income sources are wage employment and state grants (Tanser et al., 2008). The participation rate in the household surveys is above 98%, but participation in the individual-level components below 50% in a given year (Gareta et al., 2021).

A clinical dataset includes ART data and CD4 cell counts since 2007, including data collected retrospectively back to the roll-out in 2004 (Plazy et al., 2015; Houlihan et al., 2011). The coverage area includes 16 primary health clinics, with about 40% of the patients covered by the demographic surveillance area (Houlihan et al., 2011). The dataset contains HIV-positive patients only (Houlihan et al., 2011).

Most of our data falls within the first guideline period before August 2011, such that we restrict our sample to this period. During this time, eligibility was determined by a CD4 cell count ≤200 cells/μl or WHO stage IV (independent of CD4 cell count) (Plazy et al., 2015). For pregnant women and patients with TB, the threshold was raised to 350 cells/μl in April 2010 (Plazy et al., 2015). All patients below the threshold were offered antiretroviral drugs, accompanied by regular group and individual sessions and health monitoring (Houlihan et al., 2011). Patients who were not eligible initially were asked to return after six to twelve months for another CD4 measurement (Houlihan et al., 2011). However, there was a substantial loss in retention in care for patients who did not become eligible during the first test (Lessells et al., 2011). We consider only the first CD4 test in our analyses.

The clinical data can be matched with the demographic surveillance data based on a joint identifier, which itself is based either on the national identification number, or the first name, surname, age, and gender (Bor et al., 2011; Cooke et al., 2010). The resulting data on adults can be matched with their children based on parental identification numbers. We restrict our sample to children who were of school age when the first CD4 test was conducted. If both parents conducted a CD4 test, only the parent with the earlier test is matched to the child. After excluding observations with missing data (e.g., no educational data after the CD4 test), we obtain a sample of 4,056 children and 2,465 parents. A flow diagram is depicted in Figure 5.2.

Figure 5.2. Flow diagram



Note: In the ACDIS data, the sum of adults and children is larger than the number of individuals as some children became adults during the observation period.

5.3.2 Outcomes

The dependent variable of interest is children's educational attainment, defined as the highest school grade attained. School attendance is compulsory in South Africa, starting on the first school day in the year the child turns seven and ending on the last school day of the year the child turns fifteen or reaches the ninth grade (*South African Schools Act No 84 of 1996*, 2011). However, children can already be admitted to grade 1 if they are turning six by June 30th in the respective school year (*South African Schools Act No 84 of 1996*, 2011).

We also investigate impacts on parental health and economic burden. In a subset of our data, parents reported whether they were admitted to a hospital in the last 12 months, and visited a clinic or private practice in the last 6 months. We use the household’s asset index quintile as predefined in the ACDIS household data as proxy for the household’s economic situation.

5.3.3 Identification strategy

The clinical guidelines which defined ART eligibility based on a CD4 cell count threshold allow us to use a regression discontinuity design to assess the impact of ART eligibility. For this approach, we assume that in the absence of the eligibility rule, patients with a CD4 cell count just below 200 cells/µl and patients with a CD4 cell count just above 200 cells/μl would on average have the same outcomes (conditional on the CD4 cell count) (Hahn et al., 2001). Thus, we attribute any observed differences in outcomes of the two groups (controlling for the CD4 cell count) to the impact of eligibility.

To estimate the impact of ART eligibility on our main outcome, children's educational attainment, we estimate the following equation:

$$Y_{it} = \alpha + \beta\ Eligible_p + \gamma\ Eligible_p * Deviation_p + \delta\ Deviation_p + \theta C_{it} + \pi P_{pt} + \lambda_t + \varepsilon_{it} \qquad (5.1)$$

with Y_{it} as child i's educational attainment at date t, $Eligible_p$ as an indicator whether parent p's first CD4 test was ≤200 cells/μl, and $Deviation_p$ as difference of the CD4 test to the threshold. The interaction of $Eligible_p$ and $Deviation_p$ allows for a different linear trend in CD4 cell counts to the left and the right of the threshold. We control for children's age and gender (C_{it}), parents' age, gender, and education (P_{pt}), and fixed effects for the visit year and years since the CD4 test (λ_t). In further regressions, we examine heterogeneous impacts of eligibility by children's and parents' gender, interacting the eligibility indicator with the respective characteristic. Standard errors are clustered at the level of the parent. Observations are weighted with a triangular kernel to give more weight to the observations closer to the cutoff.

The estimated effect is local in the sense that it reflects the impact of eligibility at the threshold of 200 cells/μl, while the impact might differ for patients with a much lower or much higher CD4 cell count (Hahn et al., 2001). In addition, patients initially not eligible for ART are asked to return after 6-12 months for a re-assessment, as the progression of HIV/AIDS will lead to a further depletion of CD4 cells, such that they will sooner or later become eligible. Hence, β estimates the local impact of early versus deferred eligibility for ART.

We assess the impact of eligibility on parental health, survival, and economic burden using the following equation:

$$Y_{pt} = \alpha + \beta\ Eligible_p + \gamma\ Eligible_p * Deviation_p + \delta\ Deviation_p + \pi P_{pt} + \lambda_t + \varepsilon_{pt} \qquad (5.2)$$

with Y_{pt} as the outcomes for parents: Hospital visit in the past 12 months, clinical or private practice visit in the past six months, and household asset index. Given the recall period of the health care outcomes, we only include observations at least one year after the CD4 test to ensure that outcomes capture the situation after the CD4 test.

We test for heterogeneities by child and parental gender and type of state support. For the latter, we use the last information available prior to the CD4 test to separate our analyses from impacts of ART eligibility on reception of state support. As the disability grant precludes the reception of any other type of state support, we can split all parents in three categories: Received no state support prior to the CD4 test, received a disability grant prior to the CD4 test, received any other type of state support (e.g., child foster grant) prior to the CD4 test.

For the identification of the effect, the choice of the area around the threshold is crucial. The smaller this area, the more credible the assumption that patients below and above the threshold are comparable conditionally on the CD4 cell count (and the control variables). At the same time, the sample size, and with it the statistical power, drastically reduces closer to the threshold. To balance this tradeoff, we employ a data-driven bandwidth selection by minimizing the asymptotic coverage error of the confidence intervals[19]. The bandwidth selection was applied using the Stata package rdrobust as described in Calonico et al. (2017). As this procedure is sensitive to the outcome of interest, the sample and the choice of control variables, we estimate the optimal bandwidth for each of the specifications separately.

Similarly, the approach hinges on the assumption that no exact manipulation of the CD4 cell count was possible. While in principle, patients might be able to adopt strategies which reduce their CD4 cell count, they cannot manipulate their CD4 cell count exactly and thus cannot determine their eligibility. However, medical staff might report wrong CD4 cell counts such that patients become (in)eligible for ART, which would bias the estimates if this manipulation is correlated with our outcomes of interest. While we cannot prove that this was not the case, we can test for (one-sided) manipulation of CD4 cell counts by examining the distribution of CD4 cell counts around the threshold as described in Cattaneo et al. (2018). Furthermore, we employ balance checks and run placebo-regressions on the time before the first CD4 test to investigate whether differences were prevalent before the individuals were tested.

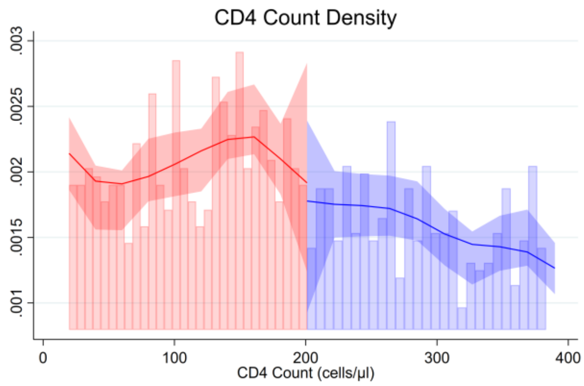
[19] This optimizer is used for inference rather than the point estimate (Cattaneo and Vazquez-Bare, 2017).

5.4 Results

5.4.1 CD4 cell count, treatment uptake and parental health

At first, we examine the distribution of CD4 cell counts around the threshold. Figure 5.3 displays the distribution of the CD4 cell counts and estimates for their density. The CD4 cell counts are relatively evenly distributed around the threshold. We cannot reject the null hypothesis of a joint distribution across the threshold (p-value 0.51).

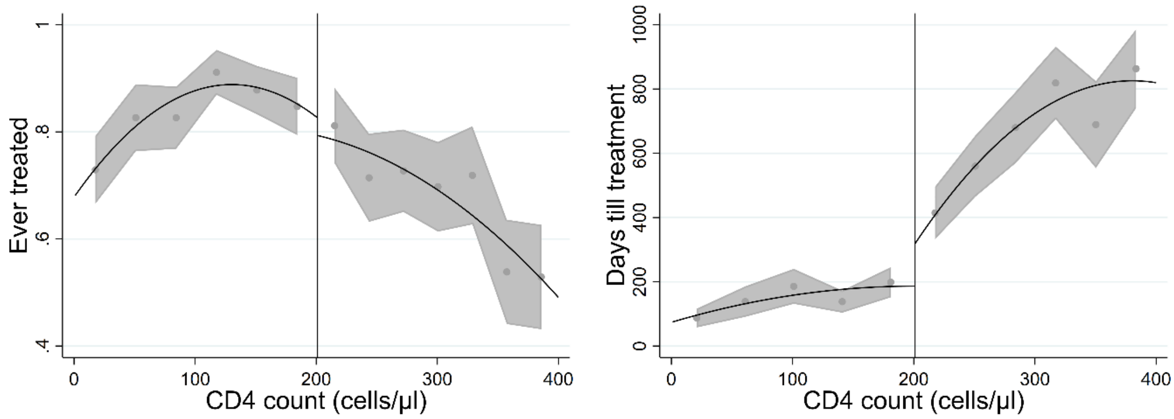
Figure 5.3. Density of the CD4 cell count around the threshold



Note: The bars represent the histogram for the CD4 cell counts. The lines refer to fitted curves from both sides of the threshold as described in Cattaneo (2018). The shaded areas represent the 95% confidence intervals for both curves.

Next, we assess whether the eligibility for ART transfers into an increased initiation of ART. As depicted in Figure 5.4, there is no clear jump in the share of individuals ever treated at the threshold. The share of individuals ever treated decreases at higher CD4 cell counts, as well as for individuals with a CD4 cell count close to zero, who are likely to be at a very late stage of the disease progression. However, among the individuals who were ever treated, the duration between the first CD4 measurement and the treatment start is much shorter for eligible patients. Moreover, the time till treatment initiation does not vary strongly across CD4 cell counts for eligible patients, but there is a quite steep trend among ineligible patients, with shorter waiting times visible for CD4 cell counts approximately between 200 and 300 cells/µl. In sum, this underlines the interpretation of any effect sizes as the impact of early versus deferred treatment.

Figure 5.4. Share of ever treated individuals and average days between CD4 test and treatment start by CD4 cell count



Note: The dots refer to the mean outcomes for evenly-spaced bins of the CD4 cell count. The shaded areas refer to the 95% confidence intervals around the means. The lines are fitted regression lines using a quadratic function of CD4 cell counts and no control variables.

For a subsample of parents, we also have information on visits to hospitals (in the past 12 months), clinics, or private practices (both in the past six months). As depicted in Table 5.1, eligible fathers are less likely to have visited a clinic in the past six months, but we cannot detect significant effects on visits to hospitals or private practices.

Table 5.1. Impact on parental health

	(1) Hospital	(2) Hospital	(3) Clinic	(4) Clinic	(5) Private pract.	(6) Private pract.
Eligible	-0.081	-0.120	-0.096	-0.375***	-0.054	-0.234
	(0.0631)	(0.1157)	(0.0815)	(0.1413)	(0.0679)	(0.1536)
Deviation	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.0028)	(0.0028)	(0.0038)	(0.0037)	(0.0025)	(0.0025)
Eligible # Deviation	0.004	0.004	0.005	0.004	0.006*	0.006*
	(0.0031)	(0.0032)	(0.0045)	(0.0045)	(0.0032)	(0.0032)
Eligible # Mother		0.043		0.308**		0.199
		(0.1062)		(0.1328)		(0.1451)
R2	0.102	0.103	0.096	0.108	0.043	0.048
Cluster	219	219	203	203	235	235
Observations	592	592	559	559	625	625
Bandwidth	38	38	36	36	42	42

Regression for parental health controlling for year of visit, years since the CD4 test and parents' age, gender and education. Deviation is the CD4 cell count minus the threshold of 200 cells/μl. Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

5.4.2 Balance and pre-trends

The optimal bandwidth for the main regression specification is estimated as +/-58 cells/µl. Demographic characteristics within this bandwidth are depicted in Table 5.2. We see significant differences with respect to the parent's sociodemographic characteristics and visit year. Eligible parents are on average older, and are less likely to be mothers. When clustering standard errors at the parent level, only the difference for mothers remains significant.

Table 5.2. Balance checks

	Not eligible		Eligible			
Variable	Mean	S.D.	Mean	SD.	p-value (unadjusted)	p-value (clustered)
Education	6.62	2.82	6.54	2.84	0.3487	0.5737
Age	13.52	2.81	13.45	2.88	0.3868	0.5700
Girl	0.50	0.50	0.49	0.50	0.7361	0.8926
Parent's age	39.24	7.77	39.89	8.41	0.0079	0.4092
Mother	0.89	0.32	0.82	0.38	0.0000	0.0918
Parent's education	7.97	3.67	8.22	3.45	0.0255	0.5271
Years since test	3.28	2.46	3.22	2.45	0.3951	0.5155
Visit year	2,012.33	2.58	2,012.26	2.61	0.3720	0.5698
Cluster	229		312			
Observations	1885		2503			

Data-driven bandwidth: +/- 58. P-values for t-tests reported, once without and once with adjustment for clustered standard errors.

As a further falsification check, we run our regression specification for the time before the first CD4 test. As depicted in Table 5.3, there are no significant pre-trends between children with eligible and children with ineligible parents.

Table 5.3. Pre-trends

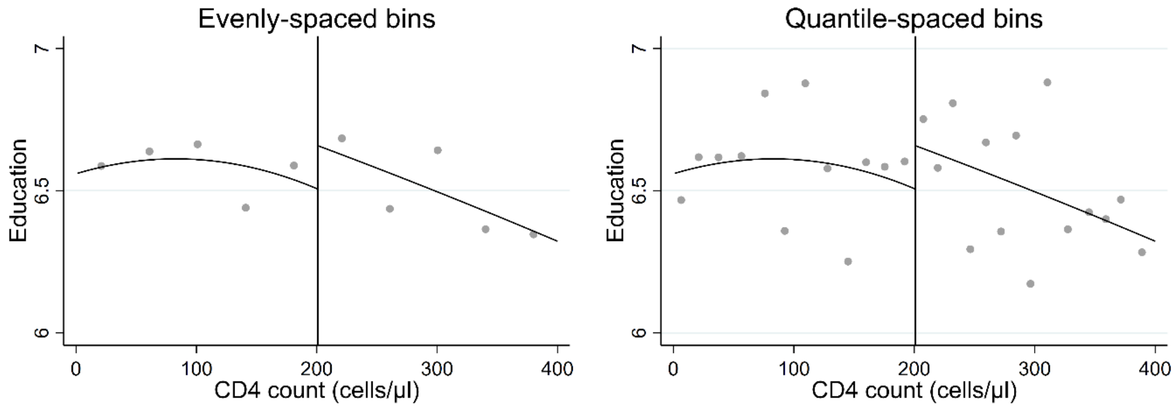
	(1) Education	(2) Education	(3) Education
Eligible	0.043	-0.086	0.234
	(0.2290)	(0.2421)	(0.2518)
Deviation	0.007	0.007	0.006
	(0.0088)	(0.0088)	(0.0088)
Eligible # Deviation	-0.011	-0.012	-0.011
	(0.0107)	(0.0108)	(0.0107)
Eligible # Girl		0.263	
		(0.2271)	
Eligible # Mother			-0.233
			(0.2284)
R2	0.787	0.787	0.787
Cluster	343	343	343
Observations	2077	2077	2077
Bandwidth	43	43	43

Regression for children's education controlling for year of visit, children's age and gender, and parents' age, gender and education. Deviation is the CD4 cell count minus the threshold of 200 cells/µl. Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

5.4.3 Impact on education

A visual inspection of the raw data indicates a possible drop in education right below the threshold, but else quite similar levels of education (Figure 5.5).

Figure 5.5. Average educational attainment by CD4 cell count



When controlling for sociodemographic characteristics, years since the test and visit year, we cannot detect an overall effect of parental ART eligibility on children's education, as shown in Table 5.4. However, when we restrict the sample to children who are in compulsory schooling, there are significant differences by the gender of the parent: paternal ART eligibility decreases children's education by 0.6 years on average, but there is no impact of maternal ART eligibility.

Table 5.4. Main analyses

	(1)	(2)	(3)	(4)	(5)	(6)
		All children			Compulsory schooling	
Eligible	-0.126	-0.294	-0.415	-0.083	-0.201	-0.587**
	(0.2120)	(0.2261)	(0.2608)	(0.2099)	(0.2143)	(0.2614)
Deviation	0.001	0.001	0.001	0.001	0.002	0.002
	(0.0054)	(0.0054)	(0.0055)	(0.0054)	(0.0054)	(0.0054)
Eligible # Deviation	-0.004	-0.004	-0.004	-0.003	-0.004	-0.004
	(0.0070)	(0.0070)	(0.0070)	(0.0066)	(0.0065)	(0.0066)
Eligible # Girl		0.378**			0.268	
		(0.1915)			(0.1875)	
Eligible # Mother			0.339			0.580**
			(0.2469)			(0.2432)
R2	0.741	0.742	0.742	0.687	0.688	0.689
Cluster	541	541	541	493	493	493
Observations	4388	4388	4388	2822	2822	2822
Bandwidth	58	58	58	60	60	60

Regression controlling for year of visit, years since the CD4 test, children's age and gender, and parents' age, gender and education. Deviation is the CD4 cell count minus the threshold of 200 cells/µl. Clustered standard errors in parenthesis.
* p<0.1 ** p<0.05 *** p<0.01.

5.4.4 The impact of state support

As depicted in Table 5.5, the impact of ART eligibility differs significantly by grant status. There is no significant impact of ART eligibility for recipients without any grant, except for a negative impact on boys at a 10% significance level. For recipients of the disability grant, ART eligibility significantly decreases educational attainment of their children by 1.7 years (significant at the 5% level). For recipients of other grants, ART eligibility has a significantly larger impact on educational attainment than for respondents without any grant. However, due to the reverse signs of the coefficients, the overall impact of eligibility on this group is not significant. Still, for children of fathers who received any other grant, there is a significant increase in educational attainment of about 1 year when their father becomes eligible.

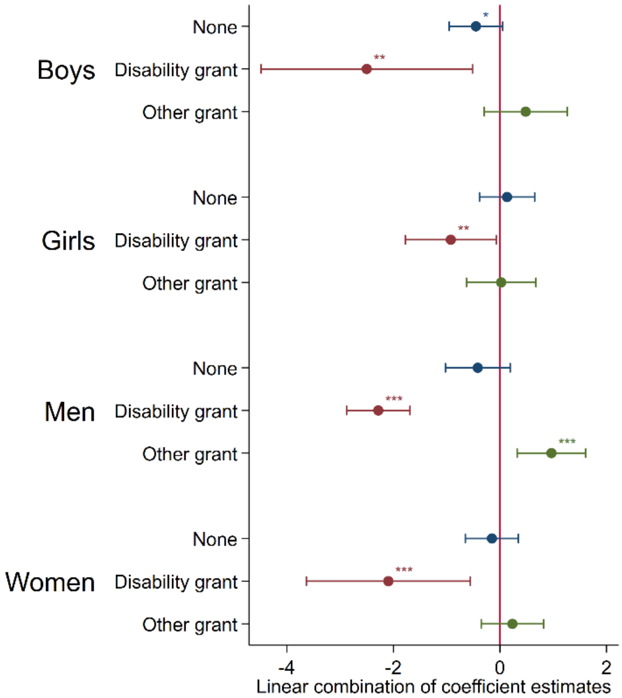
Table 5.5. Role of grants

	(1) Education	(2) By child's gender	(3) By parent's gender
Eligible	-0.184	-0.450*	-0.416
	(0.2395)	(0.2556)	(0.3094)
Deviation	-0.001	-0.000	-0.001
	(0.0064)	(0.0062)	(0.0066)
Eligible # Deviation	-0.001	-0.002	-0.001
	(0.0084)	(0.0082)	(0.0084)
Eligible # Disability grant	-1.474**	-2.050**	-1.866***
	(0.5733)	(0.9942)	(0.3244)
Eligible # Other grant	0.452*	0.933**	1.382***
	(0.2676)	(0.3901)	(0.3852)
Eligible # Female		0.583**	0.266
		(0.2333)	(0.2948)
Eligible # Female # Disability grant		0.995	-0.077
		(1.1567)	(0.8285)
Eligible # Female # Other grant		-1.043**	-0.998**
		(0.5042)	(0.4703)
R2	0.746	0.749	0.748
Cluster	429	429	429
Observations	3525	3525	3525
Bandwidth	52	52	52

Regression for children's education controlling for year of visit, years since CD4 test, children's age and gender, and parents' age, gender and education. Deviation is the CD4 cell count minus the threshold of 200 cells/μl. Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

Figure 5.6 displays the linear combinations of the coefficient estimates of Table 5.5 to demonstrate the overall impact of eligibility on the distinct groups. Children of former recipients of the disability grant experience a significant negative impact of eligibility on education, irrespective of their gender or the gender of their parents. The overall effects span from -0.9 years on average for girls to -2.5 years on average for boys. In contrast, if fathers with any other previous grant become eligible, educational attainment increases by one year on average.

Figure 5.6. Heterogeneous impact by grant and gender



5.4.5 Economic burden

The above findings suggest that the disability grant, which like ART eligibility is linked to the CD4 cell count, plays an intermediate role through decreased financial security. We further investigate this potential channel by analyzing the heterogeneous impact of grants on the household's economic situation measured by the household's asset index quintile (Table 5.6). There is a significant negative impact of eligibility for previous recipients of the disability grant on the household's asset index. We cannot detect any heterogeneous impact of other grants on the asset index.

Table 5.6. Asset index

	(1) Asset index	(2) Asset index	(3) Asset index
Eligible	-0.017	0.090	0.526
	(0.1898)	(0.2100)	(0.3289)
Deviation	-0.004	-0.001	-0.002
	(0.0058)	(0.0059)	(0.0060)
Eligible # Deviation	0.008	0.004	0.005
	(0.0077)	(0.0080)	(0.0081)
Eligible # Disability grant		-1.130***	-1.605***
		(0.2478)	(0.3260)
Eligible # Other grant		-0.210	-0.270
		(0.2462)	(0.3168)
Eligible # Mother			-0.535*
			(0.3080)
Eligible # Mother # Disability grant			0.626
			(0.4782)
Eligible # Mother # Other grant			0.125
			(0.4139)
R2	0.147	0.146	0.157
Cluster	408	369	369
Observations	1942	1789	1789
Bandwidth	50	50	50

Regression controlling for year of visit, and parents' age, gender and education. Deviation is the CD4 cell count minus the threshold of 200 cells/µl. Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

5.4.6 Robustness checks

Individuals not yet eligible for ART have shorter transitions to treatment the closer they are to the threshold. To exclude that this biases our results, we conduct a donut regression discontinuity design by dropping individuals within a bandwidth of +/-5. The differential impact of grants remain largely significant (Table 5.7). The only result that is not robust to this specification is the heterogeneous impact for recepients of other grants when not accounting for gender-specific effects (column 4). Moreover, the results remain stable when restricting the sample to CD4 tests before August 2010 to rule out any anticipatory effects of the guideline change in August 2011 (Table A 5.1).

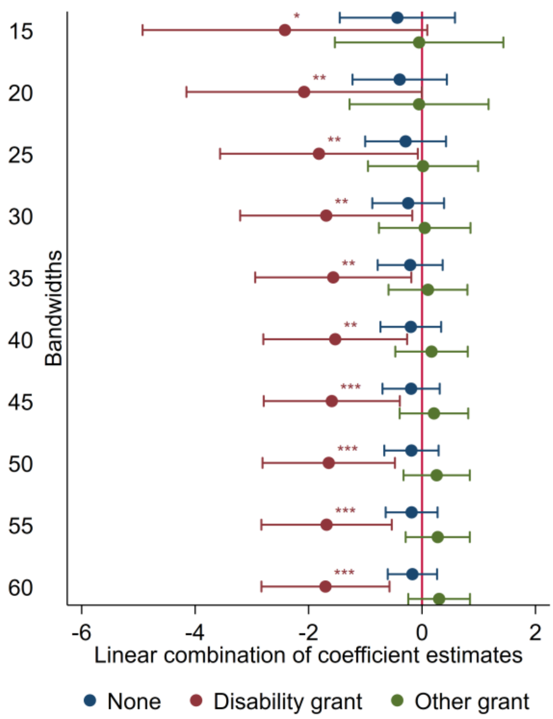
Table 5.7. Donut RDD

	(1) Education	(2) By child's gender	(3) By parent's gender
Eligible	-0.177	-0.445	-0.610*
	(0.2897)	(0.2960)	(0.3620)
Eligible # Disability grant	-1.057***	-1.228**	-1.635***
	(0.3781)	(0.6031)	(0.3538)
Eligible # Other grant	0.435	0.959**	1.574***
	(0.2811)	(0.4027)	(0.3899)
Eligible # Female		0.576**	0.463
		(0.2521)	(0.3100)
Eligible # Disability grant # Female		0.133	0.330
		(0.8425)	(0.5927)
Eligible # Other grant # Female		-1.156**	-1.228**
		(0.5233)	(0.4813)
R^2	0.745	0.748	0.747
Cluster	393	393	393
Observations	3262	3262	3262

Regression for children's education controlling for year of visit, children's age and gender, and parents' age, gender and education. Data-driven bandwidth: +/- 58 without observations in the bandwidth +/-5 (donut RDD). Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

The results are also robust to quadratic and cubic functions for the CD4 cell count (Table A 5.2 and Table A 5.3). We further test for alternative bandwidths between 10 and 60 in steps of 5. The heterogeneous negative impact for recipients of the disability grant is robust to all of these bandwidths, while the heterogeneous impact of other grants is robust to bandwidths between 35 and 60 and a bandwidth of 15, but switches sign in a bandwidth of 10 (Figure 5.7).

Figure 5.7. Different bandwidths



5.5 Discussion

Each year, access to ART saves millions of lives (UNAIDS, 2013). This positive, large impact on health is likely to affect other dimensions of well-being, too. One challenge for the examination of this channel is that ART initiation is not exogenous. Within the study setting, socio-economic factors and especially gender play an important role in HIV testing, linkage to care and retention in care (Lessells et al., 2011; Maheu-Giroux et al., 2017; Mutevedzi et al., 2010; Welz et al., 2007). We use policy guidelines on ART eligibility to employ a regression discontinuity design to identify the causal impact of ART eligibility on children's education.

We find that ART eligibility reduces clinical visits of fathers, but no overall effect on children's educational attainment. However, there is a considerable heterogeneity based on the reception of state support prior to the ART eligibility assessment: Children of parents who previously received a disability grant fare comparatively worse after their parents become eligible for ART, with a relative reduction of 1.7 years in educational attainment compared to their peers. Further analyses suggest that this heterogenous effect is due to household's worse economic situation as a consequence of losing the disability grant – eligible parents with a disability grant experience a decline in their asset index after they become eligible for ART. In contrast, children of parents who received any other type of state grant have a comparatively higher educational attainment after their parents become eligible for ART – an effect which is driven by fathers.

Taken together, these findings imply that the transmission of health improvements into children's educational attainment is mediated by the economic situation of the household. Without any previous grant, improvements in parental health do not spill over to educational attainments – possibly, because employment rates recover too slowly (Bor et al., 2012), while costs of accessing the ART clinics (Chimbindi et al., 2015) or meeting the additional food requirements for recovering patients (Patenaude et al., 2018) materialize immediately. For previous recipients of the disability grant, who are at risk of losing their grant after initiating ART, the co-occurrence of health benefits and a negative income shock even results in a decrease in children's educational attainment. In contrast, receiving other types of state support which are not linked to health seems to help the households to make use of the health improvements.

Our study speaks to the wider literature on financial support and health. Recent studies highlighted the role of financial support to foster health outcomes among the poor (Banerjee et al., 2021; Haushofer et al., 2020). Moreover, financial support can mitigate the negative impact of poor parental health on children's education (Chen et al., 2015), but might also have negative consequences, for example by crowding out adult employment (Dahl and Gielen, 2021). Our study demonstrates that this complex relationship also exists in the context of a positive health shock, underlining the importance to evaluate state support policies on their impact on all dimension of well-being.

There are several limitations to our study. Albeit both the clinical data set and the demographic panel data set are large, the final analysis sample comprises of relatively few observations for a regression discontinuity design. This implies that we cannot rule out impacts on education which are too small to be detected with our sample size. In addition, the regression discontinuity design estimates the impact of eligibility locally, i.e., at the threshold, and cannot be generalized into effect sizes further away without additional assumptions. Relatedly, the optimal bandwidths are sensitive to the exact regression specification. However, we can show that our main outcomes are robust to several bandwidths above and below the data-driven bandwidths as well as other functional forms.

The health and life expectancy improvements as a consequence of ART are impressive. Our findings indicate that the design of social policies can help or hinder to transmit improved health to wider socioeconomic impacts.

6 References

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7 Appendices

A 2. Appendix for Chapter 2

A 2.1. Random walk scheme

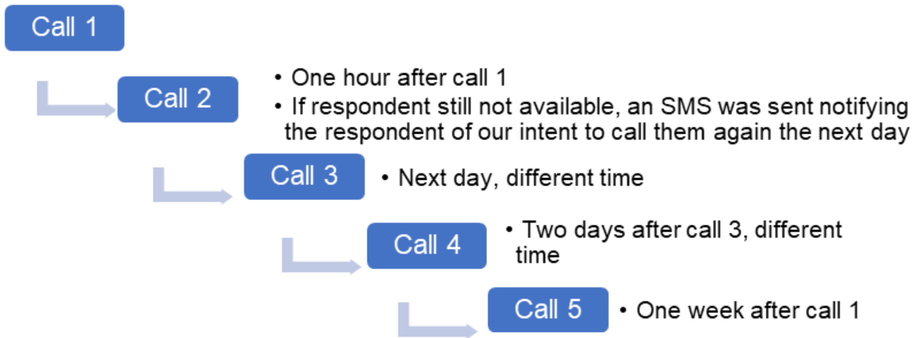
The enumerators conducted the random walk according to the following instructions:

1. Get permission and number of village subdivisions from the village head.
2. Ask for a description of the village boundaries, including remote houses.
3. Get the total number of houses in the village and divide this number by 100. This number indicates the skip-pattern of houses. It takes into account the aim of having around 20 respondents per village that should be evenly distributed throughout the village, how many interviews one enumerator can do in one day, and the likelihood of finding a household member that meets the inclusion criteria.
4. Then, randomly select which village subdivision to visit first and at which house (a random number between 1 and the skip number) to begin with. The count begins from the point of entry to the respective subdivision.
5. If a person is at home, check and record the eligibility and conduct the interview if the criteria are fulfilled and the respondent is willing to.
6. After each contact, continue with the next house according to the skip pattern.
7. In case of an empty house, contact the direct neighbor until an occupied house was found and record the number of empty houses.
8. When walking, turn left on every turn and only count houses to your left. Whenever you reach the end of the village subdivision or the road, turn around and continue.

One village was considered finished if 20 interviews were conducted or all houses that should be contacted according to the skip pattern were contacted.

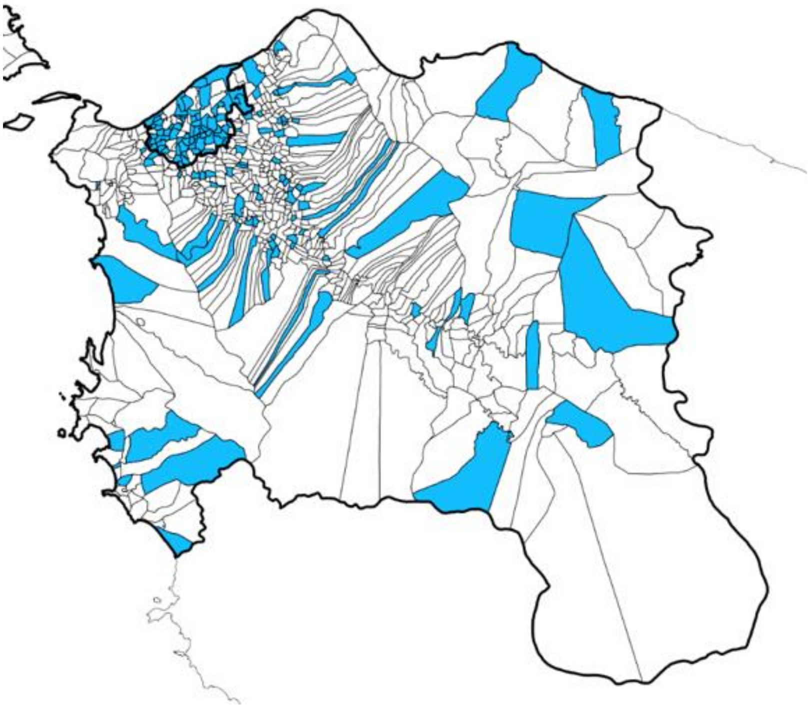
A 2.2. Calling procedure

The telephone interviews were scheduled according to the call pattern that is displayed below. Initially, each respondent received five calls, which were staggered with time delays of one hour to three days any at varying times of the day. After the second unanswered call, a standardized text message was sent announcing another call on the following day. Whenever feasible, the same enumerator who had visited the respondent during the baseline survey was deployed to call them during the phone interview, in order to maximize the response rate as well as the respondents' trust towards the enumerator. In the end of the data collection period, each number that was not answered during five calls received one additional call from another interviewer (with a different telephone number).



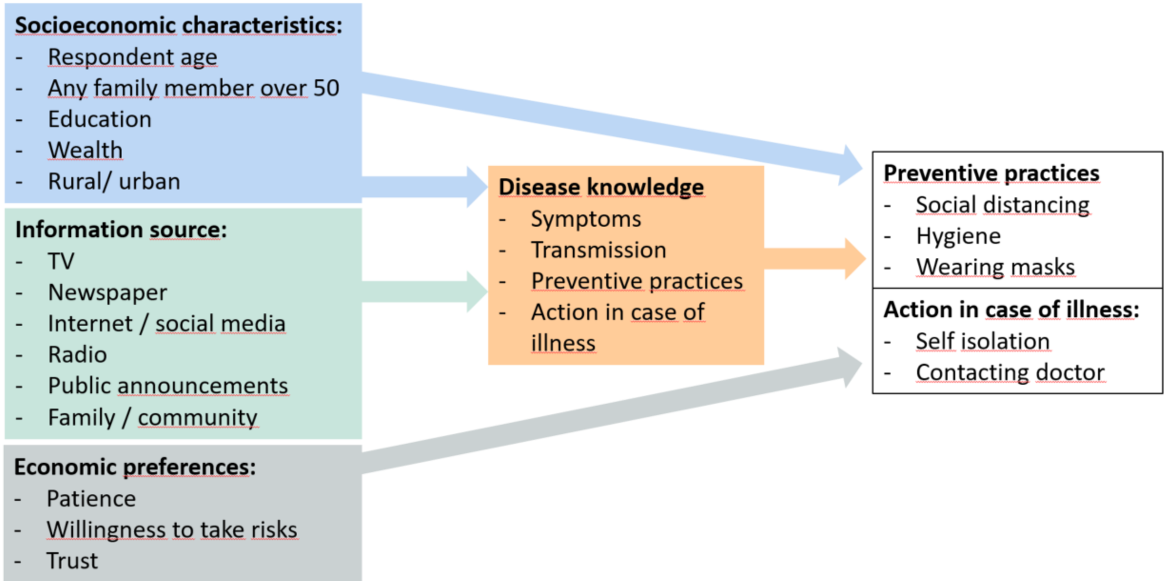
A 2.3. Figures

Figure A 2.1 Sampled villages with administrative boundaries



Sample villages. Boundaries of the city Banda Aceh and the district Aceh Besar are in bold

Figure A 2.2 Overview of contributors to disease knowledge and practices that are tested in the regression analysis



A 2.4. Tables

Table A 2.1 Overview of baseline contacts

	Total	**Of all contacts**			**Of all consenting**		**Of all eligible**		
	Contacts	Empty houses	Refusal/ busy/ other	Consent	Eligible	Ineligible	Refusal	Incomplete	Complete
N	15,128	7,682	946	6,500	2,115	4,385	11	98	2,006

	Of all ineligible			
	No member 40-70	No member 40-70 present	No phone access	No member without diagnosis/ screening/care
N	1,589	414	270	2,112

Disaggregation of the number of contacts and respondents at baseline. Contacts refer to all dwelling units drawn by the random walk within the villages. Empty houses are dwellings where no one was present at the first contact, including dwellings which might not been inhabited. Refusal/busy/other denotes to reasons for non-participation stated at the first contact. Consent signifies that at least one household member agreed to respond to the screening questions to assess eligibility. Eligible refers to all contacts where at least one eligible member was present. Ineligible are all contacts where no member was eligible or no eligible member was present. Refusal denotes those (eligible) contacts for which no eligible member was willing to participate in the study. Incomplete denotes the interviews which were missing information on the telephone number. Complete refers to all conducted interviews with information on the telephone number. The columns 'no member 40-70' till 'no phone access' refer to the household eligibility criteria, the last column to the individual-level criteria (if multiple members were eligible, one was randomly selected). Among individuals, ineligibility could occur due to previous hypertension or diabetes diagnosis (59.36%), being in continued care (8.42%), being tested for diabetes in the last year (31.98%), or not answering one of the eligibility questions (0.24%).

Table A 2.2 Variable Definitions

Vector name (as in equation)	**Variable Name** (as in output tables)	**Variable Definition**	**Questionnaire Number**
$KNOWLEDGE_i$	Knows droplet transmission	0 - respondent did not mention *droplets after coughing or sneezing* to be a transmission channel 1 - respondent mentioned *droplets after coughing or sneezing* to be a transmission channel	D3
	Knows smear transmission	0 - respondent did neither mention i) *touching the infected person* nor ii) *the use of objects used by an infected person* to be transmission channels 1 - respondent did mention i) *touching the infected person* and/or ii) *the use of objects used by an infected person* to be transmission channels	D3
	Knows fever and cough	0 - respondent did not mention that i) *fever* nor ii) *cough* are symptoms 1 - respondent did mention that i) *fever* and/or ii) *cough* are symptoms	D2
	Knows social dist.	0 - respondent did not mention i) *avoiding close contact with others* nor ii) *avoiding group gatherings* nor iii) *staying at home* to be ways of prevention 1 - respondent did mention i) *avoiding close contact with others* and/or ii) *avoiding group gatherings* and/or iii) *staying at home* to be ways of prevention	D9
	Knows hygiene	0 - respondent did not mention i) *wash hands/use hand sanitizer* nor ii) *sneeze/cough in forearm/tissue* nor iii) *clean and disinfect often* to be ways of prevention 1 - respondent did mention i) *wash hands/use hand sanitizer* and/or ii) *sneeze/cough in forearm/tissue* and/or iii) *clean and disinfect often* to be ways of prevention	D9
	Knows mask wearing	0 - respondent did not mention *wearing a mask* to be a way of prevention 1 - respondent did mention *wearing a mask* to be a way of prevention	D9

Table A 2 Variable Definitions ctd.

Vector name (as in equation)	**Variable Name** (as in output tables)	**Variable Definition**	**Questionnaire Number**
$UPTAKE_i$	Does social dist.	0 - respondent did not take up i) *avoiding close contact with others* nor ii) *avoiding group gatherings* nor iii) *staying at home* as prevention 1 - respondent did take up i) *avoiding close contact with others* and/or ii) *avoiding group gatherings* and/or iii) *staying at home* as prevention	D10
	Does hygiene	0 - respondent did not take up i) *wash hands/use hand sanitizer* nor ii) *sneeze/cough in forearm/tissue* nor iii) *clean and disinfect often* as prevention 1 - respondent did take up i) *wash hands/use hand sanitizer* and/or ii) *sneeze/cough in forearm/tissue* and/or iii) *clean and disinfect often as prevention*	D10
	Wears masks	0 - respondent did not take up *wearing a mask* as prevention 1 - respondent did take up *wearing a mask* as prevention	D10
	Isolation	0 - respondent would not i) *stay at home* nor ii) *quarantine/isolate* if feeling like he/she could have the coronavirus 1 - respondent would i) *stay at home* and/or ii) *quarantine/isolate* if feeling like he/she could have the coronavirus	D8
	Contact medical professional	0 - respondent would not i) *go to the doctor* nor ii) *call medical center* if feeling like he/she could have the coronavirus 1 - respondent would i) *go to the doctor* and/or ii) *call medical center* if feeling like he/she could have the coronavirus	D8
$SOCIOECON_i$	50 or older	0 - respondent is 50 years or younger 1 - respondent is older than 50 years	A2
	Other member 50+	0 - respondent's household does not include other members over 50 years 1 - respondent's household does include other members over 50 years	A2

Table A 2 Variable Definitions ctd.

Vector name (as in equation)	**Variable Name** (as in output tables)	**Variable Definition**	**Questionnaire Number**
SOCIOECON$_i$	Female	0 - respondent is male 1 - respondent is female	A1
	Lower Secondary	Categorical variable: 0 - no education or completed primary education (REF) 1 - completed lower secondary education (Lower Secondary) 2 - completed higher secondary or more education (Secondary and above)	A3
	Secondary and above		A3
	Wealth above median	0 - asset index is below or equal the median 1 - asset index is above the median	B1; B2; B3
	Urban	0 - respondent lives in rural Aceh Besar 1 - respondent lives in urban Banda Aceh	Geolocation & village ID (not in quest.)
INFO$_i$	TV	0 - respondent did not receive COVID information via the TV 1 - respondent did receive COVID information via the TV	D4
	Newspaper	0 - respondent did not received COVID information via newspaper 1 - respondent did receive COVID information via newspaper	D4
	Internet/social media	0 - respondent did not receive COVID information via the internet / social media 1 - respondent did receive COVID information via the internet / social media	D4
	Radio	0 - respondent did not receive COVID information via the radio 1 - respondent did receive COVID information via the radio	D4

Table A 2 Variable Definition ctd.

Vector name (as in equation)	**Variable Name** (as in output tables)	**Variable Definition**	**Questionnaire Number**
$INFO_i$	Public announcements	0 - respondent did not receive COVID information via public announcements 1 - respondent did receive COVID information via public announcements	D4
	Family/community	0 - respondent did not receive COVID information via the family / community 1 - respondent did receive COVID information via the family / community	D4
$PREF_i$	Risk taking	Scale variable from 0 to 10 on whether the respondent is generally a person who is fully prepared to take risks or tries to avoid taking risks: 0 - *completely unwilling to take risks* to 10 - *completely willing to take risks*	C1
	Patience	Scale variable from 0 to 10 on whether the respondent, in comparison to others, is generally willing to give something up today in order to benefit from that in the future: 0 - *completely unwilling to give up something today in order to benefit from that in the future* to 10 - *completely willing to give up something today in order to benefit from that in the future*	C2
	Trust	Four-point Likert scale on whether in general, one can trust people: 1 - Strongly disagree 2 - Disagree 3 - Agree 4 - Strongly agree	C3

Table A 2.3 Differences in means of Susenas and sample characteristics

	Susenas 2017 Banda Aceh, Aceh Besar	Baseline	Corona
Age	50.5935	50.1203	49.8831
	(0.3088)	(0.1825)	(0.2641)
Above 50	0.4878	0.4656	0.4577
	(0.0207)	(0.0111)	(0.0169)
Female	0.5239	0.6379***	0.6391
	(0.0207)	(0.0107)	(0.0177)
Education			
- Up to primary	0.2424	0.2926**	0.2686**
	(0.0188)	(0.0101)	(0.0175)
- Lower secondary	0.2347	0.2164	0.2210
	(0.0179)	(0.0092)	(0.0133)
- Upper secondary and above	0.5229	0.4910	0.5103**
	(0.0207)	(0.0110)	(0.0205)
Wealth above median		0.4923	0.5063
		(0.0112)	(0.0217)
Banda Aceh	0.4074	0.4372	0.4510
	(0.0181)	(0.0078)	(0.0236)
N	863	2,006	1,113

Standard errors accounting for survey design (sampling weights in Susenas, district stratification in both samples, PSU when comparing baseline and Corona sample) below mean. Stars indicate significant difference from the mean listed in the previous column based on adjusted Wald tests, * 0.1 ** 0.05 *** 0.01. Susenas 2017 includes only individuals aged 40-70 years in households that own a mobile phone.

Table A 2.4 Descriptive statistics: knowledge by group

	Knows droplet transmission	Knows smear transmission	Knows fever & cough
Total	0.62	0.66	0.73
	(0.02)	(0.02)	(0.01)
Age			
- Younger than 50 (ref)	0.68	0.67	0.76
	(0.02)	(0.02)	(0.02)
- 50 and older	0.55***	0.64	0.71*
	(0.03)	(0.02)	(0.02)
Mem. age			
- Younger than 50 (ref)	0.64	0.66	0.74
	(0.02)	(0.02)	(0.02)
- 50 and older	0.59*	0.65	0.72
	(0.02)	(0.03)	(0.02)
Gender			
- Male (ref)	0.64	0.68	0.73
	(0.03)	(0.02)	(0.02)
- Female	0.61	0.64	0.74
	(0.02)	(0.02)	(0.02)
Wealth			
- Below median (ref)	0.58	0.58	0.71
	(0.03)	(0.02)	(0.02)
- Above median	0.66**	0.73***	0.75
	(0.02)	(0.02)	(0.02)
Area			
- Urban (ref)	0.53	0.62	0.69
	(0.02)	(0.02)	(0.02)
- Rural	0.72***	0.70**	0.79***
	(0.02)	(0.03)	(0.02)
Education			
- Up to primary (ref)	0.51	0.57	0.65
	(0.03)	(0.03)	(0.03)
- Lower secondary	0.57	0.59	0.70
	(0.03)	(0.03)	(0.03)
- Higher secondary or more	0.70***	0.73***	0.79***
	(0.02)	(0.02)	(0.02)

Standard errors accounting for sampling design in parenthesis below the mean. Stars indicate significant difference from the reference category (denoted with ref), based on adjusted Wald test, *p<0.1 **p<0.05 ***p<0.01.

Table A 2.5 Descriptive statistics: practices by group

	Social distancing		Hygiene		Wear mask		Action when suspect	
	Know	Do	Know	Do	Know	Do	Isolation	Contact medical professional
Total	0.87	0.81	0.77	0.87	0.57	0.57	0.35	0.72
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Age								
- Younger than 50 (ref)	0.89	0.81	0.78	0.89	0.59	0.58	0.38	0.71
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)
- 50 and older	0.85	0.81	0.75	0.86	0.53*	0.54	0.32**	0.73
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Mem. age								
- Younger than 50 (ref)	0.87	0.81	0.77	0.87	0.57	0.60	0.35	0.69
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)
- 50 and older	0.88	0.81	0.76	0.88	0.56	0.52**	0.36	0.76***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Gender								
- Male (ref)	0.86	0.82	0.74	0.88	0.56	0.54	0.37	0.73
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
- Female	0.88	0.80	0.78	0.87	0.57	0.58	0.34	0.72
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Wealth								
- Below median (ref)	0.86	0.79	0.73	0.88	0.49	0.51	0.34	0.67
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
- Above median	0.88	0.82	0.80**	0.87	0.64***	0.61**	0.36	0.77***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Area								
- Urban (ref)	0.86	0.77	0.73	0.85	0.52	0.49	0.28	0.74
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
- Rural	0.89	0.86***	0.82***	0.90**	0.62***	0.65***	0.44***	0.69
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Education								
- Up to primary (ref)	0.82	0.79	0.67	0.89	0.45	0.46	0.30	0.67
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.05)	(0.03)	(0.03)
- Lower secondary	0.87*	0.75	0.73	0.85	0.55**	0.53	0.31	0.72
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
- Higher secondary or more	0.90***	0.84	0.83***	0.88	0.63***	0.62***	0.40***	0.74***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)

Standard errors accounting for sampling design in parenthesis below the mean. Stars indicate significant difference from the reference category (denoted with ref), based on adjusted Wald test, *p<0.1 **p<0.05 ***p<0.01.

Table A 2.6 Descriptive statistics: information source by group

	TV	Newspaper	Internet/ social media	Radio	Public announcement	Family/ community
Up to Primary	0.8161	0.0468	0.0936	0.0234	0.0769	0.6455
(ref)	(0.0222)	(0.0117)	(0.0181)	(0.0086)	(0.0160)	(0.0277)
Lower Secondary	0.8577	0.0407	0.1626**	0.0447	0.0894	0.6016
	(0.0222)	(0.0134)	(0.0241)	(0.0135)	(0.0188)	(0.0304)
Higher secondary	0.8873***	0.0687	0.3081***	0.0475*	0.0827	0.5511***
or more	(0.0127)	(0.0110)	(0.0208)	(0.0089)	(0.0119)	(0.0204)
Younger than 50	0.8856	0.0415	0.2670	0.0332	0.0779	0.5406
(ref)	(0.0121)	(0.0081)	(0.0210)	(0.0074)	(0.0109)	(0.0201)
50 or older	0.8330***	0.0747**	0.1591***	0.0491	0.0884	0.6424***
	(0.0166)	(0.0110)	(0.0177)	(0.0104)	(0.0121)	(0.0199)

Information source by group. Standard errors in parenthesis. Stars indicate statistically significant difference from the reference group (denoted with ref). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 2.7 P-values from comparing coefficients of information sources.

	Knows droplet transmission	Knows smear transmission	Knows fever and cough	Knows social dist.	Knows hygiene	Knows mask wearing
TV vs. Internet	0.4848	0.5530	0.0015	0.6261	0.1084	0.0002
TV vs. Family	0.0209	0.7066	0.0465	0.6215	0.1551	0.0228
Internet vs. Family	0.0228	0.8102	0.0554	0.1621	0.7326	0.0643

Table A 2.8. Estimates for the base model of equation 2.1

	(1) Knows droplet trans.	(2) Knows smear trans.	(3) Knows fever and cough	(4) Knows social dist.	(5) Knows hygiene	(6) Knows mask wearing
50 or older	-0.121***	-0.025	-0.032	-0.022	-0.015	-0.045
	(0.031)	(0.031)	(0.026)	(0.022)	(0.024)	(0.030)
Member 50 or older	-0.024	-0.011	-0.015	0.014	-0.010	-0.014
	(0.031)	(0.030)	(0.029)	(0.023)	(0.031)	(0.032)
Female	-0.040	-0.054*	0.003	0.014	0.045	0.006
	(0.031)	(0.030)	(0.028)	(0.023)	(0.029)	(0.034)
Lower Secondary	0.015	-0.009	0.038	0.046	0.050	0.075
	(0.042)	(0.045)	(0.043)	(0.035)	(0.042)	(0.047)
Higher secondary or more	0.110**	0.101***	0.111***	0.069**	0.124***	0.109***
	(0.043)	(0.035)	(0.034)	(0.029)	(0.036)	(0.041)
Wealth above median	0.058**	0.125***	0.015	-0.004	0.037	0.135***
	(0.029)	(0.031)	(0.032)	(0.022)	(0.027)	(0.035)
Urban	0.166***	0.050	0.082***	0.015	0.070**	0.077**
	(0.035)	(0.034)	(0.027)	(0.022)	(0.027)	(0.032)
Obs.	1090	1090	1089	1089	1089	1089
Mean	0.623	0.660	0.738	0.876	0.772	0.569
R2	0.074	0.045	0.029	0.011	0.036	0.044

Determinants of knowledge. Estimation of equation (1) with socioeconomic covariates only (information sources not included). Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 2.9. Estimates for the base model of equation 2.2

	(1) Does social dist.	(2) Does hygiene	(3) Wears masks	(4) Would isolate	(5) Would contact med. prof.
50 or older	-0.037	-0.051*	-0.036	-0.084***	0.018
	(0.031)	(0.029)	(0.032)	(0.031)	(0.028)
Member 50 or older	0.020	-0.001	-0.064**	0.041	0.068**
	(0.031)	(0.033)	(0.032)	(0.030)	(0.030)
Female	-0.007	0.019	0.038	-0.047	-0.037
	(0.028)	(0.032)	(0.027)	(0.029)	(0.030)
Lower Secondary	-0.001	0.015	0.060	-0.025	0.059
	(0.041)	(0.045)	(0.039)	(0.043)	(0.043)
Higher secondary or more	0.076**	0.095**	0.099***	0.040	0.071**
	(0.036)	(0.037)	(0.038)	(0.032)	(0.031)
Wealth above median	0.018	0.032	0.139***	0.010	0.077**
	(0.030)	(0.029)	(0.028)	(0.033)	(0.032)
Urban	0.085***	0.105***	0.120***	0.146***	-0.046
	(0.027)	(0.030)	(0.031)	(0.031)	(0.030)
Obs.	1082	1081	1081	1094	1094
Mean	0.713	0.674	0.321	0.356	0.729
R2	0.023	0.033	0.064	0.038	0.025

Determinants of protective health behavior. Estimation of equation (2) with socioeconomic covariates only (information sources not included). Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 2.10. Logit and probit estimates of Table 2.2.

	(1)	(2)	(3)	(4)	(5)	(6)
	Knows droplet transmission		Knows smear transmission		Knows fever and cough	
	Logit	Probit	Logit	Probit	Logit	Probit
50 or older	-0.497***	-0.297***	-0.120	-0.071	-0.170	-0.102
	(0.150)	(0.089)	(0.156)	(0.094)	(0.149)	(0.087)
Member 50 or older	-0.084	-0.059	-0.042	-0.025	-0.111	-0.071
	(0.152)	(0.092)	(0.142)	(0.086)	(0.155)	(0.090)
Female	-0.076	-0.049	-0.211	-0.123	0.078	0.045
	(0.145)	(0.087)	(0.144)	(0.088)	(0.157)	(0.091)
Lower Secondary	0.029	0.024	-0.087	-0.056	0.160	0.088
	(0.183)	(0.111)	(0.190)	(0.117)	(0.207)	(0.123)
Higher secondary or more	0.362*	0.225*	0.383**	0.234**	0.552***	0.317***
	(0.202)	(0.122)	(0.158)	(0.096)	(0.181)	(0.107)
Wealth above median	0.193	0.120	0.565***	0.336***	0.053	0.032
	(0.134)	(0.081)	(0.142)	(0.085)	(0.171)	(0.100)
Urban	0.650***	0.396***	0.146	0.087	0.373**	0.221**
	(0.170)	(0.102)	(0.171)	(0.102)	(0.153)	(0.090)
TV	1.322***	0.802***	0.785***	0.478***	1.314***	0.789***
	(0.213)	(0.127)	(0.190)	(0.117)	(0.193)	(0.117)
Newspaper	0.347	0.203	0.159	0.088	-0.076	-0.046
	(0.356)	(0.203)	(0.329)	(0.195)	(0.296)	(0.176)
Internet/social media	1.310***	0.757***	0.663***	0.393***	0.534***	0.303***
	(0.206)	(0.117)	(0.166)	(0.097)	(0.199)	(0.113)
Radio	-0.360	-0.222	1.055**	0.638***	0.442	0.251
	(0.365)	(0.212)	(0.413)	(0.234)	(0.362)	(0.201)
Public announcements	0.317	0.198	0.133	0.073	0.265	0.157
	(0.238)	(0.142)	(0.270)	(0.161)	(0.294)	(0.167)
Family/community	0.738***	0.450***	0.679***	0.411***	0.919***	0.536***
	(0.149)	(0.090)	(0.159)	(0.096)	(0.155)	(0.090)
Obs.	1096	1096	1096	1096	1095	1095
Mean	0.620	0.620	0.656	0.656	0.734	0.734

Determinants of disease knowledge estimated with logit and probit models. Droplet transmission indicates whether the respondent states that COVID-19 might be transmitted through droplets. Smear transmission indicates whether the respondent names touching infected persons or objects used by infected persons as transmission channels. Fever and cough indicates whether the respondent names fever and cough as symptoms for a COVID-19 infection. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. TV, newspaper, internet/social media, radio, public announcements, family/community are binary variables indicating from which information sources COVID-19 knowledge was obtained (multiple answers possible). Standard errors accounting for sampling design in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01

Table A 2.11. Logit and probit estimates of Table 2.3

	(1)	(2)	(3)	(4)	(5)	(6)
	Knows social dist.		Knows hygiene		Knows mask wearing	
	Logit	Probit	Logit	Probit	Logit	Probit
50 or older	-0.235	-0.126	-0.033	-0.023	-0.199	-0.120
	(0.202)	(0.108)	(0.155)	(0.089)	(0.139)	(0.085)
Other member 50 or older	0.118	0.061	-0.066	-0.037	-0.073	-0.048
	(0.216)	(0.118)	(0.194)	(0.111)	(0.141)	(0.085)
Female	0.193	0.099	0.356**	0.210**	0.136	0.089
	(0.211)	(0.113)	(0.170)	(0.099)	(0.152)	(0.092)
Lower Secondary	0.388	0.203	0.250	0.139	0.307	0.188
	(0.287)	(0.155)	(0.213)	(0.124)	(0.203)	(0.125)
Higher secondary or more	0.633**	0.326**	0.669***	0.393***	0.408**	0.251**
	(0.250)	(0.134)	(0.194)	(0.114)	(0.182)	(0.111)
Wealth above median	-0.075	-0.046	0.176	0.102	0.570***	0.351***
	(0.207)	(0.108)	(0.158)	(0.091)	(0.154)	(0.093)
Urban	0.062	0.038	0.326*	0.191*	0.256*	0.158*
	(0.213)	(0.114)	(0.177)	(0.103)	(0.153)	(0.093)
TV	0.881***	0.460***	1.307***	0.768***	1.443***	0.887***
	(0.252)	(0.140)	(0.200)	(0.120)	(0.213)	(0.127)
Newspaper	0.500	0.236	-0.034	-0.038	0.427	0.249
	(0.432)	(0.227)	(0.338)	(0.198)	(0.309)	(0.184)
Internet/social media	0.681***	0.359***	1.043***	0.584***	0.609***	0.373***
	(0.247)	(0.127)	(0.241)	(0.133)	(0.138)	(0.082)
Radio	0.405	0.143	-0.273	-0.166	0.339	0.205
	(0.606)	(0.311)	(0.354)	(0.208)	(0.348)	(0.207)
Public announcements	1.051**	0.501**	0.749**	0.443**	0.747***	0.464***
	(0.503)	(0.234)	(0.318)	(0.177)	(0.257)	(0.151)
Family/community	1.017***	0.533***	1.009***	0.578***	0.896***	0.552***
	(0.187)	(0.098)	(0.143)	(0.083)	(0.152)	(0.092)
Obs.	1095	1095	1095	1095	1095	1095
Mean	0.872	0.872	0.768	0.768	0.566	0.566

Determinants of preventive health knowledge estimated with logit and probit models. Social distancing includes staying at home, avoiding close contact with others, and avoiding group gatherings. Hygiene measures include washing or disinfecting hands, sneezing or coughing in forearm or tissue, and cleaning and disinfecting often. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. TV, newspaper, internet/social media, radio, public announcements, family/community are binary variables indicating from which information sources COVID-19 knowledge was obtained (multiple answers possible). Standard errors in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01

Table A 2.12. Logit and probit estimates of Table 2.4

	(1)	(2)	(3)	(4)	(5)	(6)
	Does social dist.		Does hygiene		Wears masks	
	Logit	Probit	Logit	Probit	Logit	Probit
50 or older	-0.117	-0.081	-0.379*	-0.204*	-0.181	-0.108
	(0.177)	(0.101)	(0.211)	(0.112)	(0.195)	(0.120)
Member 50 or older	0.106	0.053	0.128	0.066	-0.352*	-0.218*
	(0.187)	(0.105)	(0.214)	(0.113)	(0.181)	(0.112)
Female	-0.038	-0.017	-0.171	-0.085	0.297*	0.184*
	(0.171)	(0.095)	(0.234)	(0.123)	(0.168)	(0.104)
Lower Secondary	-0.213	-0.119	-0.296	-0.132	0.153	0.097
	(0.212)	(0.122)	(0.341)	(0.181)	(0.252)	(0.157)
Higher secondary or more	0.121	0.063	-0.214	-0.106	0.270	0.169
	(0.205)	(0.115)	(0.276)	(0.143)	(0.238)	(0.148)
Wealth above median	0.046	0.029	-0.070	-0.023	0.382**	0.235**
	(0.180)	(0.101)	(0.205)	(0.111)	(0.169)	(0.104)
Urban	0.519***	0.283***	0.549**	0.290**	0.567***	0.349***
	(0.172)	(0.096)	(0.236)	(0.121)	(0.188)	(0.116)
Knows droplet transmission	0.213	0.105			0.346*	0.214*
	(0.183)	(0.105)			(0.181)	(0.113)
Knows smear transmission	0.405**	0.230**	0.038	0.004		
	(0.175)	(0.101)	(0.243)	(0.127)		
Knows social dist.	4.626***	2.610***				
	(0.447)	(0.199)				
Knows hygiene			7.504***	3.839***		
			(1.019)	(0.343)		
Knows mask wearing					0.000	0.000
					(.)	(.)
Willingness to take risks	0.059*	0.033*	0.019	0.008	-0.025	-0.015
	(0.035)	(0.019)	(0.045)	(0.024)	(0.041)	(0.025)
Patience	-0.029	-0.019	-0.036	-0.019	0.059*	0.036*
	(0.034)	(0.019)	(0.046)	(0.024)	(0.035)	(0.022)
Trust	0.280*	0.163*	-0.276	-0.134	-0.036	-0.020
	(0.154)	(0.087)	(0.191)	(0.099)	(0.145)	(0.088)
Obs.	1077	1077	1077	1077	613	613
Mean	0.713	0.713	0.676	0.676	0.566	0.566

Determinants of preventive health behavior estimated with logit and probit models. Social distancing includes staying at home, avoiding close contact with others, and avoiding group gatherings. Hygiene measures include washing or disinfecting hands, sneezing or coughing in forearm or tissue, and cleaning and disinfecting often. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. Willingness-to-take-risk and patience are elicited on a scale from 0 to 10 using the module from the Global Preference Survey. Trust is measured as general trust in people using a four-point Likert scale. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 2.13 Logit and probit estimates of Table 2.5

	(1)	(2)	(3)	(4)
	Would isolate		Would contact medical professional	
	Logit	Probit	Logit	Probit
50 or older	-0.335**	-0.207**	0.188	0.108
	(0.148)	(0.090)	(0.160)	(0.094)
Member 50 or older	0.230	0.134	0.395**	0.232**
	(0.140)	(0.085)	(0.168)	(0.098)
Female	-0.163	-0.095	-0.224	-0.135
	(0.140)	(0.085)	(0.160)	(0.094)
Lower Secondary	-0.185	-0.118	0.298	0.173
	(0.208)	(0.124)	(0.221)	(0.132)
Higher secondary or more	0.075	0.042	0.250	0.144
	(0.156)	(0.094)	(0.160)	(0.096)
Wealth above median	-0.045	-0.024	0.423**	0.252**
	(0.158)	(0.095)	(0.171)	(0.100)
Urban	0.677***	0.415***	-0.355**	-0.210**
	(0.149)	(0.090)	(0.157)	(0.092)
Knows fever and cough	0.965***	0.582***	0.906***	0.543***
	(0.166)	(0.096)	(0.157)	(0.093)
Willingness to take risks	0.068**	0.043**	0.040	0.024
	(0.034)	(0.020)	(0.034)	(0.020)
Patience	0.058*	0.035*	-0.068**	-0.040**
	(0.032)	(0.019)	(0.030)	(0.018)
Trust	0.020	0.016	-0.164	-0.096
	(0.111)	(0.069)	(0.110)	(0.067)
Obs.	1083	1083	1083	1083
Mean	0.359	0.359	0.735	0.735

Determinants of action in case of illness estimated with logit and probit models. Isolating includes quarantining or staying at home in case of illness. Contact medical professional includes a calling a doctor or visiting a medical center. Education is grouped into no education or primary school, lower secondary school, and higher secondary school or higher. Wealth above median indicates whether the household asset index lies above the median, stratified by urban and rural area. Fever and cough indicates whether the respondent names fever and cough as symptoms for a COVID-19 infection. Willingness-to-take-risk and patience are elicited on a scale from 0 to 10 using the module from the Global Preference Survey. Trust is measured as general trust in people using a four-point Likert scale. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A 2.5. Questionnaire

The full questionnaire, replication files and data are publicly available in Göttingen Research Online at https://data.goettingen-research-online.de/ , doi:10.25625/SKTLZV.

Questions B1-B3 (Household characteristics) are derived from SUSENAS 2017 (BPS, 2018), questions C1 and C2 (willingness to take risk and patience) are taken from the World Preference Survey (Falk et al., 2016), and question C3 from the German Socioeconomic Panel (Kantar Public, 2018). Questions D1-D13 are based on previous literature on pandemic knowledge and behavior (Balkhy et al., 2010; Ibuka et al., 2010).

A 3. Appendix for Chapter 3

A 3.1. Wording of messages

Table A 3.1 Wording of messages

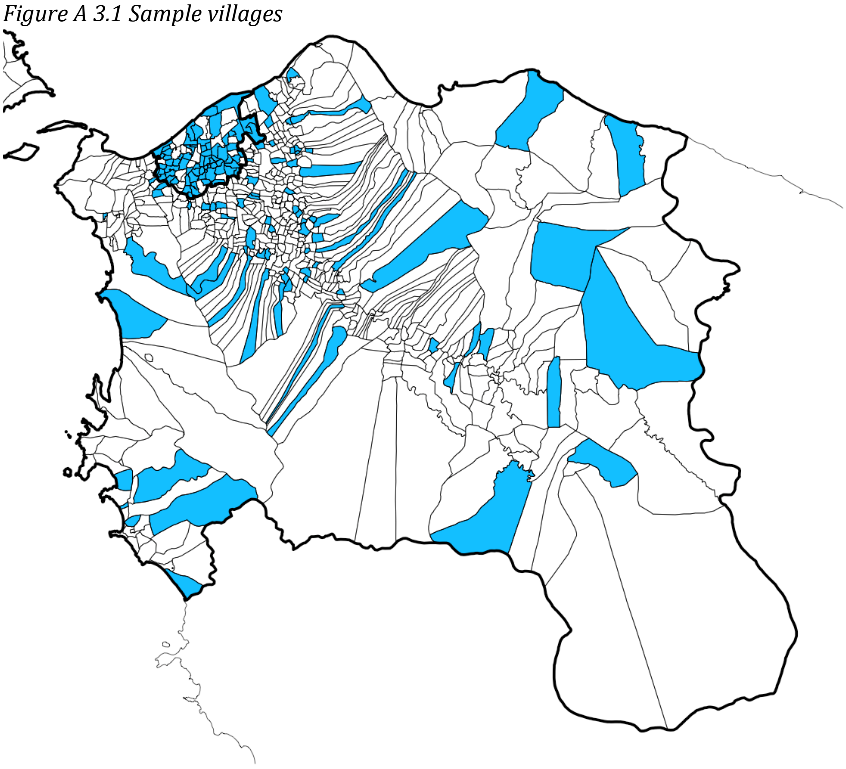
Message (English)	Message (Indonesian)	Sending date
Greetings [Mr/Ms] [name], do you know that diabetes does not always show symptoms but can be treated better if detected earlier. Check for FREE at POSBINDU [date]	Salam [Pak/Ibu] [name], tahukah Anda diabetes tdk selalu menunjukan gejala namun dapat diobati lbh baik jika diketahui lbh awal. Periksa GRATIS di POSBINDU [date]	5 days before the first village screening date
Greetings [Mr/Ms] [name], do you know that people over 40 years old have a high risk of diabetes & hypertension? Ask kader / PKM & check for FREE at POSBINDU [date]	Salam [Pak/Ibu] [name], tahukah Anda umur diatas 40 tahun memiliki risiko tinggi diabetes & darah tinggi? Tanyakan Kader/PKM & Periksa GRATIS di POSBINDU tgl [date]	3 days before the first village screening date
Greetings [Mr / Mrs] [name], remember to benefit from a FREE diabetes and hypertension CHECK in POSBINDU tomorrow morning at [place within the village]. Contact nearest kader or PKM.	Salam [Pak/Ibu] [name], Jangan Lupa untuk PERIKSA Darah Tinggi dan Diabetes GRATIS di POSBINDU Besok pagi di [place within village]. Hubungi Kader dan PKM terdekat	1 day before the first village screening date
Greetings [Mr/Ms] [name], remember that hypertension does not always show symptoms but can be treated if detected earlier. Check for FREE at POSBINDU [date]	Salam [Pak/Ibu] [name], ingatlah darah tinggi tdk selalu menunjukan gejala namun dapat diobati lbh baik jika diketahui lbh awal. Periksa GRATIS di POSBINDU [date]	5 days before the second village screening date
Greetings [Mr/Ms] [name], remember that people over 40 years old have a high risk of diabetes & hypertension. Ask Cadre / PKM & check for FREE at POSBINDU date [date]	Salam [Pak/Ibu] [name], ingatlah umur diatas 40 tahun memiliki risiko tinggi diabetes & darah tinggi. Tanyakan Kader/PKM & Periksa GRATIS di POSBINDU tgl [date]	3 days before the second village screening date
Greetings [Mr / Mrs] [name], remember to benefit from a FREE diabetes and hypertension CHECK in POSBINDU morning at [place within the village]. Contact nearest kader or PKM.	Salam [Pak/Ibu] [name], Jangan Lupa untuk PERIKSA Darah Tinggi dan Diabetes GRATIS di POSBINDU Besok pagi di [place within village]. Hubungi Kader dan PKM terdekat	1 day before the second village screening date

A 3.2. Data collection details

Table A 3.2 Data collection timeline

	2019			2020			
Month	**October**	**November**	**December**	**January**	**February**	**March**	**April**
Qualitative pre-studies							
Baseline data collection (enrolment)							
Treatment allocation				X			
Pilot Intervention				X			
Intervention							
Endline data collection							

Figure A 3.1 Sample villages



Boundaries of the city Banda Aceh and the district Aceh Besar are in bold. Taken from the supplementary material in Chavarría et al. (2021).

Inclusion Criteria

We targeted the population at high risk for NCDs, who do not yet adhere to the recommended screening schedule. Based on this, we formulated six inclusion and exclusion criteria:

1. The respondent must be between 40 and 70 years old. The WHO PEN Protocol for essential NCD interventions for primary health care in low-resource settings specifies that individuals over 40 years old should undergo routine screening for hypertension and diabetes (WHO, 2010a).
2. The respondent cannot already be diagnosed with diabetes or hypertension, as this would render screening unnecessary.
3. The respondent did not undergo diabetes screening within the last year. Individuals that have done so seem to be adhering to recommended screening schedules, and would therefore not fall within our target population. Hypertension screening is not included in this restriction, as blood pressure checks are usually carried out whenever individuals visit a community health center and are hence much more common in this context.
4. The respondent must not be in regular care for another disease. If they are in regular contact with health system services, a lack of NCD screening may not stem from a lack of demand but rather from further downstream health system failures, which we do not aim to address in our intervention.
5. The respondent must be reachable via phone and text messages on either their own or another household member's phone.
6. The respondent must be at home at the time of the interview. Logistically, it was not feasible to re-visit households. Furthermore, seeking out respondents outside of their home would have violated the comparability of interview conditions across our sample. For instance, respondents might feel most comfortable answering sensitive questions regarding their health in their own home. This criterion might bear the risk to exclude the working population, which we sought to reduce by extending the enumeration time to the evening and the weekends. Overall, this might not be as severe in our age group as in younger age groups, as some are retired already or work from home.

Random walk scheme

Taken from the supplementary material in Chavarría et al. (2021).

The enumerators conducted the random walk according to the following instructions to ensure that the walk yields a representative sample of the target population:

1. Get permission and number of village subdivisions from the village head.
2. Ask for a description of the village boundaries, including remote houses.
3. Get the total number of houses in the village and divide this number by 100. This number indicates the skip-pattern of houses. It takes into account the aim of having around 20 respondents per village that should be evenly distributed throughout the village, how many interviews one enumerator can do in one day, and the likelihood of finding a household member that meets the inclusion criteria.
4. Then, randomly select which village subdivision to visit first and at which house (a random number between 1 and the skip number) to begin with. The count begins from the point of entry to the respective subdivision.
5. If a person is at home, check and record the eligibility and conduct the interview if the criteria are fulfilled and the respondent is willing to.
6. After each contact, continue with the next house according to the skip pattern.
7. In case of an empty house, contact the direct neighbor until an occupied house was found and record the number of empty houses.
8. When walking, turn left on every turn and only count houses to your left. Whenever you reach the end of the village subdivision or the road, turn around and continue.
9. One village was considered finished if 20 interviews were conducted or all houses that should be contacted according to the skip pattern were contacted.

Table A 3.3 Overview of baseline contacts

	Total	Of all contacts			Of all consenting		Of all eligible		
	Contacts	Empty houses	Refusal/ busy/ other	Consent	Eligible	Ineligible	Refusal	Incomplete	Complete
N	15,128	7,682	946	6,500	2,115	4,385	11	98	2,006
	Of all ineligible								
	No member 40-70		No member 40-70 present		No phone access		No member without diagnosis/ screening/care		
N	1,589		414		270		2,112		

Disaggregation of the number of contacts and respondents at baseline. Contacts refer to all dwelling units drawn by the random walk within the villages. Empty houses are dwellings where no one was present at the first contact, including dwellings which might not be inhabited. Refusal/busy/other denotes to reasons for non-participation stated at the first contact. Consent signifies that at least one household member agreed to respond to the screening questions to assess eligibility. Eligible refers to all contacts where at least one eligible member was present. Ineligible are all contacts where no member was eligible or no eligible member was present. Refusal denotes those (eligible) contacts for which no eligible member was willing to participate in the study. Incomplete denotes the interviews which were missing information on the telephone number. Complete refers to all conducted interviews with information on the telephone number. The columns 'no member 40-70' till 'no phone access' refer to the household eligibility criteria, the last column to the individual-level criteria (if multiple members were eligible, one was randomly selected). Among individuals, ineligibility could occur due to previous hypertension or diabetes diagnosis (59.36%), being in continued care (8.42%), being tested for diabetes in the last year (31.98%), or not answering one of the eligibility questions (0.24%). Taken from the supplementary material in Chavarría et al. (2021).

A 3.3. Power Calculations

The following procedure of power calculation was set in the pre-analysis plan and under the assumption of an in-person endline data collection, which we had to deviate from due to the start of the COVID-19 pandemic.

The sample size was determined based on sufficient statistical power to determine a meaningful change in the primary outcome, screening uptake. Prior to baseline data collection, we could approximate the base levels of diabetes and hypertension separately from the most recent round of the Indonesian health survey Riskesdas (Riskesdas, 2018). This data supplies self-reported figures on whether the individual respondent attends screening regularly, irregularly or never, where regularly is defined as according to the doctor's advice for patients and once a year for the non-diagnosed. As our outcome is measured during approximately two months, the most appropriate base value is the *regular* category. The national average of the age group between 45 and 74 years is 5.2% for diabetes and 16.7% for hypertension screening[20]. As there are no previous studies on the effect of text message reminders on diabetes and hypertension screening, the minimum detectable effect size was approximated from studies that measure the effect of text message reminders on the initial take-up of other health services. A review on vaccination uptake found an average effect size of 4.5 percentage points (Jacobson Vann et al., 2018). With a power of 80% and 5% significance, a sample size of 1,800 individuals would be required to detect such an effect for both diabetes and hypertension screening. We would be able to detect a 4.4 percentage point increase for blood pressure

[20] From our baseline data, we know that slightly more individuals (23%) had a blood pressure check during the previous year. This would increase the minimal detectable effect size by 0.5 percentage points.

measurement and a 2.6 percentage point increase in blood glucose measurement.[21] This implies that we would be able to detect a significant effect on any screening if at least 24 more respondents of the treatment group attend diabetes screening during the intervention period compared to the control group at the same time. With this sample size, we will also be likely to detect a small change in the secondary knowledge outcomes. For the SMS knowledge, the mean points of the treatment group need to be 0.1 points higher than for the control group, which means that on average every tenth respondent needs to know one item more. For the broader health knowledge index, we will be able to detect a 0.56 point difference, which means that on average about every other individual in the treatment group needs to know at least one item more than the control group. As these changes are smaller than a meaningful effect that we would expect to be a channel for the primary outcome, we expect to be able to detect every meaningful effect of the intervention on health knowledge.

We account for potential sample reductions by over-sampling by about 15%. The main reason for a high over-sampling rate is that we rely on functioning phone numbers for the intervention. The over-sampling also accounts for respondents that need to be excluded from the treatment group because the messages could not be delivered to their mobile phone. One reason might be that the respondent changed his/her telephone number, which is common in this context. We tried to avoid this by asking for a contact number that is likely to be active until April 2020, and by planning a short duration between baseline interview and intervention. Another reason might be a typo when entering the phone number. Non-compliance might be a problem if the respondent does not own a mobile phone and the stated contact person does not transfer the message. We minimize this by specifically asking for a contact person from whom a message can be received and by including the name of the recipient in each message. Finally, we expect attrition at endline as it is likely that some respondents either cannot be found or are unavailable or unwilling to participate in a second interview. However, we expect overall attrition to be low: at baseline, each respondent has agreed to a second interview, we have taken detailed information on the place of residence (name, address, and geolocation), and we can contact him/her through the mobile phone number.

Calling procedure at endline

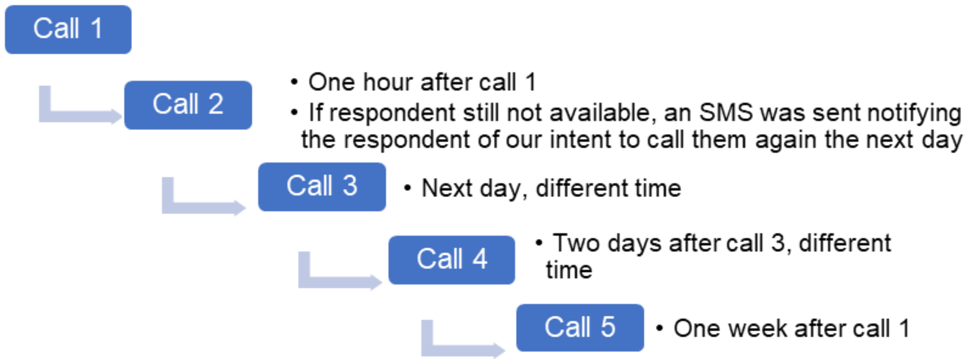
Taken from the supplementary material in Chavarría et al. (2021).

The telephone interviews were scheduled according to the call pattern that is displayed below. Initially, each respondent received five calls, which were staggered with time delays of one hour to three days any at varying times of the day. After the second unanswered call, a standardized text message was sent announcing another call on the following day. Whenever feasible, the same enumerator who had visited the respondent

[21] We used the 3ie Sample size and minimum detectable effect calculator as described in Djimeu and Houndolo (2016). For screening uptake, we used the formula for binary outcomes and for the knowledge index the formula for continuous outcomes.

during the baseline survey was deployed to call them during the phone interview, in order to maximize the response rate as well as the respondents' trust towards the enumerator. In the end of the data collection period, each number that was not answered during five calls received one additional call from another interviewer (with a different telephone number).

Figure A 3.2 Call Pattern at endline



A 3.4. Variable definitions

Table A 3.4 Composition SMS knowledge index

Question	***Coding***
"One can feel whether one experiences diabetes/ hypertension "	0 if (strongly) agree, 1 if (strongly) disagree
"It makes a difference to start diabetes/ hypertension treatment early"	0 if (strongly) disagree, 1 if (strongly) agree
Which risk factors of diabetes/ hypertension do you know?	1 if mentioned age, 0 otherwise
Have you ever heard of *Posbindu*?	0 if (strongly) disagree, 1 if (strongly) agree

Note: Each question with diabetes / hypertension is included for both diseases separately. "Don't know" coded as 0.

Table A 3.5 Composition knowledge index

Question	***Coding***
"Which risk factors of diabetes / hypertension do you know?"	1 count for each correctly identified factor
Do you know someone with diabetes/ hypertension?	Binary variable for the answers: Family member, friend, neighbour, other, none.
Which complications of disease diabetes/ hypertension do you know?	1 count for each correctly identified factor
"Who do you think should be screened?"	0 if "everyone who feels sick", 1 if "everyone" or "people at risk"
Which ways of controlling diabetes/ hypertension do you know?	1 count for each correctly identified factor
"It makes a difference to start treatment early"	0 if (strongly) disagree, 1 if (strongly) agree
"There is nothing one can do to prevent diabetes/ hypertension, it is destiny."	0 if (strongly) agree, 1 if (strongly) disagree
"One can feel whether you experience diabetes/ hypertension "	0 if (strongly) agree, 1 if (strongly) disagree
"Checking your level regularly helps to detect diabetes/ hypertension early"	0 if (strongly) disagree, 1 if (strongly) agree
"Diabetes/ hypertension is treatable"	0 if (strongly) disagree, 1 if (strongly) agree

Note: Each question with diabetes / hypertension is included for both diseases separately. "Don't know" coded as 0.

A 3.5. Intervention piloting

We piloted the messages in January 2020 to find out whether the contents were understandable, deemed trustworthy, and to assess whether the time of sending (morning/evening) and order of information (age as risk factor/having it without feeling it) mattered. However, the messages were not sent according to the time schedule of the intervention, i.e., not 5, 3 and 1 day before a *Posbindu* date. The messages 1 and 2 were sent to the respondents on two consecutive days, and respondents were interviewed via phone a few days after. In 10 out of 14 cases, the phone was answered on the designated survey day (no second contact attempts on another day were made). The messages were received in 9 out of 10 cases, although in two cases they were received by the children of the main respondent and were not yet transferred to him/her. In both cases, the *Posbindu* dates were a few weeks ahead, so the children might not have felt the urgency to deliver the message directly. We assumed that this would be different when the dates are close by.

Qualitative semi-structured interviews were conducted with the remaining eight respondents. All respondents confirmed that they trusted the message. Reasons stated were the connection to the interview conducted two months before, the mentioning of a public program (*Posbindu*) and the *kaders*, the mentioning of the respondent's name, and confirmation of the content by the *kader*. Most respondents remembered that the messages were reminding them to go to *Posbindu*, and some specifically mentioned the *Posbindu* date. Three respondents could recall that the messages contained information regarding diseases, and two additional respondents recalled information regarding risk factors. The respondents liked in particular that the messages served as reminders, and two respondents explicitly stated that they liked how the messages were written. Time of message sending and order of the messages did not appear to make a difference in how the messages were perceived.

While experimenter demand biases are always a concern in these types of interviews, we believe them to be minimal here. First of all, respondents may feel less inclined to cater to experimenter demand during phone interviews, as they are less personal than in-home visits. This was confirmed by our enumerators, who qualitatively assessed that respondents were likely to report their true opinions. Second of all, respondents always gave specific reasons and arguments for their opinions, making them more credible.

A 3.6. Sample characteristics and attrition

Table A 3.6 Baseline balance across treatment and control group

	Control group			Treatment group			
	Mean	Standard deviation	N	Mean	Standard deviation	N	p-value
Age	50.35	8.24	1,002	49.91	8.08	1,003	0.226
Female	0.64	0.48	1,001	0.64	0.48	1,003	0.936
Highest level of schooling							0.876
None	0.05	0.22	49	0.05	0.22	49	
Primary	0.25	0.43	253	0.24	0.42	236	
Junior Secondary	0.21	0.41	215	0.22	0.41	219	
Senior Secondary	0.35	0.48	346	0.35	0.48	348	
Tertiary	0.14	0.35	139	0.15	0.36	152	
Wealth quintile							0.611
1	0.22	0.42	225	0.21	0.41	213	
2	0.20	0.40	203	0.18	0.39	182	
3	0.19	0.39	192	0.20	0.40	200	
4	0.19	0.39	188	0.20	0.40	198	
5	0.19	0.39	193	0.21	0.41	211	
Own phone	0.58	0.49	995	0.62	0.49	1,000	0.044
Posbindu in own village	0.90	0.30	1,002	0.90	0.30	1,004	0.666
Ever had blood pressure or blood glucose checked	0.58	0.49	999	0.59	0.49	1,002	0.610
Disease knowledge index	18.30	5.53	923	17.97	5.42	936	0.196
Patience	5.73	2.83	1,002	5.70	2.86	1,004	0.823
Willingness to take risks	4.57	2.66	1,002	4.45	2.62	1,004	0.298
Joint F-test				0.880			

Means, standard deviation and number of observations of main respondent characteristics by treatment group; p-values based on t-tests of difference in mean between treatment and control group, except in the case of education and wealth quintile, where we used Pearson chi-squared tests due to the categorical nature of the variables.

Table A 3.7 Comparison of sample characteristics to SUSENAS

	SUSENAS Banda Aceh, Aceh Besar	Baseline	Endline
Age	50.5935	50.1203	49.9404
	(0.3088)	(0.1826)	(0.2306)
Above 50	0.4878	0.4656	0.4592
	(0.0207)	(0.0111)	(0.0142)
Female	0.5239	0.6379***	0.6224**
	(0.0207)	(0.0107)	(0.0161)
Education			
- Up to primary	0.2424	0.2926**	0.2720***
	(0.0188)	(0.0100)	(0.0162)
- Lower secondary	0.2347	0.2164	0.2188
	(0.0179)	(0.0092)	(0.0120)
- Upper secondary and above	0.5229	0.4910	0.5092**
	(0.0207)	(0.0109)	(0.0194)
Wealth above median		0.4923	0.5082**
		(0.0112)	(0.0201)
Banda Aceh	0.4074	0.4372	0.4511*
	(0.0182)	(0.0061)	(0.0220)
N	863	2,006	1,412

SUSENAS samples are obtained from SUSENAS 2017 and restricted to respondents aged 40 – 70 with a mobile phone in the household. Standard errors accounting for survey design (sampling weights in SUSENAS, district stratification in both samples, PSU when comparing base- and endline sample) below mean; stars indicate significant difference from mean listed in previous column based on adjusted Wald test, * 0.1 ** 0.05 *** 0.01. Columns on SUSENAS and Baseline as in (Chavarría et al., 2021).

Attrition

We test for differential attrition using three approaches. First, we test whether attrition differs across treatment and control group:

$$Attrit_i = \alpha + \beta T_i + \omega_{ij} \quad \text{(A1)}$$

Second, we analyze attrition based on the set of baseline characteristics used for testing balance across treatment and control group – namely age, sex, education, wealth quintile, knowledge index, time preferences, risk preferences, phone ownership and *Posbindu* in own village:

$$y_i = \alpha + \beta Attrit_i + \omega_{ij} \quad \text{(A2)}$$

Third, we examine whether these baseline characteristics of attrited treated individuals are significantly different from the attrited control individuals, restricting the sample to attriting respondents only:

$$(y_i | Attrit = 1) = \alpha + \beta T_i + \omega_{ij} \quad \text{(A3)}$$

Table A 3.8 Attrition I: between treatment and control group

	(1) Attrition
Treated	0.0273
	(0.0207)
Observations	2006

Regression of a binary attrition indicator (not re-interviewed at endline) on a binary treatment indicator (equation A1). Standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.9 Attrition II: endline sample compared to those lost to follow-up

	(1) Age	(2) Female	(3) Education	(4) Wealth quintile	(5) Baseline disease knowledge	(6) Willingness to take risks	(7) Patience	(8) Own phone	(9) Own Posbindu
Attrition	0.630	0.055**	-0.218***	-0.182**	-2.465***	-0.057	-0.111	-0.200***	0.008
	(0.406)	(0.023)	(0.056)	(0.071)	(0.304)	(0.129)	(0.138)	(0.024)	(0.015)
Observations	2005	2004	2006	2005	1580	2006	2006	1995	2006

Separate regressions of each characteristic on the binary attrition indicator (not re-interviewed at endline) (equation A2). Standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.10 Attrition III: between treatment and control in those lost to follow-up

	(1) Age	(2) Female	(3) Education	(4) Wealth quintile	(5) Baseline disease knowledge	(6) Willingness to take risks	(7) Patience	(8) Own phone	(9) Own *Posbindu*
Treated	0.149	0.060	0.047	0.042	-0.849*	-0.236	-0.246	0.065	0.029
	(0.688)	(0.038)	(0.096)	(0.119)	(0.487)	(0.218)	(0.230)	(0.041)	(0.024)
Observations	594	593	594	594	532	594	594	590	594

Separate regressions of each characteristic on the binary treatment indicator in the sample that was not re-interviewed at endline (equation A3). Standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.11. Role of phone ownership for attrition

	(1) Own phone	(2) Attrition
Age	-0.008***	-0.000
	(0.001)	(0.001)
Female	-0.113***	0.032
	(0.021)	(0.021)
Primary	0.088*	-0.142***
	(0.050)	(0.054)
Junior Secondary	0.156***	-0.155***
	(0.053)	(0.056)
Senior Secondary	0.360***	-0.121**
	(0.051)	(0.055)
Higher	0.517***	-0.146**
	(0.053)	(0.060)
Wealth quintile 2	0.011	0.001
	(0.032)	(0.033)
Wealth quintile 3	0.043	-0.048
	(0.033)	(0.031)
Wealth quintile 4	0.042	-0.012
	(0.033)	(0.033)
Wealth quintile 5	0.079**	-0.028
	(0.034)	(0.033)
Own phone		-0.161***
		(0.023)
Observations	1991	1991

Regression of the binary phone ownership indicator (column 1) and the binary attrition indicator (column 2) on the respective characteristics in the whole intervention sample. Reference categories: No formal education, wealth quintile 1; Coefficient estimates for education in column (2) are statistically not distinguishable from each other. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A 3.7. Main tables and robustness checks

Table A 3.12 Treatment effects on screening uptake, with and without covariates

	(1) ITT	(2) ITT	(3) LATE	(4) LATE	(5) Any other member	(6) Any other member
Treated	0.0576**	0.0656***	0.144	0.172*	0.0152	0.0106
	(0.0257)	(0.0254)	(0.0970)	(0.0969)	(0.0250)	(0.0250)
Covariates	No	Yes	No	Yes	No	Yes
Observations	1386	1386	1175	1175	1070	1070
Control group mean	0.331	0.331	0.357	0.357	0.205	0.205

Results of regressing the binary screening uptake indicator following equation 1 for the message recipient (columns 1 and 2) and any other household member (columns 5, 6) and the local average treatment effect following equation 3 (columns 3, 4); if covariates are included, they are message recipient age, gender, wealth and phone ownership; standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 3.13. Adjustments for multiple hypothesis testing in main specification for primary and secondary outcomes.

	(1) Screening uptake (ITT)	(2) Screening uptake (LATE)	(3) Spillovers	(4) SMS Knowledge	(5) General Knowledge
Treated	0.066	0.172	0.011	-0.002	-0.336
	(0.010)***	(0.076)*	(0.672)	(0.962)	(0.340)
	[0.090]*	[0.227]	[0.808]	[0.962]	[0.510]
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	1386	1175	1070	1088	1042

Results of regressing the binary screening uptake indicator following equation 1 for the message recipient (col 1) and any other household member (col 3), the respective knowledge index (col 4, 5), and the local average treatment effect following equation 3 (col 2); controlling for message recipient age, gender, wealth, and phone ownership; unadjusted p-values in parentheses, adjusted q-values following the Benjamini-Hochberg method for the 9 main hypotheses in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 3.14. Adjustments for multiple hypothesis testing in main specification of heterogeneity analysis.

	Screening uptake	Screening uptake
Willingness to take risk	0.082	
	(0.105)	
	[0.236]	
Patience		0.118
		(0.037)**
		[0.165]
Treated x Willingness to take risk	-0.004	
	(0.719)	
	[0.808]	
Treated x Patience		-0.009
		(0.301)
		[0.541]
Covariates	Yes	Yes
Observations	1386	1386

Treatment coefficients from estimating equation 4 controlling for message recipient age, gender, wealth, and phone ownership; unadjusted p-values in parentheses, adjusted q-values following the Benjamini-Hochberg method for the 9 main hypotheses in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 3.15. Binary outcomes with probit and logit specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Screening uptake		Heterogeneity: Risk		Heterogeneity: Time		Spillover	
	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Treated	0.182***	0.301***	0.229	0.375	0.332**	0.546**	0.033	0.063
	(0.070)	(0.116)	(0.141)	(0.231)	(0.158)	(0.260)	(0.088)	(0.153)
Preference			0.019	0.031	0.022	0.036		
			(0.019)	(0.032)	(0.018)	(0.029)		
Treated x Preference			-0.010	-0.016	-0.026	-0.043		
			(0.027)	(0.044)	(0.025)	(0.040)		
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1386	1386	1386	1386	1386	1386	1065	1065

Results of regressing the binary screening uptake indicator following equation 1 for the message recipient (col 1, 2) and any other household member (col 7, 8), as well as heterogeneous treatment effects along a continuous risk and time preference scale following equation 4; controlling for message recipient age, gender, wealth and phone ownership; each model is separately estimated using probit and logit; standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A 3.16. Knowledge outcomes measured through PCA

	SMS knowledge (PCA)	SMS knowledge (PCA)	Disease knowledge (PCA)	Disease knowledge (PCA)
Treated	0.0215	0.00198	-0.0328	-0.0551
	(0.0596)	(0.0581)	(0.0612)	(0.0594)
Covariates	No	Yes	No	Yes
Obs.	1088	1088	1042	1042
Control group mean	-0.00301	-0.00301	0.0215	0.0215

Regressions for an alternative definition of both knowledge indices via Principal Component Analysis; if covariates are included, they are message recipient age, gender, wealth, and phone ownership; standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 3.17 Treatment effect on each element of the SMS knowledge index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Feel it		Early treatment		Age risk		Knows
	Hypertension	Diabetes	Hypertension	Diabetes	Hypertension	Diabetes	Posbindu
Treated	0.0051	-0.0133	0.0040	-0.0033	-0.0171	0.0178	0.0047
	(0.0089)	(0.0156)	(0.0109)	(0.0129)	(0.0173)	(0.0163)	(0.0171)
Covar.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1088	1088	1088	1088	1088	1088	1088
C. mean	0.0185	0.0775	0.9613	0.9502	0.1015	0.0664	0.9151

Regressions of the components of the SMS knowledge index as defined in Table A 3.4 on the binary treatment indicator controlling for message recipient age, gender, wealth, and phone ownership; standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 3.18 Treatment effect on each element of the disease knowledge index (Hypertension)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Number of				Share with correct answer				
	Risk Factors	Compli-cations	Control	Target group	Start early	Destiny	Feel it	Regular checks	Treat-able	Know someone
Treated	-0.0627	0.0311	-0.0959	-0.0044	0.0026	0.0010	0.0072	-0.0134	-0.0022	0.0014
	(0.0680)	(0.0439)	(0.0705)	(0.0306)	(0.0106)	(0.0283)	(0.0140)	(0.0101)	(0.0189)	(0.0251)
Covar.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1042	1042	1042	1042	1042	1042	1042	1042	1042	1042
C. mean	2.1612	1.1478	2.1440	0.5566	0.9655	0.2917	0.9424	0.9789	0.8983	0.7908

Regressions of the components of the disease knowledge index as defined in Table A 3.5 on the binary treatment indicator controlling for message recipient age, gender, wealth, and phone ownership; the outcomes in columns 1-3 are the number of correct items and binary measures in columns 4-10; standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.19 Treatment effect on each element of the general knowledge index (Diabetes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Number of				Share with correct answer				
	Risk Factors	Compli-cations	Control	Target group	Start early	Destiny	Feel it	Regular checks	Treat–able	Know someone
Treated	-0.0623	-0.1026	-0.0722	0.0138	-0.0047	0.0072	0.0258	0.0061	0.0172	0.0321
	(0.0607)	(0.0706)	(0.0628)	(0.0307)	(0.0125)	(0.0278)	(0.0226)	(0.0105)	(0.0268)	(0.0297)
Covar.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1042	1042	1042	1042	1042	1042	1042	1042	1042	1042
C. mean	1.8330	1.6046	1.7697	0.5182	0.9559	0.2726	0.8292	0.9655	0.7486	0.6180

Regressions of the components of the disease knowledge index as defined in Table A 3.5 on the binary treatment indicator controlling for message recipient age, gender, wealth, and phone ownership; the outcomes in columns 1-3 are the number of correct items and binary measures in columns 4-10; standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.20 Different versions of spillover analysis

	Any member (main specification)	Member 40-70	Other phone owner
Treated	0.0106	0.0134	0.0167
	(0.0250)	(0.0308)	(0.0305)
Other's phone			0.0399
			(0.0392)
			-0.0180
Treated x other's phone			(0.0530)
			0.0399
Covariates	Yes	Yes	Yes
Obs.	1070	727	1070
Mean	0.205	0.212	0.205

Results of regressing the binary indicator of household member screening uptake (col 1), screening uptake among other household members aged 40-70 years (col 2) on the binary treatment indicator following equation 1, and the heterogeneous treatment effect of the binary phone ownership indicator, which takes value 1 if the intervention was either received on a family phone or the private phone of another household member, and zero if it belongs to the message recipient; controlling for age, gender, wealth and phone ownership; standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.21 Treatment effect on screening uptake by month

	(1) January	(2) February	(3) March	(4) April
Treated	0.0156	0.0363	0.0560***	0.0068
	(0.0159)	(0.0228)	(0.0201)	(0.0090)
Covariates	Yes	Yes	Yes	Yes
Obs.	1386	1386	1386	1386
Control group mean	0.0895	0.2216	0.1435	0.0256

Results of regressing different binary screening uptake indicators on the binary treatment indicator (equation 1), controlling for age, gender, wealth and phone ownership; the outcome indicator takes the value 1 only if the individual indicated to have gone to screening in the respective month and zero otherwise; standard errors clustered at the phone-number level in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.22 Treatment effect on screening uptake by location

	(1) Went on correct date to Posbindu	(2) Posbindu	(3) Puskesmas	(4) Private doctor/midwife
Treated	0.0067	0.0081	0.0298*	0.0201
	(0.0177)	(0.0178)	(0.0158)	(0.0162)
Covariates	Yes	Yes	Yes	Yes
Obs.	1386	1386	1386	1386
Control group mean	0.1335	0.1335	0.0810	0.0895

Results of regressing different binary screening uptake indicators on the binary treatment indicator (equation 1), controlling for age, gender, wealth and phone ownership; the outcome indicator takes the value 1 only if the individual indicated to have gone to screening in the respective facility and zero otherwise; the screening outcome in col 1 additionally conditions on the correct month; standard errors clustered at the phone-number level in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.23 Treatment effect on disaggregated screening outcome: kind of check done

	(1) Medical history	(2) Physical measurement	(3) Blood pressure	(4) Blood glucose	(5) Other blood check
Treated	0.0420**	0.0151	0.0652**	0.0302	0.0091
	(0.0176)	(0.0165)	(0.0254)	(0.0200)	(0.0134)
Covariates	Yes	Yes	Yes	Yes	Yes
Obs.	1386	1386	1386	1386	1386
Mean	0.1023	0.1009	0.3295	0.1548	0.0639

Results of regressing different binary screening indicators on the binary treatment indicator (equation 1), controlling for age, gender, wealth and phone ownership; the outcome indicator takes the value 1 only if the individual indicated that at the screening visit the respective check was conducted and zero if the respondent either did not go for screening or did not get the respective check done despite going for screening; standard errors clustered at the phone-number level in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A 3.24 Characteristics of sub-groups of treatment group who remember receiving messages on NCDs and specific elements of these messages

	Total treatment	Received message	LATE definition	Remembers content on: Screening need	Posbindu logistics	Posbindu free	Age risk
Demographics							
Age	49.52	48.31***	48.54	47.79	48.36	48.42	49.60*
	(7.85)	(7.55)	(7.43)	(7.31)	(6.76)	(7.54)	(8.01)
Female	0.61	0.56*	0.57	0.55	0.60	0.55	0.56
	(0.49)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
Education							

- None							
	0.03	0.02	0.02	0.01	0.00	0.00	0.02
- Primary	(0.18)	(0.12)	(0.13)	(0.11)	(0.00)	(0.00)	(0.13)
	0.24	0.18**	0.17	0.14	0.19	0.19	0.18
- Lower Secondary	(0.42)	(0.39)	(0.38)	(0.35)	(0.40)	(0.39)	(0.39)
	0.21	0.18	0.17	0.21	0.21	0.17	0.11
- Higher Secondary	(0.41)	(0.39)	(0.38)	(0.41)	(0.41)	(0.38)	(0.31)
	0.36	0.43***	0.43	0.41	0.42	0.45	0.38
- Tertiary	(0.48)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
	0.17	0.20	0.21	0.23	0.18	0.19	0.31**
Banda Aceh	(0.37)	(0.40)	(0.41)	(0.42)	(0.39)	(0.39)	(0.47)
	0.52	0.50	0.49	0.49	0.44	0.31***	0.51
SMS-related characteristics							
Phone owner	0.68	0.80***	0.80	0.79	0.81	0.77	0.80
	(0.47)	(0.40)	(0.40)	(0.41)	(0.40)	(0.43)	(0.40)
Messages							
- daily	0.48	0.57***	0.58	0.67**	0.58	0.60	0.61
	(0.50)	(0.50)	(0.50)	(0.47)	(0.50)	(0.49)	(0.49)
- < daily	0.36	0.39	0.38	0.29**	0.36	0.38	0.39
	(0.48)	(0.49)	(0.49)	(0.46)	(0.48)	(0.49)	(0.49)
- never	0.16	0.04***	0.04	0.04	0.06	0.02	0.00*
	(0.37)	(0.19)	(0.20)	(0.20)	(0.24)	(0.13)	(0.00)
Messenger use	0.47	0.48	0.49	0.61***	0.55	0.56	0.52
	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.51)
Prefers less SMS							
- in general	0.15	0.22***	0.23	0.23	0.29*	0.14**	0.24
	(0.36)	(0.42)	(0.42)	(0.42)	(0.46)	(0.35)	(0.43)
- advertisement	0.60	0.57	0.57	0.61	0.54	0.66*	0.53
	(0.49)	(0.50)	(0.50)	(0.49)	(0.50)	(0.48)	(0.50)
- no	0.25	0.21*	0.20	0.16	0.17	0.21	0.22
	(0.44)	(0.41)	(0.40)	(0.37)	(0.38)	(0.41)	(0.42)
Baseline characteristics							
Disease knowledge	18.42	19.58***	19.76	20.07	19.10	19.87	20.00
	(5.30)	(4.88)	(4.99)	(5.18)	(4.42)	(4.99)	(4.44)
H- feel it	0.12	0.10	0.11	0.10	0.07	0.06	0.09
	(0.33)	(0.30)	(0.31)	(0.31)	(0.26)	(0.24)	(0.29)
D- feel it	0.19	0.19	0.20	0.23	0.13	0.16	0.18
	(0.39)	(0.39)	(0.40)	(0.42)	(0.34)	(0.37)	(0.39)
H- start early	0.95	0.96	0.95	0.93*	1.00**	0.95	0.98
	(0.22)	(0.20)	(0.21)	(0.25)	(0.00)	(0.21)	(0.13)
D- start early	0.94	0.94	0.94	0.92	0.99**	0.94	0.96
	(0.24)	(0.23)	(0.24)	(0.28)	(0.12)	(0.25)	(0.19)
H- age risk	0.06	0.05	0.05	0.07	0.03	0.05	0.02
	(0.23)	(0.22)	(0.21)	(0.25)	(0.17)	(0.21)	(0.13)
D- age risk	0.04	0.05	0.06	0.09**	0.06	0.06	0.04
	(0.20)	(0.22)	(0.24)	(0.29)	(0.23)	(0.25)	(0.19)
Knows Posbindu	0.50	0.56*	0.56	0.53	0.53	0.62	0.64
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)
Ever screened	0.59	0.61	0.57**	0.57	0.65	0.64	0.64
	(0.49)	(0.49)	(0.50)	(0.50)	(0.48)	(0.48)	(0.49)
Last year screened	0.29	0.28	0.25*	0.06***	0.15***	0.22	0.37
	(0.45)	(0.45)	(0.43)	(0.24)	(0.36)	(0.42)	(0.49)
N	682	199	170	87	72	65	55

Simple means of the respective characteristic across groups: complete treatment group, individuals who stated to have received a message on Posbindu, those who received at least one full message cycle according to the delivery reports and remember any message content (LATE definition) and the four most commonly recalled content elements: the recommendation to take up screening, when and where Posbindu takes place, that Posbindu is free and higher age implies a higher NCD risk. Standard deviations in parentheses below mean; stars indicate the p-value of the two-sample t-test for difference of the respective group and characteristic compared to the rest of the treatment group; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A 4. Appendix for Chapter 4

Table A 4.1. Summary statistics for each screening item

	Mean	SD	Min	Max	p50	N
SRQ-20						
Headaches	0.4015	0.4904	0	1	0	1487
Poor appetite	0.2349	0.4241	0	1	0	1477
Sleeping badly	0.2618	0.4398	0	1	0	1478
Easily frightened	0.1039	0.3053	0	1	0	1472
Hands shaking	0.0819	0.2743	0	1	0	1478
Nervous, tense, worried	0.1671	0.3732	0	1	0	1454
Poor digestion	0.2186	0.4135	0	1	0	1482
Trouble thinking clearly	0.0665	0.2493	0	1	0	1458
Feeling unhappy	0.0605	0.2385	0	1	0	1455
Crying more often	0.0483	0.2145	0	1	0	1469
Difficult enjoying activities	0.0807	0.2724	0	1	0	1475
Difficult making decisions	0.0516	0.2213	0	1	0	1473
Daily work suffering	0.1141	0.3181	0	1	0	1472
Unable to play useful part	0.0266	0.1611	0	1	0	1464
Lost interest in things	0.0534	0.2249	0	1	0	1424
Feeling worthless	0.0179	0.1326	0	1	0	1454
Feeling always tired	0.2066	0.4050	0	1	0	1476
Easily tired	0.2268	0.4189	0	1	0	1468
Uncomfortable feelings in stomach	0.2686	0.4434	0	1	0	1478

Table A 4.2. Outcome variables

Categorical variables	Share	N	Continuous variables	Mean	S.D.	N
Marital status			Any state support	0.79	0.41	1,490
Never married	0.27	397	Any member with CMD*	0.26	0.44	589
Married	0.62	920	Head with CMD*	015	0.35	361
Divorced/Widowed	0.12	172	Is working	0.40	0.49	1,480
Occupation code			Working days per week	5.88	1.14	575
Government	0.05	79	Working hours per week	32.26	20.28	557
Farmer	0.05	75	Log of earnings	14.25	0.86	572
Fisher	0.02	32	Daily tasks affected	0.10	0.30	1,468
Self-employed	0.16	244	Affected days	0.50	2.33	1,472
Market seller	0.08	126	Sought treatment due to feelings	0.09	0.29	1,478
Laborer	0.04	57	Feelings caused by phys. prob.	0.06	0.24	1,469
Student	0.07	108	Any health complaints	0.43	0.50	1,485
Housewife	0.34	508	Sought treatment	0.78	0.41	640
Pensioner	0.02	35	Number of facilities visited	1.13	0.34	497
Unemployed	0.13	192	Community health center	0.43	0.50	497
Area			Government clinic	0.16	0.37	497
Aceh Besar	0.42	622	Private clinic	0.02	0.15	497
Banda Aceh	0.38	568	Private practice	0.17	0.37	497
Sabang	0.20	300	Joint clinic/practice	0.24	0.43	497
Relation to head			Traditional healer	0.05	0.21	497
Head	0.28	420	Travel time [min]	17.70	35.87	468
Spouse	0.30	445	Waiting time [min]	29.06	61.69	466
Child	0.30	449	Treatment time [min]	11.60	13.31	466
Parent	0.04	65	Travel costs [k IDR]	21.16	68.36	468
Sibling	0.02	29	Treatment costs [k IDR]	27.78	79.86	464
Other relative	0.04	55	Medication costs [k IDR]	50.74	183.43	469
Other	0.02	24				

* Collapsed by household.

Table A 4.3. Predicted probabilities by marital status, occupation, state support and area

	Predicted probability		Predicted probability
Marital status		**Occupation**	
Never married	0.164	Government	0.113
	[0.117,0.210]		[0.046,0.181]
Married	0.113	Farmer	0.131
	[0.089,0.136]		[0.029,0.233]
Div./Wid.	0.204	Fisher	0.116
	[0.117,0.291]		[0.015,0.217]
State support		Self-employed	0.110
No	0.151		[0.071,0.148]
	[0.102,0.201]	Market seller	0.158
Yes	0.132		[0.086,0.230]
	[0.110,0.155]	Laborer	0.073
Area			[0.014,0.132]
Aceh Besar	0.118	Student	0.129
	[0.088,0.147]		[0.073,0.184]
Banda Aceh	0.157	Housewife	0.147
	[0.120,0.193]		[0.105,0.190]
Sabang	0.134	Pensioner	0.277
	[0.090,0.177]		[0.101,0.452]
		Unemployed	0.159
			[0.104,0.214]

Predicted probabilities are obtained by employing a linear probability model regressing the indicator of CMD (i.e., SRQ-20≥6) on the characteristic of interest controlling for gender, age and education. Then, the model is used to predict probabilities over each category of the characteristic of interest. Standard errors are clustered at the household level. 95% confidence intervals in square brackets.

Table A 4.4. Predicted probabilities by family characteristics

	Predicted probability		Predicted probability
Relation to household head		**Any other member with CMD**	
Head	0.125	No	0.116
	[0.083,0.167]		[0.096,0.136]
Spouse	0.146	Yes	0.220
	[0.102,0.189]		[0.155,0.285]
Child	0.127	**Head with CMD**	
	[0.090,0.164]	No	0.084
Parent	0.183		[0.060,0.107]
	[0.025,0.342]	Yes	0.207
Sibling	0.393		[0.115,0.298]
	[0.176,0.611]		
Other relative	0.078		
	[0.019,0.136]		
Other	0.121		
	[0.020,0.222]		

Predicted probabilities are obtained by employing a linear probability model regressing the indicator of CMD on the characteristic of interest controlling for gender, age and education. Then, the model is used to predict probabilities over each category of the characteristic of interest. Standard errors are clustered at the household level. 95% confidence intervals in square brackets.

Table A 4.5. Marginal effects of CMD on FAD items

	Total	Strongly disagree	Disagree	Agree	Strongly agree
If there is a problem in the family, we make a decision to solve it together	0.2598	-0.0015	-0.0022	-0.0323	0.0360
	(0.2456)	(0.0014)	(0.0020)	(0.0328)	(0.0359)
After our family tries to solve a problem, we usually discuss whether it worked.	0.1864	-0.0004	-0.0018	-0.0186	0.0208
	(0.2571)	(0.0006)	(0.0024)	(0.0269)	(0.0297)
We can solve the problems that come to our family.	0.0310		-0.0007	-0.0022	0.0029
	(0.2983)		(0.0063)	(0.0218)	(0.0281)
We try to think of different ways to solve problems.	0.0155	-0.0000	-0.0012	0.0001	0.0011
	(0.2360)	(0.0002)	(0.0182)	(0.0011)	(0.0173)
When someone in our family is sad, the others know why.	-0.1107	0.0015	0.0188	-0.0138	-0.0065
	(0.1853)	(0.0027)	(0.0320)	(0.0241)	(0.0107)
We do not know what family members are feeling aside from what they say.	0.2494	-0.0016	-0.0353	0.0260	0.0110
	(0.2149)	(0.0014)	(0.0288)	(0.0197)	(0.0106)
Every member of the family is free to express his/her opinion.	0.1373		-0.0009	-0.0177	0.0186
	(0.2686)		(0.0017)	(0.0359)	(0.0376)
When we don't like what someone has done, we tell them.	0.0687		-0.0024	-0.0049	0.0073
	(0.2757)		(0.0092)	(0.0207)	(0.0299)
Each of us has particular duties and responsibilities	0.2607	-0.0004	-0.0112	-0.0108	0.0224
	(0.2740)	(0.0005)	(0.0111)	(0.0141)	(0.0253)
We discuss who are responsible for household jobs.	0.3611	-0.0018	-0.0440	0.0220*	0.0238
	(0.2191)	(0.0012)	(0.0243)	(0.0106)	(0.0163)
We have trouble meeting our financial obligations.	0.3672	-0.0234*	-0.0616	0.0597	0.0252
	(0.1950)	(0.0114)	(0.0344)	(0.0310)	(0.0148)
There is little time to explore personal interests.	0.1643	-0.0057	-0.0350	0.0387	0.0019
	(0.1892)	(0.0062)	(0.0407)	(0.0445)	(0.0024)
We do not confront problems involving feelings.	-0.0216	0.0002	0.0038	-0.0034	-0.0005
	(0.2058)	(0.0017)	(0.0365)	(0.0330)	(0.0052)
We do not show our love for each other.	0.0349	-0.0023	-0.0044	0.0062	0.0005
	(0.2171)	(0.0141)	(0.0278)	(0.0388)	(0.0030)
We express tenderness.	0.3736	-0.0003	-0.0141	-0.0208	0.0351
	(0.2632)	(0.0003)	(0.0087)	(0.0193)	(0.0278)
We cry openly.	0.0403	-0.0016	-0.0081	0.0087	0.0011
	(0.1850)	(0.0073)	(0.0373)	(0.0396)	(0.0049)
Our family helps each other when someone is having problems.	0.5753*	-0.0011	-0.0066*	-0.0593	0.0670
	(0.2594)	(0.0007)	(0.0029)	(0.0322)	(0.0349)
We are too self-centered.	-0.2510	0.0468	-0.0295	-0.0157	-0.0016
	(0.1949)	(0.0380)	(0.0257)	(0.0114)	(0.0013)
We only help each other when it matters.	0.2699	-0.0250	-0.0379	0.0550	0.0079
	(0.1923)	(0.0166)	(0.0295)	(0.0394)	(0.0065)
Even though we mean well, we intrude too much into each other's lives.	-0.4234*	0.0791	-0.0349	-0.0422*	-0.0021
	(0.2051)	(0.0415)	(0.0233)	(0.0183)	(0.0012)
You can easily get away with breaking the rules.	-0.4929**	0.0888*	-0.0583*	-0.0277**	-0.0027*
	(0.1902)	(0.0375)	(0.0280)	(0.0096)	(0.0012)
We know what to do in an emergency.	0.0540	-0.0003	-0.0028	0.0018	0.0013
	(0.4045)	(0.0025)	(0.0204)	(0.0130)	(0.0100)
Our family has rules on how to behave when engaging in conflict with others	-0.0721	0.0002	0.0029	-0.0012	-0.0020
	(0.4173)	(0.0014)	(0.0173)	(0.0076)	(0.0112)
We don't hold to any rules or standards.	-0.5157*	0.0645	0.0186*	-0.0803*	-0.0028*
	(0.2328)	(0.0343)	(0.0077)	(0.0321)	(0.0014)
There are rules in our family about dangerous situations.	-0.0904	0.0002	0.0073	-0.0033	-0.0042
	(0.2703)	(0.0005)	(0.0223)	(0.0107)	(0.0121)
In times of crisis we can turn to each other for support.	0.4628	-0.0003	-0.0046*	-0.0488	0.0537
	(0.2397)	(0.0003)	(0.0023)	(0.0293)	(0.0313)
We cannot talk to each other about the sadness we feel.	-0.3325	0.0111	0.0654	-0.0744	-0.0021
	(0.2018)	(0.0079)	(0.0373)	(0.0438)	(0.0013)

Individuals are accepted for what they are.	-0.2255	0.0002	0.0014	0.0382	-0.0397
	(0.2239)	(0.0003)	(0.0016)	(0.0359)	(0.0376)
We confide in each other.	-0.0299		0.0005	0.0036	-0.0041
	(0.2789)		(0.0045)	(0.0335)	(0.0380)

Coefficient estimates and marginal effects from an ordered logistic model regressing FAD items on the CMD indicator controlling for gender, age and education. Standard errors are clustered at the household level. The answer scale ranges from 1 – Strongly disagree to 4 – Strongly agree. Positive coefficients indicate a higher likelihood to agree to a statement, and vice versa. Stars indicate significant differences between categories, with * p<0.05, ** p<0.01.

A 5. Appendix for Chapter 5

Table A 5.1. Robustness to CD4 tests before August 2010

	(1) Education	(2) By child's gender	(3) By parent's gender
Eligible	-0.228	-0.559**	-0.409
	(0.2534)	(0.2769)	(0.3207)
Deviation	0.000	0.000	-0.000
	(0.0069)	(0.0066)	(0.0071)
Eligible # Deviation	-0.004	-0.004	-0.004
	(0.0088)	(0.0086)	(0.0090)
Eligible # Disability grant	-1.408**	-1.696*	-1.886***
	(0.5647)	(0.9951)	(0.3458)
Eligible # Other grant	0.467*	0.982**	1.119***
	(0.2759)	(0.4021)	(0.4277)
Eligible # Female		0.676***	0.206
		(0.2534)	(0.3221)
Eligible # Female # Disability grant		0.440	0.014
		(1.1741)	(0.8885)
Eligible # Female # Other grant		-1.107**	-0.705
		(0.5176)	(0.5113)
R2	0.748	0.752	0.751
Cluster	366	366	366
Observations	3056	3056	3056
Bandwidth	52	52	52

Regression for children's education controlling for year of visit, children's age and gender, and parents' age, gender and education. Sample restricted to parents with a CD4 test at least one year before the guideline change. Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

Table A 5.2. Robustness to squared function

	(1) Education	(2) Education	(3) By child's gender	(4) By parent's gender
Eligible	-0.211	-0.186	-0.381	-0.415
	(0.3041)	(0.2973)	(0.2998)	(0.3317)
Eligible # Disability grant		-1.496***	-2.196**	-1.392**
		(0.5296)	(0.8846)	(0.6021)
Eligible # Other grant		0.506**	0.930***	1.214***
		(0.2298)	(0.3429)	(0.4484)
Eligible # Female			0.444**	0.272
			(0.1990)	(0.2518)
Eligible # Female # Disability grant			1.334	-0.485
			(1.0152)	(0.8655)
Eligible # Female # Other grant			-0.908**	-0.779
			(0.4420)	(0.5144)
R2	0.745	0.749	0.752	0.752
Cluster	614	614	614	614
Observations	4961	4961	4961	4961
Bandwidth	71	71	71	71

Regression for children's education controlling for year of visit, children's age and gender, and parents' age, gender and education. Polynomials of the deviation from the cutoff and their interactions with eligibility omitted to improve readability. Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

Table A 5.3. Robustness to cubic function

	(1) Education	(2) Education	(3) By child's gender	(4) By parent's gender
Eligible	-0.336	-0.303	-0.454	-0.493
	(0.4145)	(0.3966)	(0.3910)	(0.4177)
Eligible # Disability grant		-1.495***	-2.171**	-1.221
		(0.5168)	(0.8597)	(0.7501)
Eligible # Other grant		0.494**	0.897***	1.184***
		(0.2266)	(0.3380)	(0.4481)
Eligible # Girl			0.420**	0.260
			(0.1945)	(0.2470)
Eligible # Girl # Disability grant			1.315	-0.649
			(0.9836)	(0.9589)
Eligible # Girl # Other grant			-0.851**	-0.755
			(0.4325)	(0.5140)
R2	0.745	0.750	0.752	0.752
Cluster	629	629	629	629
Observations	5070	5070	5070	5070
Bandwidth	74	74	74	74

Regression for children's education controlling for year of visit, children's age and gender, and parents' age, gender and education. Polynomials of the deviation from the cutoff and their interactions with eligibility omitted to improve readability. Clustered standard errors in parenthesis. * p<0.1 ** p<0.05 *** p<0.01.

8 Declarations

Essays as publications

Chavarría, E. et al., 2021. Knowing Versus Doing: Protective Health Behaviour Against COVID-19 in Aceh, Indonesia. The Journal of Development Studies 57, 1245–1266. https://doi.org/10.1080/00220388.2021.1898594

Marcus, M.E., Reuter, A., Rogge, L., Vollmer, S., 2021. The Effect of SMS Reminders on Health Screening Uptake: A Randomized Experiment in Indonesia. Courant Research Centre: Poverty, Equity and Growth – Discussion Papers (No. 284). https://www.econstor.eu/handle/10419/237669

Reuter, A., Vollmer, S., Aiyub, A., Susanti, S.S., Marthoenis, M., 2020. Mental distress and its association with sociodemographic and economic characteristics: community-based household survey in Aceh, Indonesia. BJPsych Open 6. https://doi.org/10.1192/bjo.2020.108

Reuter, A., Bärnighausen, T., Vollmer, S., 2022. Parental Health, Children's Education and Unintended Consequences of State Support: Quasi-experimental evidence from KwaZulu-Natal, South Africa. Courant Research Centre: Poverty, Equity and Growth – Discussion Papers (No. 291). http://www2.vwl.wiso.uni-goettingen.de/courant-papers/CRC-PEG_DP_291.pdf.

Author contributions / Eigenanteil der Arbeit

Essay 1

Joint work with Eliana Chavarría (EC), Farah Diba (FD), Maja E. Marcus (MM), Marthoenis (M), Lisa Rogge (LR), and Sebastian Vollmer (SV)

EC, MM, LR, SV and I conceptualized the study. FD, MM, M, LR and I contributed to the data collection. EC, MM, LR and I analyzed the data and wrote the first draft of the manuscript. SV contributed to the interpretation of results and writing. All authors read and approved the final manuscript.

Essay 2

Joint work with Maja E. Marcus (MM), Lisa Rogge (LR), and Sebastian Vollmer (SV)

LR, MM and I jointly developed the idea. LR, MM, SV and I conceptualized the study. LR, MM and I prepared and monitored the data collection in the field, conducted the analysis and wrote the draft. SV contributed to the interpretation of results and writing. All authors read and approved the final manuscript.

Essay 3

Joint work with Marthoenis (M), Aiyub (A), Suryane Sulistiana Susanti (SSS), and Sebastian Vollmer (SV)

All authors contributed to the conception and design of the study. M, SSS, A and I conducted data collection. I analyzed the data and wrote the first draft of the manuscript. SV contributed to the interpretation of results and writing. All authors read and approved the final manuscript.

Essay 4

Joint work with Till Bärnighausen (TB) and Sebastian Vollmer (SV)

All authors contributed to the conception and design of the study. I analyzed the data and wrote the first draft of the manuscript. SV and TB contributed to the interpretation of results and writing. All authors read and approved the final manuscript.

Hiermit bestätige ich den oben genannten Anteil an der vorliegenden Arbeit.

Datum, Unterschrift

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