Essays on Health and Development

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Abstract

Motivated by the interdependence of good health and economic development, I study different interventions that might strengthen the health system in improving the usage of specific health services in four essays. Lack of access, high costs, information or behavioral barriers can keep individuals from taking the decision to take up a health service. In the first essay, we examine the implications of a large health insurance reform in Indonesia, which has the potential to reduce the cost barrier to health care usage. We find that the reform appears to facilitate particularly the use of higher level health services, and that the newly eligible benefit to a lesser degree. In the remaining essays, I turn to preventive health behavior and low-touch text messaging interventions that could address information and behavioral barriers. On the one hand, my co-authors and I show that simple personalized SMS invitations to regular diabetes and hypertension screening services in Indonesia can increase their uptake. On the other hand, we identify factors that facilitate the uptake of individual preventive practices against a COVID-19 infection in Indonesia and Pakistan. On this basis, we further show that a personalized and targeted text messaging intervention delivered through a health insurance database can help particularly those who are at risk to suffer from a complicated COVID-19 infection to adhere to more preventive practices.

Keywords: Health system, Health behavior, Health insurance, Preventive health, SMS intervention, COVID-19

Kurzzusammenfassung

Motiviert durch die enge Verbindung von guter Gesundheit und Entwicklung, untersuche ich in vier Aufsätzen verschiedene Interventionen, durch die das Gesundheitssystem darin gestärkt werden kann die Nutzung von spezifischen Gesundheitsleistungen zu erhöhen. Zugang, Kosten, aber auch Informations- und Verhaltensbarrieren können Individuen daran hindern Entscheidungen zur Aufnahme von Gesundheitsleistungen zu treffen. Im ersten Aufsatz untersuchen wir die Implikationen einer großen Krankenversicherungsreform in Indonesien, die das Potenzial hat die Zugangsbarriere zu lockern. Wir zeigen, dass gerade die Nutzung von komplexeren Behandlungen in Krankenhäusern zunimmt, dass diese Zuwächse die neu Versicherten aber weniger erreichen. In den folgenden Aufsätzen wende ich mich zwei Aspekten der Gesundheitsvorsorge zu, bei denen einfache SMS Interventionen Informations- und Verhaltensbarrieren adressieren können. Zum einen zeigen meine Koautoren und ich, dass personalisierte SMS Einladungen zu regelmäßigen Diabetes und Blutdrucktests deren Nutzung in Indonesien erhöhen können. Zum anderen identifizieren wir Faktoren, die die Aufnahme von persönlichen COVID-19 Präventionsmaßnahmen in Indonesien und Pakistan begünstigen. Auf dieser Grundlage zeigen wir zudem, dass SMS Nachrichten, die über das Informationssystem einer Krankenversicherung in Pakistan verschickt werden speziell Risikogruppen dabei helfen kann sich mehr durch regelmäßige Prävention zu schützen.

Schlagworte: Gesundheit und Entwicklung, Gesundheitssystem, Gesundheitsverhalten, Gesundheitsvorsorge, SMS Intervention, COVID-19

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Contents

Main text figures

Main text tables

Appendix figures

Appendix tables

Chapter 1

Introduction

1.1 Background and Motivation

General Background: Health and Development

A functioning health system is the backbone of a healthy society – this encompasses both the supply of necessary health services and the population making use of them. The COVID-19 pandemic has made weaknesses of systems across the globe particularly visible. We have seen major inequalities between low- and middle-income countries (LMIC) and high-income countries (HIC) for example in retaining their population's access to essential health services (WHO 2020). According to the United Nations, pre-pandemic progress on challenges such as the double burden of communicable and non-communicable diseases (NCD) has been halted or even reversed (United Nations 2021). Consequently, the call to strengthen health systems during but especially in recovery of the pandemic remains.

Long before the current pandemic, it has been acknowledged that good health can be a contributor to and consequence of economic development. Scholars across disciplines have identified several pathways through which improved health has the potential to stimulate economic development (e.g. Bloom and Canning (2000)). There is growing empirical evidence for these channels, but often limited to certain health conditions (Ogbuoji et al. 2020). First, the direct treatment costs in times of a health shock can hinder households from smoothing their consumption over time. In the absence of full insurance, common coping strategies to raise the money for treatment makes the household more vulnerable in the future and reduces the ability to cope with health or other shocks (Dercon 2002). Second, the indirect costs of a health shock are also substantial: healthier individuals can have less time out of work or school, be more productive during the working hours, and obtain respectively better outcomes. For example, Seuring et al. (2015) have detected lower employment among diabetes patients in Mexico, and Miguel and Kremer (2004) have shown that a positive health shock via a mass-deworming program can increase school attendance among children in Kenya. Third, expecting a longer life can alter other economically important decisions such as savings or education, for instance when AIDS treatment becomes available in Malawi (Baranov and Kohler 2018).

Motivated by this interplay, I study three health system interventions that aim to reduce particular barriers in the uptake of favorable health behavior in resource-constrained settings.

Barriers to beneficial health behavior

Individual health behavior pertains to the uptake of a curative health service in times of an acute health shock, and any personal health practice, like prevention, that follows recommendations independent of an acute health need. One reason for not taking up care can be classic economic barriers such as the lack of health service supply or inability to pay for them. Public health insurance has been found to effectively reduce the cost barrier and increase the use of health services in high- and low-income settings (e.g. Buchmueller et al. (2005), Giedion and Díaz (2010)). Informal coping mechanisms such as the sale of assets can also reduce the cost barrier but tend to leave the households more vulnerable to future shocks compared to pre-paid insurance schemes (e.g. Townsend (1994), Flores et al. (2008)). Over the past decades, LMICs have increasingly introduced public health insurance schemes. Earlier in the reform process, countries often focused on enrolling clearly defined population groups such as civil servants (Lagomarsino et al. 2012). Researchers have gathered evidence on the effectiveness of these earlier schemes for example in China (Lei and Lin 2009), Vietnam (Wagstaff 2010), or Indonesia (Sparrow et al. 2013). More recent reforms have the goal to cover broader groups or even the whole population with a comprehensive benefit package (Lagomarsino et al. 2012), like in Indonesia from 2014. This raises new questions: It remains to be demonstrated whether the results from the more fragmented schemes can be replicated, and new topics such as the enrollment of difficult-to-reach populations in the informal sector become relevant (Banerjee et al. 2019).

In addition to, or even after lifting the cost barrier, behavioral factors might keep individuals from deciding to take up care. In this context, the low uptake of available technologies such as low-cost tools to prevent the spread of communicable diseases poses a challenge for researchers and policymakers. Dupas and Miguel (2017) and Kremer et al. (2019) depict preventive health decisions as often being characterized by a low-cost investment with a high expected return. In this case, behavioral factors appear to play a big role and require a different toolkit compared to when the binding barrier is cost or a lack of health service supply. Potential interventions are commonly tested via randomized controlled trials, for example on providing targeted information about the risk of contracting HIV to teenagers in Kenya (Dupas 2011a), or different nudges to increase child vaccination uptake in India (Banerjee et al. 2021). Increasing digitization of health systems and mobile phone coverage have contributed to and continue to expand this toolbox. Mobile phone based interventions represent a particular opportunity here (Aker 2017). Specifically, text messaging interventions have been widely applied to reach specific population groups for preventive behavior in the past (e.g. Armanasco et al. (2017)), but applications in the general population remain scarce. While message broadcasting can have a wide outreach like applied in Banerjee et al. (2020) and is a reasonable response in emergency settings, more targeted and personalized solutions are desirable for more regular health issues to avoid an overflow of information.

1.2 Chapter Overview

With this dissertation, I contribute to the outlined academic discourse on the barriers in the health decision process that contribute to unfavorable health outcomes in LMICs. The individual essays focus on different parts and functions of the health system. The first essay addresses a large-scale public health insurance reform in Indonesia that has the potential to reduce the cost barrier to care seeking in times of an acute health need. The remaining essays focus on individual preventive health behavior and low-touch interventions. The kind of preventive health behaviors differ though: essay two focuses on screening for diabetes and hypertension, and chapters three and four on protective behavior against COVID-19.

The essays employ diverse data sources and methodologies. Essay one makes use of a large-scale secondary household survey dataset that is representative for all Indonesian districts. The remaining essays rely on more fine-grained but geographically more limited primary, in-person, and phone survey data, which is enriched with administrative health insurance data in essay four. Methodologically, I use field experiments (essays two and four) to evaluate the effectiveness of a specific new intervention but also employ quasi-experimental methods for the analysis of changes in the national-level Indonesian health insurance reform (essay one). Essay three relies on in-depth descriptive analyses, which are also built into the remaining essays to provide a snapshot of the situation or associations of interest.

Essay 1: Health Insurance Reform in Indonesia: Implications for Health Care Usage and Health Expenditure

The first essay addresses the introduction of the national health insurance scheme (JKN) in 2014, which aimed to cover the entire population, and by that marked a milestone in the history of Indonesian health insurance, and across LMICs. Sebastian Vollmer and I investigate whether this reform induced changes in in- or outpatient health care usage and health expenditure beyond the previous fragmented schemes. Many of these previous Indonesian health insurance schemes have been analyzed along similar indicators in the past (e.g. Cuevas and Parker (2010), Vidyattama et al. (2014), Hidayat et al. (2004), Sparrow et al. (2013)), but evidence on the national scheme remains scarce. The growing literature on the JKN reform examines socio-economic disparities in health care usage around the reform (Johar et al. 2018), its effect on maternal health, and health care usage (Anindya et al. 2020;

Kreif et al. 2020), and explore how previously uninsured informal sector employees can be enrolled (Banerjee et al. 2019).

We make use of seven rounds of the Indonesian socio-economic survey (SUSENAS, 2011-2017) to first explore developments in health insurance membership, health care usage and health expenditure over the survey years. We then apply two versions of difference-in-difference estimation: In an aggregated district-level panel dataset, we estimate whether an increase in the share of the district's population that is covered by insurance is associated with a change in health care usage and health expenditure. In a second analysis, we use the pooled cross-sectional dataset at the individual level and compare the post-policy change in health care usage and health expenditure between the group that was covered by a pre-JKN health insurance and the newly eligible. This way, our analyses provide detailed disaggregation across health facilities, in- and outpatient care, time, and population groups.

We find that health insurance membership increased by 18 percentage points to 67% of Indonesian households from the reform year 2014 to 2017. At the district level, we detect significant increases in inpatient care usage associated with the coverage expansion, particularly in public hospitals. The individual level analysis revealed that these increases tend to be stronger among households who were already insured before the reform. In neither of these analyses we detect strong changes in outpatient care usage and health expenditure. These findings hint that the reform indeed increased health care usage but highlight the need for additional efforts to extend these benefits to the large newly eligible population.

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

Essay two focuses on screening for diabetes and hypertension, which is located at the first point of contact between an individual who is unaware of his / her disease status and the health system. Hence, it is a specific type of preventive behavior that does not aim to avoid an illness altogether but detect a condition early to initiate treatment. The burden of NCDs has been rising in Indonesia (IHME 2018), and similar to other LMICs, substantial gaps in detection, treatment, and control of diabetes and hypertension remain (Geldsetzer et al. 2019; Manne-Goehler et al. 2019). This is despite the fact that the government offers several opportunities for free screening, for which uptake remains limited (Riskesdas 2018).

Together with Maja Marcus, Anna Reuter, and Sebastian Vollmer, I conducted a community-based RCT in two districts of Aceh province in Indonesia. During mixed-method pre-studies, we identified barriers to the uptake of existing public screening services for diabetes and hypertension. Then, we designed a personalized and targeted text messaging campaign addressing the identified barriers, and tested whether it can increase the demand for these services in the age-based risk group, for which WHO PEN guidelines recommend annual screenings. With an intention-to-treat analysis we show that our intervention increased screening uptake by approximately 6.6 percentage points, which is a 20% increase compared to the pure control group. The local average treatment effect reveals the potential for an even higher potential impact as mobile phone coverage and familiarity in usage increases: Among those, who received and read the messages, the effect size is 17 percentage points. We further find no effect of the intervention on disease and prevention knowledge, and suspect that the intervention rather works through a reminder effect. All in all, our text messaging intervention can be a cheap and easily scalable tool to reduce testing gaps in a middle-income country setting.

Essay 3: Knowing versus Doing: Protective Health Behavior against COVID-19 in Aceh, Indonesia

Essays three and four consider individual preventive behavior against COVID-19, which is an individual health decision that does not require an interaction with the health system for the action itself. Nevertheless, it can relieve pressure from fragile health systems that are not equipped to attend to a high number of patients with a complicated disease course. As individual preventive behavior such as physical distancing, wearing masks, and hygiene measures can reduce the risk of an infection, essay three studies factors that facilitate knowledge and adoption of preventive practices, which allowed us to identify groups that were lagging behind. It is co-authored with an interdisciplinary research team from German and Indonesian universities: Eliana Chavarría, Farah Diba, Maja Marcus, Marthoenis, Anna Reuter, and Sebastian Vollmer, and has been published in the Journal of Development Studies.

For this study, we use data from telephone interviews with the general population between 40 and 70 years in Aceh province in Indonesia that were conducted between March and May 2020 during the endline data collection for essay two. This part of the population is not only relevant for studying NCDs but is also at increased risk to suffer from a complicated COVID-19 disease course due to the higher age (Williamson et al. 2020). At the time of data collection, little was known on protective behavior in the COVID-19 pandemic, so that we first identified potential factors from the literature on previous pandemics (e.g. Bish and Michie (2010), Tooher et al. (2013), Yap et al. (2010)). By now, similar studies have emerged for COVID-19 such as Fitzpatrick et al. (2021) studying the uptake of non-pharmaceutical interventions in four African countries. Our study presents a descriptive overview of the levels of COVID-19 and particularly prevention knowledge and practice in Aceh. We then use simple correlation analysis with linear probability models to examine correlated of prevention knowledge and uptake with 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 were relatively high at this early point in the pandemic. Knowing the respective practice was the largest explanatory driver of protective health behavior. The fact that knowledge itself was strongly shaped by socioeconomic gradients shed light on which parts of the population needed to be targeted with further information.

Essay 4: The Effect of Personalized Health Information on Preventive Behavior amongst COVID-19 Risk Groups: a Randomized Experiment in Pakistan

With essay four, our German-Pakistani research team with Sheraz Khan, Zohaib Khan, Jawad Noon, Andreas Landmann, and Sebastian Vollmer, first conducted descriptive analyses similar to essay three in a sample of low-income households in Khyber Pakhtunkhwa province. Our rapid response telephone survey from April to October 2020 showed that gaps in knowledge and practice of individual preventive practices prevailed, and that particularly risk group households did not adhere to more preventive behavior. In addition to considering the age-based risk definition like in essay three, we classified all households that had a member with a precondition (cardio-vascular, respiratory disease, cancer, diabetes, or hypertension) (Nishiga et al. 2020; Williamson et al. 2020; Zhou et al. 2020) that was also targeted with specific recommendations from the government (Government of Pakistan 2020).

Then, we went one step further and tested in a randomized experiment whether a more intensive and personalized text messaging intervention exploiting health insurance records could contribute to increasing prevention uptake. This contributes to a growing literature that examines low-touch interventions to increase individual preventive behavior during different stages in the pandemic, and with different designs such as celebrity-messaging in India (Banerjee et al. 2020), more generic text messaging interventions in Peru (Boruchowicz et al. 2020) and India (Bahety et al. 2021), or a combined telephone- and text messaging intervention in Bangladesh (Siddique et al. 2020). We find that the intervention helped message recipients to adhere to 6 percentage points more handwashing compared to the control group (16% increase) in the time between the first and second wave of infections, and adopt twice as much tele-medical services compared to the control group. The effect on handwashing is driven by a differential behavior in risk group households only, while the effect on telemedicine usage can be detected in the whole sample. Beyond the experimental outcome, this study demonstrates the possibility to use health insurance records for such an intervention at large scale, which addresses a major limitation of other text messaging interventions that rely on self-collected contact data like in essay two.

1.3 General Summary and Conclusion

On the way to improving health outcomes in LMICs in the wake of the COVID-19 pandemic, this dissertation provides four perspectives on facilitators and barriers to the uptake of health care and preventive health behavior. It gives a retrospective view on how the Indonesian health insurance reform affected health care utilization, and a prospective outlook on how low-touch text messaging interventions can complement the policymaker's toolbox to improve early detection of diabetes and hypertension and increase COVID-19 prevention in at-risk groups.

By studying the latest health insurance reform in Indonesia we show that combining fragmented public health insurance schemes and expanding coverage to the previously uninsured population can further increase the usage of higher-level health care. Our analyses point in the direction that the major gains were made by population groups that were already insured under previous schemes. This highlights the potential of efficiency gains in the context of such a large-scale scheme but also the importance of additional efforts to make sure that the newly eligible population benefits to the same degree. This opens the door for more formative research on why this disparity persists and for the design of counteracting interventions.

With essay two we showed that text message reminders for diabetes and hypertension screening in the general at-risk population can be an effective and cheap complement to ongoing efforts to address the increasing burden of NCDs in Indonesia. The study also demonstrated the limits of such low-touch interventions: among others, an update of the belief that screening is necessary irrespective of feeling symptoms, which poses a major barrier to early screening uptake, could not be reached and calls for different policy responses.

As health systems become more digitized and mobile phone coverage increases, more opportunities for such low-touch text messaging interventions might arise. One such application is the possibility of the health system to react quickly in times of a health crisis such as the COVID-19 pandemic when reliable information needed to be spread. We demonstrated this possibility to leverage health insurance records to first interview the relevant constituency, and then field a targeted and personalized intervention for the risk group in Pakistan.

Chapter 2

Health Insurance Reform in Indonesia:
Implications for Health Care Usage and Health Expenditure

with: Sebastian Vollmer

Abstract

The introduction of a single-payer health insurance covering the entire population marked not only a milestone in the history of Indonesian health insurance, but across low- and middle-income countries. After the reform in 2014, health insurance membership has increased by 18 percentage points to 67% of Indonesian households in 2017. We study whether this reform changed health care usage and health expenditure beyond previous public insurance schemes. We apply two versions of difference-in-difference estimation to seven rounds of the Indonesian socio-economic survey (SUSENAS, 2011-2017). We find significant increases in inpatient care usage associated with the coverage expansion, particularly in public hospitals. In addition, we show that these increases tend to be stronger among households who were already insured before the reform. We do not detect strong changes in outpatient care usage and health expenditure. These findings hint at a reduction in the economic risk of illness associated with the health insurance reform, but highlight the need to make these benefits accessible for the large newly eligible population.

2.1 Introduction

Universal Health Coverage is an important goal of the international development agenda, and it is an integral part of the third sustainable development goal to reach "good health and wellbeing". Health insurance is a building block of these efforts because it has the potential to reduce the cost barrier to necessary health services. In addition, the sudden or repeated costs of an illness can be a shock that prevents households from smoothing consumption over time and hence poses a poverty risk (Deaton 1997). Past research has shown that health shocks cannot be fully insured against by informal coping strategies (e.g. Townsend (1994)). The introduction of the national Indonesian health insurance scheme Jaminan Kesehatan Nasional (JKN) in 2014 that pools and extends all previously operating schemes, is a milestone towards Universal Health Coverage. The public scheme aims to cover the whole population, which makes it the largest single-payer scheme globally and unique across low- and middle-income countries (LMICs) in the region and beyond.

We examine the changes in health facility utilization and health expenditure that can be attributed to the reform beyond the fragmented previous schemes. We do so by tracking the differential associations between insurance coverage, health facility utilization and health expenditure across districts, time, and likely pre-reform insurance status. If the reform improved the financial protection from illness, it can be expected that the association between health insurance membership and health facility usage would increase after the reform. For the reform to foster equity in health care usage, the change should be more pronounced for the previously uninsured population group.

The research question is addressed empirically using seven rounds of the Indonesian socio-economic survey (SUSENAS, 2011-2017). The repeated cross-sectional dataset includes a representative sample of households from all Indonesian districts. First, health insurance membership patterns, health facility usage and health expenditure are compared descriptively before and after the reform. Then, we conduct a fixed-effects estimation at the district level to test for changes in the association between health insurance coverage rates and the outcomes around the reform. In the third step, we apply a difference-in-differences type model, but at the individual or household level in the pooled cross-section. With this approach, the rates of change in the outcomes can be compared across groups that likely belonged to either the previously non-insured, or one of the previous health insurance schemes.

We find that after the implementation of JKN the proportion of households with health insurance has increased by 18 percentage points to 67% in 2017. This increase in coverage already appears to affect health facility usage and, to a lesser degree, health expenditure. We find a significantly higher increase in the use of public inpatient care for districts that expanded their insurance coverage beyond the previous schemes. This association does not hold for outpatient care usage across most facility types. Health expenditure appears to decrease, driven by a decrease in medication expenditure. The individual level estimation reveals sizeable differences across the groups. The previously uninsured group seems to only benefit from the reform in terms of a slightly steeper increase in outpatient care usage, whereas the increases in inpatient and public care usage tend to be stronger in the groups that were previously part of other insurance schemes. Similarly, the decrease in health expenditure is significantly lower in the previously uninsured group. These results suggest that the reform indeed contributed to increasing the use of health services in Indonesia, and reveals that this increase pertains to higher level care in public facilities and not primary care for acute illnesses. The finding that post-reform increases in health care usage and decreases in health expenditure are higher in the group that was likely already covered before the reform highlights the need to focus on better integrating the newly eligible population.

This study contributes to the existing literature on public health insurance in LMICs and Indonesia in several ways: First, it adds to the evidence base of the implications of large-scale public health insurance schemes in a middle-income country (Lagomarsino et al. (2012), Galárraga et al. (2010)). Due to its size and comprehensiveness, the Indonesian case is of particular interest, and the detailed categories of insurance membership, in- and outpatient care usage and health expenditure allow us to draw nuanced conclusions. Second, even though several of the fragmented Indonesian health insurance schemes before JKN have been evaluated (see chapter 2.2.2), there is still limited national-level evidence on the JKN reform. There is already evidence on socio-economic disparities in health care usage around the reform from a similar, but slightly shorter dataset (SUSENAS 2011-2016) (Johar et al. 2018), on the use of maternal health and health care using the Indonesian Demographic and Health Survey (Anindya et al. 2020) or the Indonesian Family Life Survey (Kreif et al. 2020). In addition, some prospective studies are tackling specific aspects of the scheme such as enrollment of the informal sector (Banerjee et al. 2019) or detailed measures of equity (Wiseman et al. 2018). We complement these studies by providing national level evidence on both health care usage and health expenditure and particularly by focusing on the newly eligible population group. Additionally, we are exploiting the structure of SUSENAS as both a panel at the district level and the pooled cross-section, which is new in the analysis of health insurance in Indonesia and allows us to account for more potential sources of endogeneity.

2.2 Background

2.2.1 Country context and the reform process

Indonesia has a long history of health insurance schemes, which are now merged into JKN (see Table A 2.1 for timeline). The legal foundation for public engagement in health services was laid in 1960 with the adoption of the basic health law. It states every citizen's right to physical and mental health and acknowledges the state's responsibility to provide equal access to health services for all Indonesians (Government of Indonesia 1960). After independence, the first efforts to establish public health insurance for civil servants had been continued and developed further. This led to the introduction of the first mandatory health insurance for active and retired civil servants in 1968 (Askes, *Asuransi Kesehatan*). Together with Asabri (*Asuransi Sosial Angkatan Bersenjata Republik Indonesia*), which covered active military and police forces, Askes was the largest employment-based health insurance scheme that was in place up until 2014. The second biggest employment-dependent public health insurance scheme (Jamsostek, *Jaminan Sosial Tenaga Kerja)* covered formal sector workers, namely employers and employees in large private enterprises from 1992. Only companies with more than ten employees, or those paying salaries of more than IDR 1 million per month, were obliged to enroll their employees. Even then, there was an opt-out option if the company offered its employees a social security plan with more benefits than the public one. For smaller companies and the self-employed, sign up was possible on a voluntary basis. Due to these regulations and the large informal sector, the coverage of Jamsostek remained low (Rokx et al. 2012). Since shortly after Askes was introduced, there were several efforts to also cover the non-civil servants, particularly the poor, but with limited success. There was for example a health fund (Vidyattama et al. 2014) or several health card programs such as the one in response to the Asian Financial Crisis (Pradhan et al. 2007). It was only in 2004 that the largest and most successful subsidized arm of public health insurance was implemented: Askeskin (*Asuransi Kesehatan Masyarakat Miskin*). It originally targeted the lowest income quintile and was expanded in 2008 to additionally cover the near poor and was renamed Jamkesmas (*Jaminan Kesehatan Masyarakat*). Different from the previous health card schemes, it was not a targeted fee waiver but financed through capitation in primary care facilities and fees-for-service in hospitals (Sparrow et al. 2013). It was more successful than previous schemes in covering informal sector workers and poor households, but leakage to higher wealth quantiles remained high (Harimurti et al. 2013). At the same time, regional health insurance programs (Jamkesda, *Jaminan Kesehatan Daerah*) were established in some provinces. The implementation differed a lot ranging from having target groups similar to Jamkesmas to the entire (uninsured) population of the province.

All these fragmented schemes existing until 2014 were merged into the national health insurance JKN (*Jaminan Kesehatan Nasional*) (see Figure A 2.1). As of the 1st of January 2014, the separate agencies that administered the abovementioned schemes were dissolved and fully integrated into the new national social security agency BPJS (*Badan Penyelenggaran Jaminan Sosial*), which has been the single-payer agency since then. Likewise, all members of Askes, Jamsostek, Jamkesmas, and parts of Jamkesda, were transferred to be members of JKN, while their original cards remained valid. Step by step, all regional Jamkesda schemes, and their members have been incorporated into JKN. Employers of enterprises of all sizes were obliged to register their employees between 2014 and 2019. The same holds for the self-employed, who have to register themselves (TNP2K 2015). As the enforcement of these steps is difficult, particularly within the informal workforce, universal enrollment is only expected to be achieved within the next decade (Agustina et al. 2019). Banerjee et al. (2019) have shown in a large-scale field experiment that even with full premium subsidies and comprehensive administrative help, enrollment in the informal contributory arm of JKN can only be boosted to 30%.

After the reform, there is a non-contributory arm, which builds on the structures of Jamkesmas and a contributory arm based on Askes and Jamsostek that extends its coverage to non-poor informal workers. Premiums for the beneficiaries of the non-contributory arm are paid from general taxation and are higher than previously for Jamkesmas. While formal sector workers pay their premiums through payroll deductions, informal sector workers need to contribute fixed monthly premiums. The basic benefit package is the same across all membership categories in terms of covering treatment in public and selected private health facilities as well as prescription medicine. The only difference is that members of the contributory arm can choose to pay higher premiums that entitle them to the use of higher class hospital beds with more amenities, such as one-bed rooms (TNP2K 2015).

2.2.2 Related literature

This study can be placed at the intersection of two bodies of literature. First, it relates to a vast literature that examines the impact of health insurance on health facility usage, health expenditure, and health itself. As we are not primarily studying the effect of being newly insured, but rather the difference in the outcomes associated with the new compared to previous schemes, it also relates to the literature on heterogeneities in health and health care access.

Having health insurance has the potential to increase health care usage if it lifts the financial barrier to accessing care. Heterogeneities in this effect can be expected along the lines of how binding this financial constraint was in the decision to take up care prior to insurance membership. The overall increase in health care usage seems to hold for formal health insurance across different countries and health insurance systems. As summarized in Hadley (2003), initial evidence from high income countries (HIC) showed a positive impact of health insurance membership on access to health care. Buchmueller et al. (2005)'s literature review on the impact of Medicaid on health service utilization in the Unites States found that being insured resulted in about one extra health facility visit per year, which tended to be used for preventive care. An overall positive association seems to also hold in LMICs, even though the types of insurance schemes vary a lot across countries and studies: it ranges from voluntary schemes that only cover part of the system (e.g. Waters (1999) for Ecuador, Lei and Lin (2009) for China) to very comprehensive schemes (e.g. Wagstaff (2010) for Vietnam).

Preceding studies on Indonesia found a significant increase in health facility usage for most of the previous schemes jointly (Cuevas and Parker 2010; Vidyattama et al. 2014), and also found differences in distribution depending on the scheme. For the mandatory formal sector health insurance schemes, Hidayat et al. (2004) found that Askes membership led to an increase in the use of public health facilities and a decrease in the use of private health facilities for outpatient care, while both increased with Jamsostek. This can be explained by the Askes benefit package only covering public health services at the time as opposed to Jamsostek, which already covered both. This substitution effect was also found for the Health Card program following the Asian Financial Crisis but was only detectable in rural areas (Pradhan et al. 2007). A similar concentration of the bulk of the impact in rural areas was also detected for the voluntary health insurance scheme Askeskin (Sparrow et al. 2013) and for all schemes that were in place then jointly (Cuevas and Parker 2010). Such evidence for JKN is still limited. Johar et al. (2018) have studied the distribution of health care usage along different socio-economic lines in a similar sample of the SUSENAS dataset around the JKN reform. Using concentration indices, they map out various prevailing geographic and socio-economic differences that seem to remain mostly pro-rich. For the use of maternal care in particular, Anindya et al. (2020) find that socio-economic differences decrease among insured individuals, but that level differences remain high.

The expected impact on health expenditure is not as clear: it could either decrease if the same amount of care is sought, but now covered by insurance; increase if more care was sought and copayments remain; or stay the same if more care is sought at no additional cost. Previous studies have found evidence for all these associations, though fewer studies address health expenditure as an outcome (Giedion et al. 2009). For HICs, there is evidence for decreased out-of-pocket expenditure (OOP) as a consequence of insurance coverage (Moreno-Serra and Smith 2012), but for LMICs, the evidence is rather mixed. As opposed to finding none or even a slightly negative impact on access to health care, Wagstaff and Yu (2007) found clear reductions in both OOP and the incidence of catastrophic spending through the health sector reform in China, with a particularly high reduction in expenditure for medicines, and stronger effects for the poorest wealth quintiles. In their study on a voluntary health insurance reform in rural China, Wagstaff et al. (2009) found the opposite, which indicates that design and benefit packages are likely to influence the response to a reform, even within one country. The authors speculated the reason for increasing OOP to be supply-side incentives encouraging the use of more costly technology and the provision of unnecessary care. Lei and Lin (2009) did not find any significant effect for OOP in rural China. Even though Wagstaff (2010) could not identify a significant impact of the Vietnamese health fund for the poor on utilization, they found a decrease in OOP for both in- and outpatient care. In one of the few studies that can rely on experimental data, Galárraga et al. (2010) found a robust decrease in OOP for the Mexican health insurance program Seguro Popular. The Vietnamese social health insurance also seems to offer the desired financial protection with Wagstaff and Pradhan (2006) finding a significant reduction in cash and in-kind OOP for outpatient care.

The evidence base on the effect of the Indonesian health insurance schemes on health expenditure is limited. Aji et al. (2013) found a significant reduction in OOP only for Askes and Askeskin, but none for Jamsostek. Two studies examined OOP as one of many outcomes and found either no effect (Cuevas and Parker 2010) or a significant increase in urban areas only (Sparrow et al. 2013).

The new JKN scheme can be expected to increase health care usage beyond the previous schemes through two channels. First, by including more members who were until then subject to the financial barrier to health care access and experience the benefits of new membership as described above. Second, efficiency gains through unifying administrative procedures or empaneling more hospitals might reduce the remaining non-financial barriers for all, so that take-up might also increase for members of previous schemes if their need for health care was not yet saturated.

2.3 Methodology

2.3.1 Data

We use the Indonesian socio-economic survey (SUSENAS). The cross-sectional household dataset is collected at least annually since 1963 by the Indonesian statistical office. It covers all Indonesian provinces and their districts with a probability proportional to size sampling design that yields representative data up to the district level (Badan Pusat Statistik 2016). The sampling design is a multistage stratified random sample, which can be accounted for in the analysis by including sampling weights. Each round contains around 1,100,000 individuals from 290,000 households living in one of approximately 500 districts.[1]

Out of the rich dataset, we use socio-economic information, and health seeking behavior on both the household and all its members from the core module 2011 until 2017 as well as health expenditure from the expenditure module from 2011 until 2016. This yields a dataset with three rounds pre and four rounds post the introduction of JKN. See appendix Table A 2.3 for details on how the underlying variables for exposure, outcomes and further covariates are defined across survey waves.

The outcome variables are health facility usage and health expenditure. Health facility usage is measured with indicator variables capturing whether an individual used outpatient care during the previous month, or inpatient care during the previous year. Outpatient care usage is only recorded for individuals who reported an acute illness during the previous month, which applies to roughly 30% of the sample and hence excludes preventive and routine care. The aggregate of any use can be broken down to the kind of facility used: public or private and primary and secondary[2]. Public facilities include public health centers (Puskesmas) at the primary level and hospitals at the secondary level. Puskesmas are located in each sub-district, secondary level hospitals have been established in every district and higher level hospitals are typically located in larger cities. Similarly, private facilities include private doctor's practices or clinics for primary care and hospitals for higher levels of care. JKN covers care in all public and associated private facilities, but for a valid claim, the referral guidelines need to be adhered

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[1] In an ongoing process of decentralization, several districts and one province were split within the study period. For consistency, we apply the definition of the 2010 census to all rounds. Changes are documented in Table A 2.2.

[2] SUSENAS also reports the use of traditional care, but we do not include it in the analysis as it cannot be covered by health insurance, and the incidence in the data is very low.

to. If a referral is necessary, transportation in the primary facility's ambulance is covered by the insurance.

The health expenditure outcome is measured using real quarterly household health expenditure in Indonesian Rupiah (IDR)[3]. We grouped the 16 categories of health expenditure into five categories: total treatment, treatment in public facilities, treatment in private facilities, preventive measures, and medicines[4]. It needs to be noted that, as opposed to health facility usage, the expenditure measurement in SUSENAS underlies limitations that require more cautious interpretation of changes in expenditure patterns. First, the measure cannot be interpreted as out-of-pocket expenditure alone as the survey protocol requires the respondent to not only mention own expenditure but estimate the full amount in case s/he received a subsidy. Especially in the case of health expenditure that is covered by health insurance, this introduces major measurement error as the beneficiary is not informed about the actual cost of a covered procedure, but still asked to estimate it. Therefore, each health expenditure measure contains a fairly certain self-paid component and an uncertain estimated subsidy component, which cannot be disentangled. Secondly, the recall period in the health expenditure module changed within the study period. Before 2014, it was collected for one, two, and three months prior to the survey, and from 2015 on as the aggregate of the entire year prior to the survey. Therefore, none of the measures of health expenditure captures the same value in all survey rounds. Comparing them is likely to be biased as longer recall periods have been found to be subject to underreporting (Deaton 1997). To best approximate health expenditure over the years, we calculate a quarterly average for each expenditure category and household containing the sum of the last three months for the years 2011-14 and the quarterly average of the last year in the rounds 2015-16. Using quarterly instead of monthly averages is recommended by Johar et al. (2017) in a detailed critique of the SUSENAS expenditure module to better account for seasonality in expenditure. At the district level, data is available for the rounds 2011-2016, and at the household level for 2013-2016.

Health insurance membership is the basis for the policy exposure variables. It is measured using indicator variables at the household level, which capture whether at least one household member has health insurance. Even though health insurance membership is recorded at the individual level from 2015, we use the household measure in all rounds. It is reasonable to define insurance membership at the household level as in many of the pre-JKN schemes, a

[3] IMF's consumer price index for Indonesia with the base year 2010 is used as a deflator for all expenditure.
[4] Refer to appendix Table A 2.3 for exact elements, which are similar to Sparrow et al. 2013's definition.

number of dependents were insured under one member's insurance. We further distinguish whether a household has a member of self-paid or subsidized health insurance.

The dataset gives a wide variety of socio-economic characteristics of the household and the individual that can be included as control variables. At the household level, we include whether the household resides in an urban or rural area and several wealth proxies (an asset index, household expenditure, access to electricity, house ownership and membership in social protection programs other than health insurance). At the individual level, we include the basic demographics age and gender as well as the highest level of education completed and the sector of employment. The choice of the main set of control variables was guided by similar previous studies such as Sparrow et al. (2013), Vidyattama et al. (2014), and Pradhan et al. (2007). Additionally, data on the number of public health centers per province and year is included from reports of the ministry of health (KKRI 2018).

2.3.2 Estimation strategy

When examining the impact of health insurance schemes, one major challenge is that health insurance membership is prone to endogeneity, due to remaining possibilities of self-selection into membership based on unobservable characteristics that might also determine the outcomes. This would ideally be dealt with in a randomized experiment, but such studies on public health insurance schemes are rare for practical reasons. Exceptions are the RAND (Manning et al. 1987), Oregon health insurance experiment (Finkelstein et al. 2012) and Galárraga et al. (2010) in connection to the Mexican Seguro popular experiment. Consequently, many authors have turned to quasi-experimental research designs to evaluate health reforms.

In our case, it is possible to apply neither pure panel data methods as SUSENAS has a different sample of households each year, nor pure cross-sectional methods as the group of newly eligible individuals cannot be clearly identified in the post-policy years alone. We apply two difference-in-differences type models in the pooled cross-section:

In the first part of the analysis, we construct a pseudo-panel at the district level to identify whether post-reform increases in the district-level health insurance coverage are associated with changes in health facility usage and health expenditure. If this association increases after the reform, it would point towards the new scheme being more effective than previous ones. This can work either through enrolling more individuals for whom the financial barrier to care was then reduced or by further improving access for the already enrolled as the number of members in the own district increases. For this analysis, we aggregate the household information to have a pseudo-panel of the means of the household characteristics of all 500 districts for all years. The outcome variables are then the proportions of the district population who use the respective health service and the average household health expenditure. The policy exposure variable is the proportion of insured households in the district population. Based on their employment and wealth structure, pre-reform insurance coverage, and hence exposure to the reform differs across districts.

Following equation 1, we estimate the association between health insurance coverage *ins_cov* and all outcomes *Y* for district *i* and year *t*. The coefficients of interest are β_t, which capture the change in the outcome on a one percentage point increase in a district's insurance coverage from the last pre-policy year 2013 to the respective post-policy year (2014-2017).

$$(1)\ Y_{i,t} = \alpha + \beta_t(ins\_cov_{i,t} * year_t) + \gamma\ ins\_cov_{i,t} + \delta_t\ year_t + \zeta C_{i,t} + \theta P_{j,t} + \eta_i + \varepsilon_{i,t}$$

Both the insurance coverage and year fixed effects enter separately to account for coverage level differences and the time trend. District fixed effects η_i account for all observable and unobservable time-invariant differences between the districts. As it can be expected that some relevant characteristics change in a non-constant way across the districts, a vector C of additional district- and time-specific control variables is included. In the main specification, these comprise the fraction of households living in urban areas as geographic characteristic, wealth (average per capita household expenditure, the proportion of households with access to electricity and owning a house) and socio-demographic characteristics (categories of the main employment sector, the proportion with more than primary education, and membership in other social protection programs). In addition, the number of public health centers (Puskesmas) per province j and year (P) captures time-variant health care supply factors. We are not aware of any other large supply-side interventions during the study period that affected only some districts. Nonetheless, time and district fixed effects account for any unobserved time- or location-independent supply-side factors. Standard errors are clustered at the district level. We conduct a falsification test with the same regression framework on the pre-policy years, using 2011 as the base year, comparing it with 2012 and 2013.

The second part of the analysis is conducted in the pooled cross-section at the individual level. Even though we do not observe the same households before and after the reform, we can, based on their socio-demographic characteristics, identify the groups that were likely to be members of a pre-reform health insurance scheme and those who likely became newly eligible (as described in section 2.2.1 and Figure A 2.1). This allows us to track differences in health facility usage and health expenditure from before to after the reform between these groups.

To identify the groups, we first turn to the dataset of the year 2013, in which the pre-reform insurance status of each household is known. We then regress several covariates that were likely to influence pre-reform insurance status and are observable in all study years on an indicator of having any, subsidized or self-paid health insurance. As described in detail in section 2.2.1, employment, wealth as well as location of residence were the main eligibility criteria for pre-JKN schemes. The covariates include: household wealth quintile, location of the residence (province, urban/rural), characteristics of the household head (gender, education, occupation) and the household (number of household members, the share of members in working and retirement age, being beneficiaries of other social protection programs). Then, we perform an out-of-sample prediction to assign the probability of being a beneficiary of a health insurance scheme in 2013 to each household in the rounds 2014 to 2017 given the aforementioned covariates. Likely group membership is then assigned to those households that were most likely part of one or several of the groups keeping the group proportions from 2013. Finally, a treatment variable (hins) can be defined in all years, so that it takes value 0 if the household was likely to have at least one member of a previous scheme and value 1 if it was likely to have no member of a previous scheme. Insurance coverage remained largely the same for all groups whose previous insurance schemes were integrated in the national scheme, which is why we consider them as the comparison group relative to the newly eligible. Using this, regressions similar to equation 1 can be estimated for individual n living in household m:

$$(2)\ \Pr\left(hfuse_{n,\,t}\right) = \alpha + \beta_t\left(hins_{m,\,t} * year_t\right) + \gamma\ hins_{m,t} + \delta_t\ year_t + \zeta C_{n,t} + \theta H_{m,t} + \eta_i + \varepsilon_{n,t}$$

Here, the health facility usage outcomes are binary indicators of usage or non-usage. In the main specification, we estimate equation 2 in a linear probability model and compare it to the marginal effects of estimating a Probit model as a robustness check. The coefficients of interest, β_t, capture the change in outcomes in the group that was likely newly eligible for health insurance after the reform compared to those who were likely to be in a pre-reform health insurance scheme. The group indicator as well as time fixed effects enter separately. Control variables are included at the household level $H_{m,t}$ (an indicator of living in an urban area, the household's wealth quintile) and the individual level $C_{n,t}$ (age, gender, education, and occupation). Finally, district fixed effects η_i are included. Standard errors are clustered at the household level as this is the level of health insurance membership and by design perfectly correlated within one household.

The association with average quarterly health expenditure is estimated at the household level with equation 3:

$$(3)\ hexp_{m,\,t} = \alpha + \beta_t\left(hins_{m,\,t} * year_t\right) + \gamma\ hins_{m,t} + \delta_t\ year_t + \theta H_{m,t} + \eta_i + \varepsilon_{n,t}$$

In addition to the household-level control variables that are included in equation 2, $H_{m,t}$ includes the further household characteristics: occupation sector, education of the household head, the share of household members in working and retired age as well as membership in other social protection programs. All other definitions are the same as in equation 2.

2.4 Results

2.4.1 Descriptive statistics

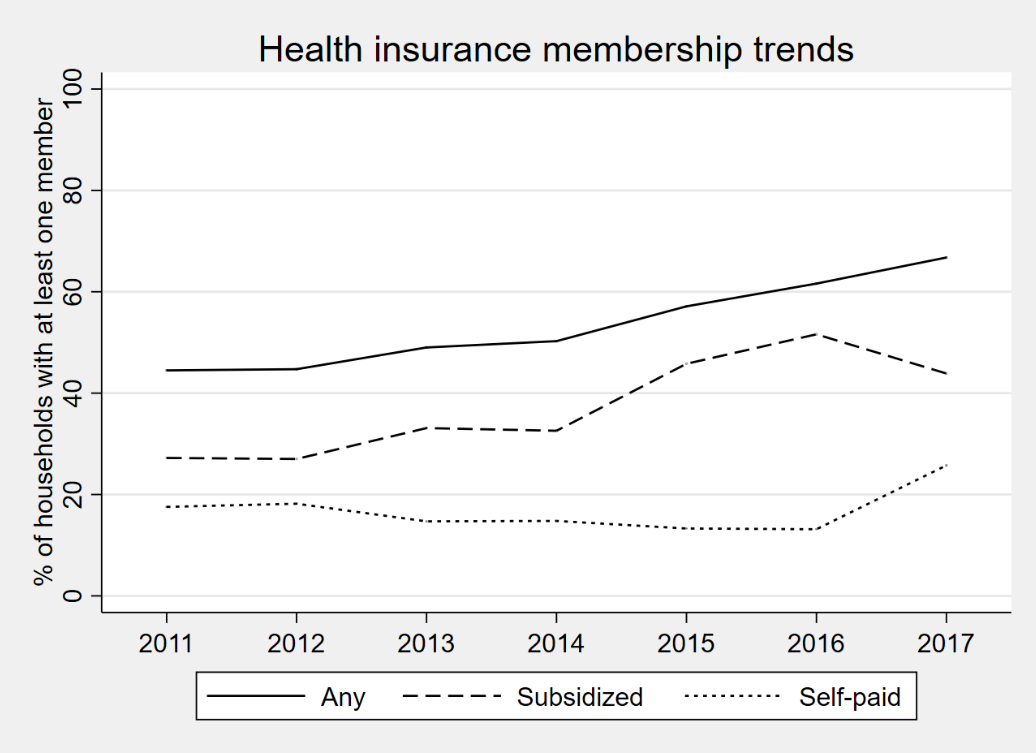
On average, respondents are 29-30 years old, the gender composition is balanced and slightly more than half of the adult respondents have more than primary education (Table A 2.4). Households have on average four members, and around half live in urban areas. Within the study period, wealth and education increase: the share of respondents with only primary or no education decreased by five percentage points from 2011 until 2017. Both, household expenditure and main elements of the asset index (access to electricity and the size of the dwelling) increased: Over 90% of households have access to electricity, around 80% own a house and live on about 70 m². Around 30% of the sample population reported illness during the previous month, which will be the reduced sample for the estimation of outpatient care usage[5].

Turning to the health insurance membership patterns, the data shows an overall increase in health insurance membership over the years, with the expected more pronounced increase after 2013 (Figure 2.1 displays the aggregate trends, Table A 2.5 shows all statistics). Taking all insurance schemes together, household coverage increased within four years of JKN implementation by 18 percentage points to 67%. This figure is comparable to the official membership reports of the insurance agency, who reported 175,739,499 members in March 2017, which is roughly 66% of the population (BPJS 2017). Even though the interpretation of the subsidized and employment-based self-paid schemes over the years is difficult due to changes in the survey categories, it seems like the bulk of the increase in coverage can be attributed to the subsidized schemes, formerly Jamkesmas and now the non-contributory arm of JKN (PBI). Private health insurance membership is small in magnitude throughout the years (roughly 2% of households have any member). The distribution of health insurance coverage shares across districts reveals strong disparities, as in some, almost no households reported membership, whereas others have near full coverage (see Figure A 2.2 for a map of district-wise coverage in 2013 and Figure A 2.3 for a map of the district-wise coverage changes

[5] This subsample is on average about 3 years older, slightly less educated, more likely to be married, male and living in larger households.

between 2013 and 2017). Therefore, it is reasonable to expect that the districts will also have benefited differentially from the reform.

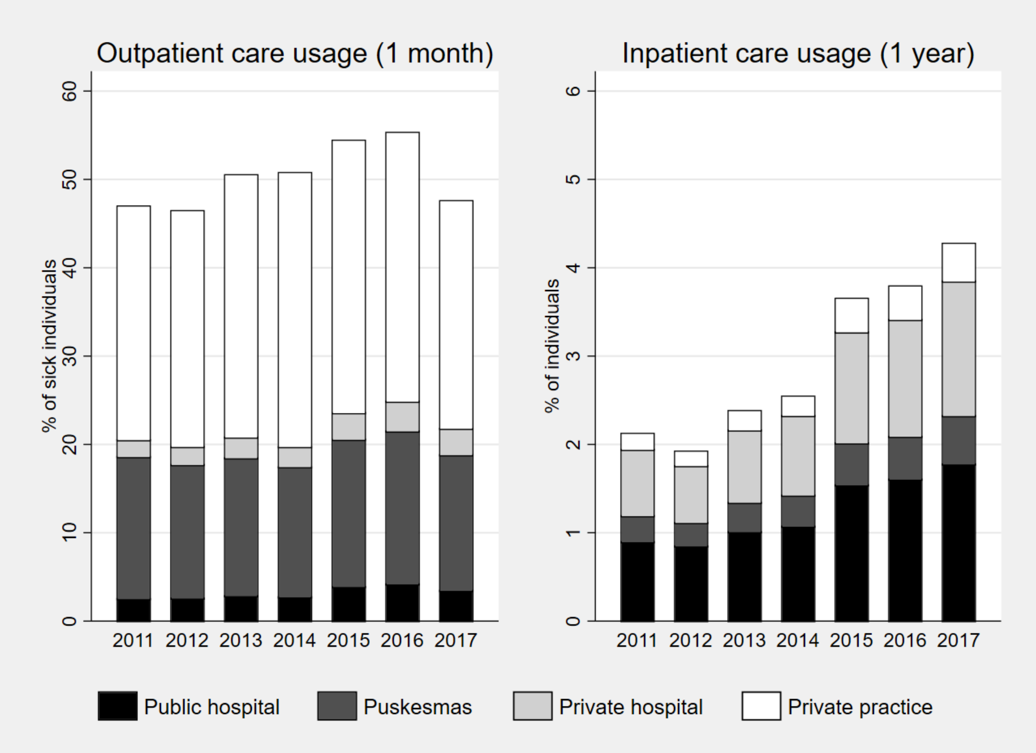
Figure 2.1 Health insurance membership trends



Share of households with at least one member in any health insurance in each year (bold line), a subsidized (dashed; includes Jamkesmas, Jampersal, Health fund, JKN (in 2015 all and in 2017 only PBI)) or self-paid scheme (dotted; includes Askes, Jamsostek, company insurance, JKN non-PBI (in 2017)); see appendix Table A 2.5 for the respective shares and their standard deviations.

Overall, the proportion of reported in- and outpatient visits in the respective recall periods increased significantly in the aggregate and some subcategories from 2013 to most of the subsequent years. As depicted in Figure 2.2 and Table A 2.6, 2.3% of the population used any kind of inpatient care in 2013, which almost doubled to 4.2% in 2017. Comparing the proportions across facility types, public health facilities are on average used twice as frequently for inpatient care as private facilities. As providers of higher-level care, hospitals serve around 75% of individuals for inpatient care. Traditional health facilities are only reported to be used by less than 0.1% and hence not depicted. Around half of the respondents who indicated an acute illness in the previous month sought outpatient care, from 2013 to 2015 this increased by approximately 14%, and decreased again in 2017. As opposed to inpatient care, private and public facilities each served about half of the reported outpatient care cases in 2013, but the increase in the usage proportion until 2016 was almost twice as high in public compared to private facilities. When looking at these usage patterns at the district level, we see that even though many districts have average usage patterns similar to the national average, there are substantial differences in both the level of pre-reform in- and outpatient care usage and in the respective post-reform changes (see maps of aggregate usage and change in Figure A 2.4 to Figure A 2.7).

Figure 2.2 Health care usage patterns



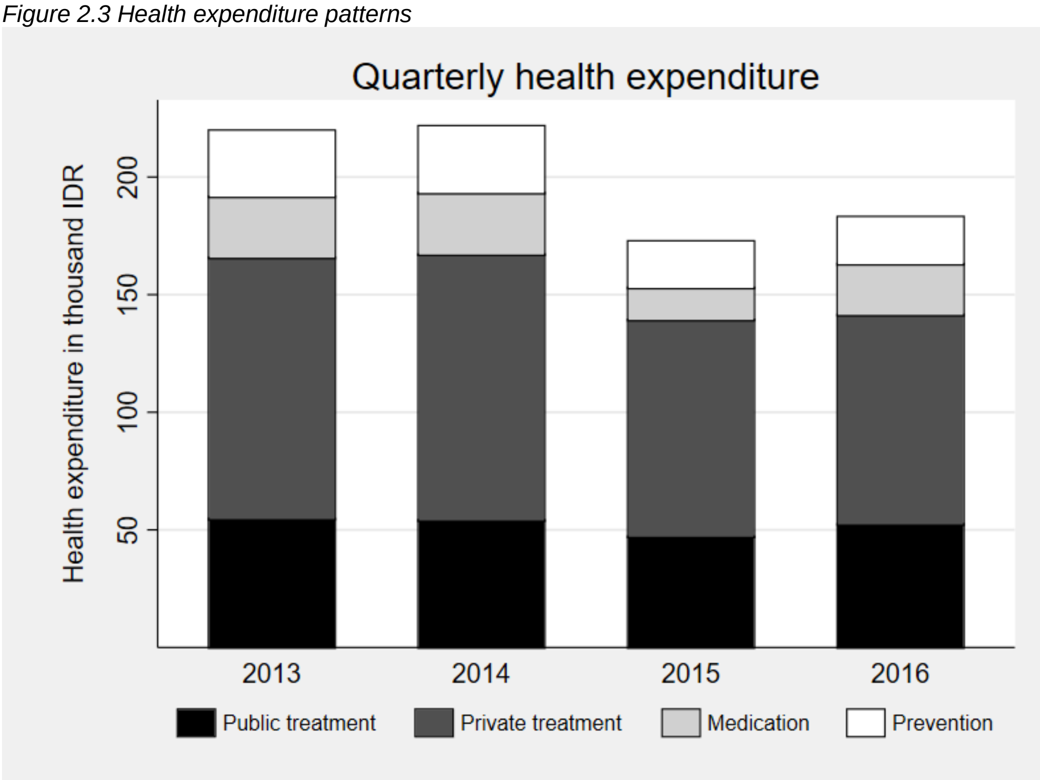
Weighted shares of individuals using outpatient care during the past month and inpatient care during the past year across facilities and years; see Table A 2.6 for details.

Treatment costs[6] remain the largest component of health expenditure throughout the years (around 70%), while medication and preventive care each account for slightly more than 10% (Figure 2.3 and appendix Table A 2.7). Even though expenditure appears to decrease in most categories (most likely due to the change in the recall period), some of the components of preventive care seem to increase, such as expenditure for pregnancy examination, or immunization. See Figure A 2.8 and Figure A 2.9 for the district-wise total health expenditure and post-reform change. From the rounds 2013 and 2014 we see that on average health expenditure makes up 2% of total household expenditure and for around 2% of households (Table A 2.7), this share surpasses the 15% threshold, which marks one commonly used cutoff for catastrophic health expenditure (Wagstaff and van Doorslaer 2003). Even though these shares can only be computed in 2013 and 2014 due to the difference in the recall periods for total and health expenditure in the later years, similar figures from SUSENAS 2001 (van

[6] According to the instructions in the questionnaire, these contain all expenses that are part of the health facility's bill, so that medication provided by the facility on the same bill is included in the "treatment" category, and only medication that is separately bought at a pharmacy is in the "medication" category.

Doorslaer et al. 2007) and 2005/6 (Sparrow et al. 2013) suggest that health expenditure shares remain rather stable.

Figure 2.3 Health expenditure patterns

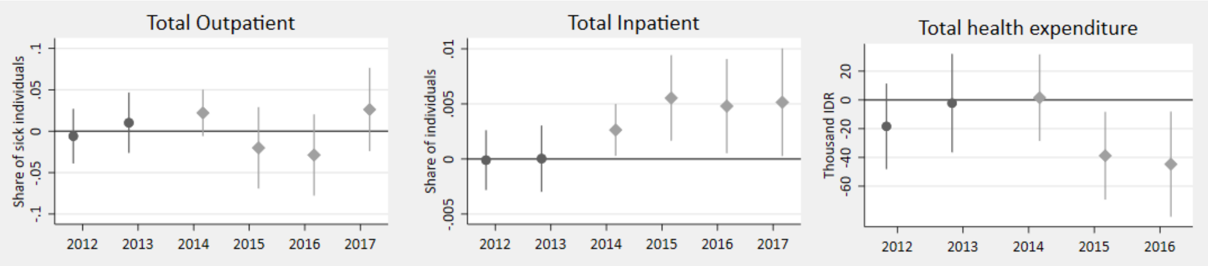


Mean quarterly real health expenditure across years in thousand IDR; accounting for sampling weights; see Table A 2.7 for details.

2.4.2 Estimation results district level

The following presents the results of estimating equation 1 using the district-level dataset to find out whether increases in insurance coverage affect the outcomes differently after the reform. Figure 2.4 displays the plotted coefficients of the interaction between the years and the district proportion with health insurance both for the years preceding the reform (dark grey) and after the reform (light grey). The association is not significantly different from zero in the pre-policy periods for any of the aggregate outcomes. After 2014, it becomes positive and significant for inpatient care usage, meaning that a one percentage point increase in a district's health insurance coverage led on average to an increase in inpatient care usage by half a percentage point, an increase of 23% compared to the 2013 average. No change can be detected for outpatient care. For 2015 and 2016, we see that the association between health expenditure and insurance coverage decreases and becomes negative, implying that a one percentage point increase in insurance coverage is associated with a 20% lower health expenditure.

Figure 2.4 District-level estimation results for main outcomes



Plot of the interaction coefficients β_t between the districts' health insurance coverage shares and the respective year from equation 1 in SUSENAS 2011-13 with base year 2011 (dark grey) and SUSENAS 2013-2017 with base year 2013 (light grey), point estimates with 95% confidence intervals; covariates: health insurance coverage share, year fixed effects, district fixed effects, province level control variable: number of Puskesmas, district-level control variables: urban fraction, district average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; accounting for sampling weights.

To better understand the dynamics of this aggregate effect, the same estimations are performed for the facility and expenditure types separately. For inpatient care usage (Figure 2.5, panel A; appendix Table A 2.8, Table A 2.9), the positive association seems to be driven by a clear increase in public, and particularly public hospital care usage. This increase in public inpatient care usage is both significantly different from zero and the coefficients of the pre-policy periods for the years 2015 to 2017 (Table A 2.10). On the contrary, usage of private health care providers appears to decrease as health insurance coverage increases. This association is driven by a decrease in the usage of private practices, but as this is not a main provider of inpatient care and the decrease is smaller than the increase in public hospital usage, this does not outweigh the total increase in inpatient care usage. This points towards a substitution of private primary for public secondary care.

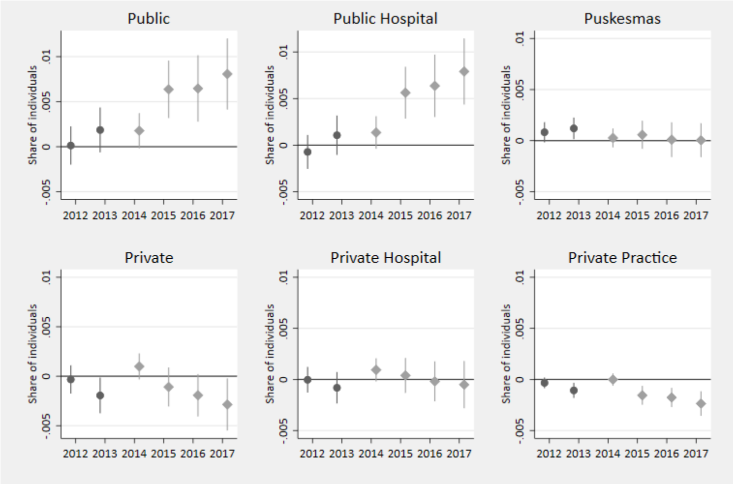
For outpatient care usage (Figure 2.5, panel B; appendix Table A 2.13, Table A 2.14, Table A 2.15), the results are not as clear. Similar to the post-reform patterns in inpatient care usage, before the reform there was a relatively small, but weakly significant positive association between coverage expansion and public care usage and a negative association of similar size for private care usage. Different from inpatient care use, these associations become weaker to the point where they are not significantly different from zero after the reform.

The negative association between insurance coverage and health expenditure appears to be driven by decreases in medication and public treatment expenditure (Figure 2.5, panel C; appendix Table A 2.18, Table A 2.19, Table A 2.20). For medication expenditure in particular, there seems to be a reversal of the association as it was slightly positive before and decreasing after the reform.

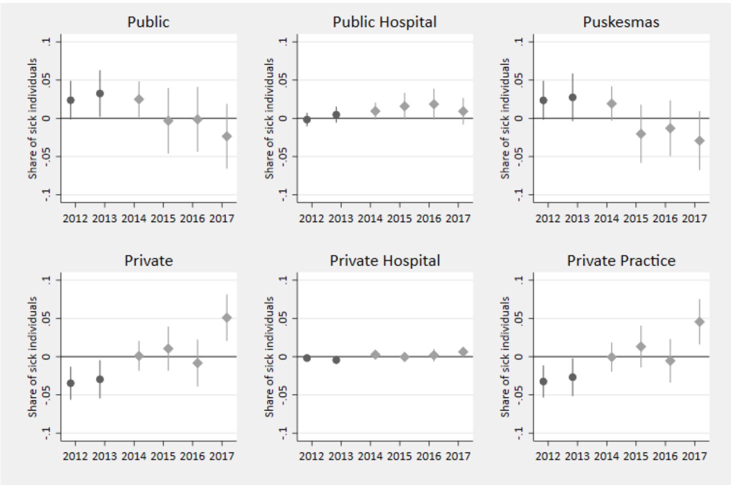
Several alternative specifications yield similar results and give confidence in their robustness. First, we test four different sets of district and time-specific control variables: none, the main set plus district size, the main set plus the proportion of sick individuals per district and proxying wealth via an asset index instead of average household expenditure (Table A 2.11, Table A 2.16, Table A 2.21). As a second test for robustness, we test different reference years to rule out that the main reference year 2013 is special in a way that we are not aware of. In a basic specification, we pool all pre-reform periods (2011-2013) and compare them to the pooled post-reform years (2014-2017), and present the results of estimating equation 1 in all rounds with reference year 2011, rounds 2012 until 2017 with reference year 2012 in addition to the main specification in rounds 2013 until 2017 with reference year 2013 (Table A 2.12, Table A 2.17, Table A 2.22).

Figure 2.5: District-level estimation results for disaggregated outcomes

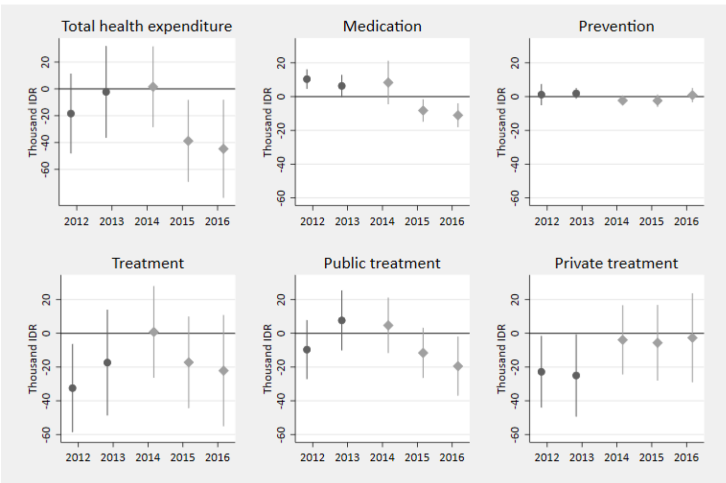
A. Changes in inpatient care usage (1 year)



B. Changes in outpatient care usage (1 month)



C. Changes in quarterly health expenditure



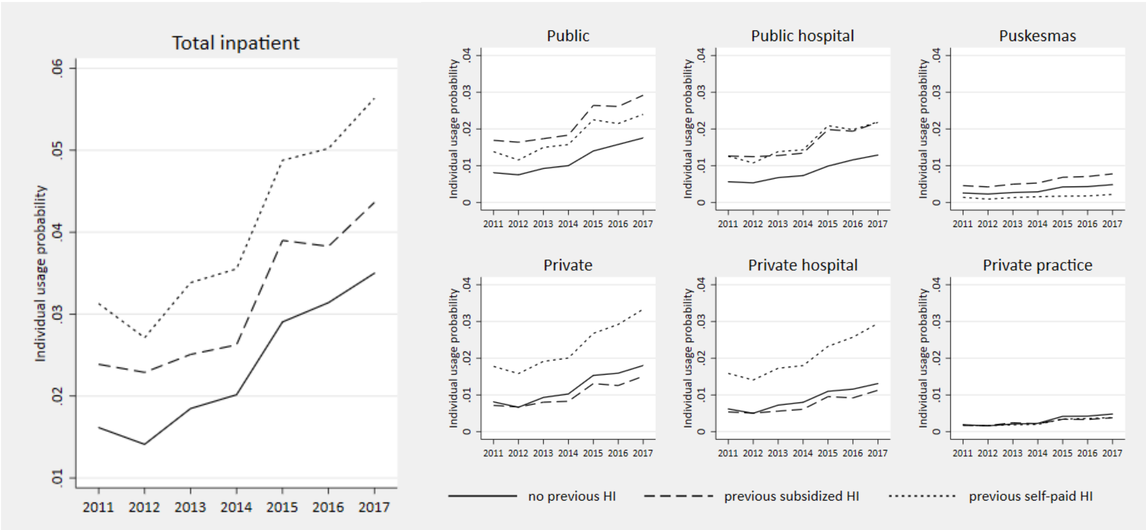
Coefficient plot of interaction coefficients β_t between the district's share of insured households and the respective year from equation 1 with 95% confidence intervals, standard errors clustered by district; covariates: district's share of insured households, year fixed effects, district fixed effects, number of Puskesmas per year and province, district- and time-specific control variables: share of urban households, average per capita household expenditure, share of households with electricity, house ownership, or any social protection program, share of individuals with up to primary education; in SUSENAS 2011-13 with base year 2011 (dark grey), SUSENAS 2013-17 with base year 2013 (light grey).

2.4.3 Estimation results at the individual and household level

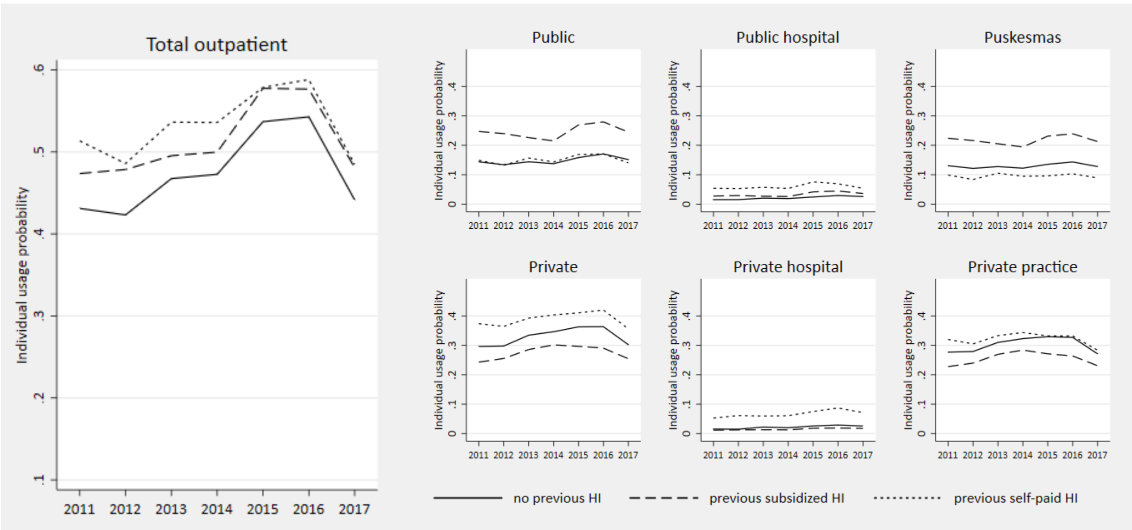
In addition to the whole sample descriptive statistics in section 2.4.1, Figure 2.6 displays the differential levels and trends in the outcomes for the groups that were (likely to be) either not insured (solid line), covered by subsidized (dashed line) or self-paid (dotted line) health insurance before 2014 (see Table A 2.23 for yearly means and standard deviations). First, it becomes apparent that there are clear differences in the levels of health facility usage and expenditure between the groups, which differ again depending on the facility type or expenditure category. The total figures show that the group with self-paid health insurance has continuously the highest usage rates and expenditures. Proportionally, members of the previously uninsured group used inpatient care only half as much as those in the self-paid schemes. The difference is not as pronounced and stable for outpatient care. Looking at the different facility types, there seems to be a clear pattern of those with self-paid health insurance using primarily and increasingly private health facilities, whereas the public ones are utilized to a larger extent by those with subsidized insurance. A difference in the trends of the previously insured and uninsured group seems to be the clearest in the private category, and particularly for private practices: for inpatient care, they continue to increase usage beyond the other groups, whereas for outpatient care, a steep increase is followed by a flattening and then even decrease around the same level as the self-paid health insurance group. In parallel to the usage patterns, health expenditure is also highest for the self-paid group across all categories. There are no substantial changes in the health expenditure patterns over the observation period.

Figure 2.6 Trends in outcomes according to likely pre-reform insurance status

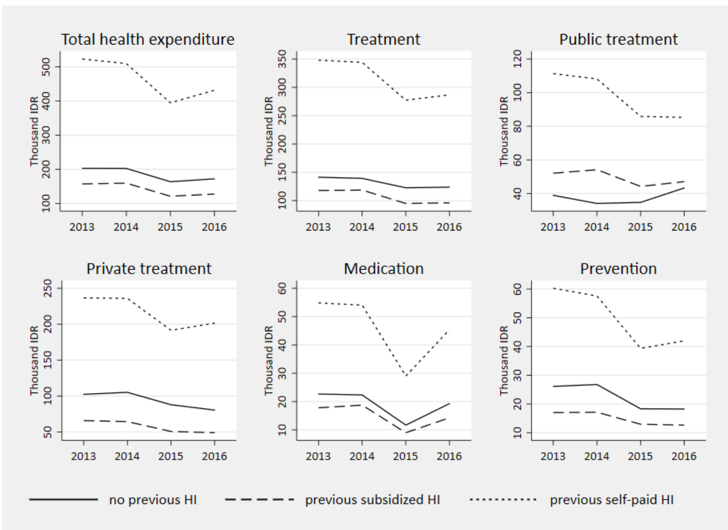
A. Inpatient care usage proportion



B. Outpatient care usage proportion (if any illness in previous month)



C. Changes in health expenditure



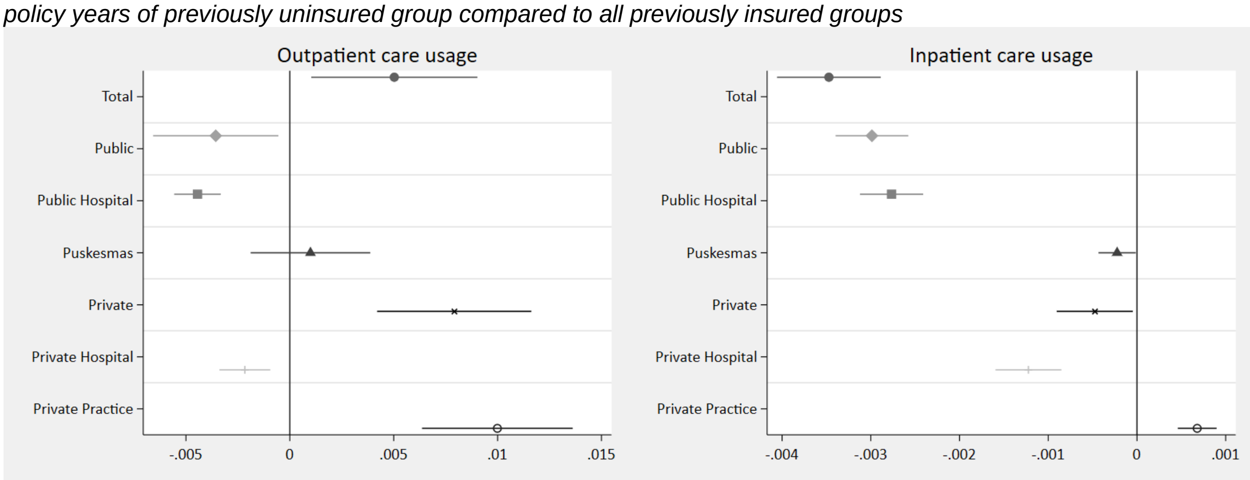
Group-wise individual probability to use inpatient care during the previous year, outpatient care during the previous month if there was an acute illness and average real quarterly health expenditure in thousand IDR; computes as uncontrolled means over years accounting for sampling weights; in SUSENAS (A, B: 2011-2017; C: 2013-2016); see Table A 2.23 for details.

The estimates of the interaction coefficient in equations 2 and 3 identify the difference across groups over time holding level and time differences as well as the above-listed socio-economic factors constant. Figure 2.7 and Table A 2.24 display the respective usage difference coefficients of all in- and outpatient facility types in its most basic version: comparing the change in usage probabilities from pre- to post policy years between the likely previously uninsured and insured group.[7]

The increase in the probability of inpatient care usage is significantly lower for the previously uninsured group. This association is rather low in magnitude, but indicates that for the facility types that matter most for inpatient care (public and private hospitals), there is no detectable catching-up effect for the previously uninsured group. Absolute usage increases in both groups (Table A 2.24) but the gap between the groups seems to stay the same or increase. Only the change in likelihood to use a private practice is positively associated with being in the previously uninsured group. As private practices provide mostly primary services, which cannot fully cover the demand for inpatient care and the coefficient being small, this development is unlikely to be able to work against the other facility type's negative associations.

[7] The results of this linear probability model are robust to alternative model specification: see Table A 2.26 for a comparison of the marginal effects of the interaction coefficient of interest with a Probit model.

Figure 2.7 Individual level estimation results: average change in health facility usage probability from pre- to post-policy years of previously uninsured group compared to all previously insured groups

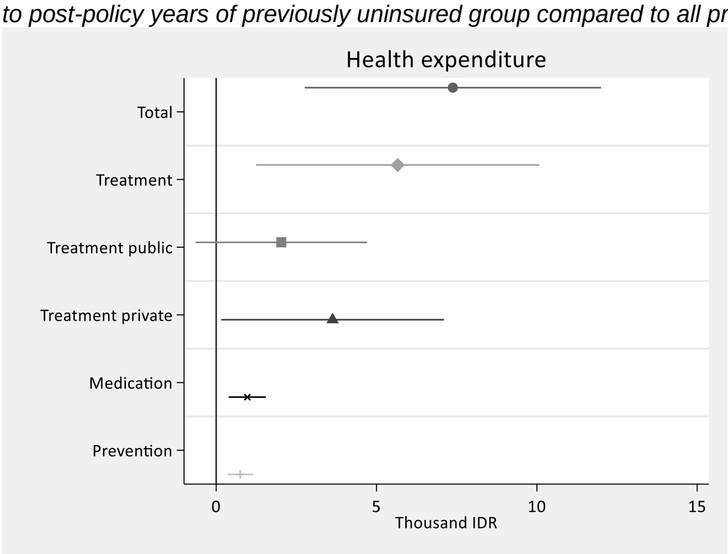


Coefficient plot of interaction coefficient β from equation 2 of binary group indicator (1= likely not part of a previous insurance scheme, 0=likely member of any previous subsidized or self-paid scheme), and a binary post-policy indicator (1= all post-policy years 2014-2017, 0= all pre-policy years 2011-2013); in SUSENAS 2011-2017; with 90% confidence intervals, standard errors clustered at the household level; covariates: group indicator, post-policy indicator, district fixed effects, individual age, gender, education, employment and household wealth quintile, living in urban indicator. See Table A 2.24, Table A 2.25 for full estimation results.

The change in the likelihood of using total outpatient care is significantly higher than in the previously insured group. This points to improved access to outpatient care for the previously uninsured population, which is driven by an increase in the likelihood to use private practices.

Estimating the respective coefficient for health expenditure using equation 3 hints that health expenditure increased slightly in the previously uninsured group compared to the previously insured group, particularly in terms of expenditure for treatment (Figure 2.8). Taken together with the overall time effect, one can see that this is not an increase in absolute terms, but a decrease at a lower rate (appendix Table A 2.27).

Figure 2.8 Household level estimation results: average change in real quarterly health expenditure in IDR from pre- to post-policy years of previously uninsured group compared to all previously insured groups



Coefficient plot of interaction coefficient β from equation 3 of binary group indicator (1= likely not part of a previous insurance scheme, 0=likely member of any previous subsidized or self-paid scheme), and a binary post-policy indicator (1= all post-policy years 2014-2016, 0= all pre-policy year 2013); in SUSENAS 2013-2016; with 90% confidence intervals, standard errors clustered at the household level; covariates: group indicator, post-policy indicator, district fixed effects, individual age, gender, education, employment and household wealth quintile, living in urban indicator. See Table A 2.27 for full estimation results.

2.5 Discussion and conclusion

In summary, at the district level, we find a strong and sizeable increase in inpatient, and particularly public hospitals care usage in districts that expanded their coverage after the reform. The individual-level analysis revealed large differences in the health facility usage patterns, with the previously uninsured group often displaying the lowest usage. For outpatient care, the gap seems to be narrowing after the reform, driven by an increased use of private practices among the previously uninsured group. However, the relatively larger gap in inpatient care usage tends to widen as the increase in inpatient care usage remains steeper for the individuals who likely already had access to health insurance before JKN.

The positive association with health facility usage outcomes is in line with the general narrative of health insurance impact evaluations as stated in section 2.2.2. Even though it does not hold in the individual level analysis, the concentration of the effect in public facilities at the district level is in line with previous findings for members of the health insurance for civil servants in Indonesia (Askes) (Hidayat and Pokhrel 2010). In the case of JKN, the fact that only some private facilities are also covered could be a channel for a stronger increase in public health facility usage. Considering the strict referral guidelines, it is surprising that at least in the aggregate, outpatient care, which would be the gatekeeper for inpatient care, does not increase. The different usage levels across previous insurance groups might shed light on this. An increase in outpatient care usage was previously found for the pre-JKN subsidized scheme

Askeskin in particular (Sparrow et al. 2013), and for any previous Indonesian health insurance in general (Cuevas and Parker 2010), and seems to also be relevant here for the previously uninsured group. The overall increase in public and inpatient care might point to the fact that the need for primary and outpatient care is already close to being met for the previously insured groups. For the newly eligible group, this need must first be met before effects on higher levels of care can be detected. Another possibility is that the main barrier to accessing higher levels of care is not the financial barrier that could be lifted by the insurance. This is reflected in the survey question about the reason why respondents did not seek care even though they reported an illness during the past month, where only 2.6% reported the reason to be lack of financing and the vast majority opted for self-treatment.

We identify a weaker negative association between increased insurance coverage and health expenditure at the district level, and see decreases at a lower rate for the uninsured group. The conclusions are limited by the change in the expenditure recall period just after the reform, which makes the measure prone to downward bias and the fact that not only out-of-pocket expenditure is reported. In terms of the subcategories, treatment costs might still be captured more accurately as these tend to be large expenditures easier to remember over a longer period of time than, for example, a self-administered medicine for a minor illness. The measure is also missing important parts such as transportation to the health facility or the cost for someone to accompany the patient. In this light, one can expect the levels of health expenditure to be an underestimate of the actual costs. The finding that expenditure for the previously uninsured group decreases at a lower rate than for the previously insured group might also be a reflection of the increased usage.

The results need to be treated with caution in light of their methodological and contextual limitations. The methodological design was chosen as the best available option to give useful insights without claiming clearly identified causality. The problem of the endogeneity of insurance membership was reduced by conducting the analysis at two levels and controlling for as many confounding factors as the dataset and structure allow for. It would, for example, be useful to include more district characteristics that go beyond the means of household characteristics such as determinants of the health care supply and its quality. Nevertheless, these nationally representative results with possibilities of disaggregation go beyond existing studies of the previous and the new scheme. Furthermore, the results can be used to validate the results of geographically more limited studies with a higher internal validity. For further research, it would be interesting to check the robustness of the increase in facility usage using health facility data such as bed occupancy rates, as was done for the analysis of a health insurance reform in China by Wagstaff et al. (2009), the availability of health insurance claims data might be an opportunity (Ng et al. 2019). Additionally, health outcomes should be analyzed directly as to date, there is only initial evidence for a reduction in child mortality immediately around the reform (Kreif et al. 2020).

Looking back at the history of Indonesian health insurance, the reform process has been forward-oriented towards a broader coverage in terms of the target population and the benefit package. Whether this trend has the potential to continue will on the one hand depend on sustainable financing as a large and growing part of members requires subsidized premiums. Our results suggest that aside from expansion, a crucial step is to better integrate the large newly eligible population into the scheme, so that they can benefit to the same degree as those with previous coverage.

Chapter 3

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

with: Maja E. Marcus, Anna Reuter and Sebastian Vollmer

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.

Study pre-registration: Marcus, Maja E. et al. 2019. "A Mobile Phone-based Intervention to Improve Health Screening Uptake: A Randomized Experiment in Indonesia." AEA RCT Registry. November 2019. https://doi.org/10.1257/rct.5047-1.0.

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 community-based randomized controlled trial, 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 2010). 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, this 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 health center rather than the specific village screening meeting 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 the single options, 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 via text messages. In LMICs, text messages have been found effective to increase immunization rates among children (e.g. Jacobson Vann et al. (2018)) or specific preventive behavior like dengue prevention (Dammert et al. 2014). As NCDs are rather new to the disease burden, community-wide screening programs, their benefits and relevance might not yet be salient to the population. Thus, it is unclear whether light-touch interventions such as text messages are sufficient to increase screening uptake, even if they were proven effective in high-income countries with a longer tradition of screening (e.g. Sallis et al. (2019)). To our knowledge, the only text message interventions addressing screening in LMICs focus on diseases that are very different from diabetes and hypertension, for example sexually transmitted diseases (Taylor et al. 2019). Other interventions to increase screening demand for diabetes and hypertension in LMICs are also rare; the only other study we know of uses a more intensive treatment, in-person scripts and pharmacy vouchers, in Armenia (Walque et al. 2020; Gong et al. 2020). We expand this literature by demonstrating that text message reminders can also be an effective tool to increase diabetes and hypertension screening in the general population at risk in a middle-income country. Beyond the main treatment effect, we contribute to the scarce evidence base of spillover effects, particularly within the household, of preventive health interventions (Dupas and 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 basic screening at the local *Puskesmas* at all times. 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[8]. The *kaders* perceive it as more difficult to motivate the general population to attend the meetings even though sufficient time and equipment 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 A3.4 for takeaways) and fielded from late January until March 2020.

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[9] (see Table A 3.2 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 section 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 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

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

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

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). Information on the urgency of early action might reinforce this heterogeneity, by making the time sensitivity more salient, 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 a special concern, 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.

Content & Personalization

The messages' content included the village-level *Posbindu*[10] 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 (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 Table A 3.1 in the appendix for the translation of each message):

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.

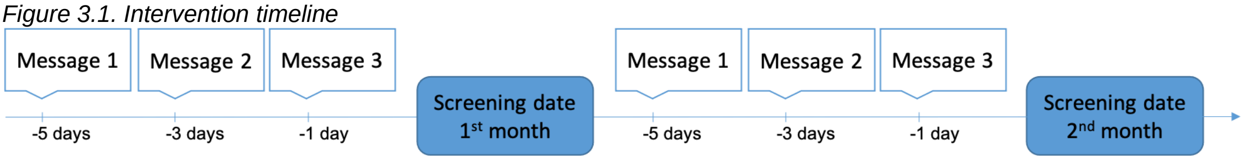
Implementation

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. As depicted in Figure 3.1, three messages were sent before the first village screening date and three were sent before the

[10] 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.

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.[11] 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.

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 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).

[11] 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. 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 when case numbers were still very low in Indonesia (and none in Aceh) and there were no restrictions in place.

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.[12] 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 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 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 single 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.

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

[12] 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.

content of the NCD/ screening related message in an unaided recall question, if the respondent claims to have received such a message.

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. 2016; Falk et al. 2018). 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.

Control Variables

We measure age, sex, education, and phone ownership[13] 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.

Regression Specifications

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

a) Intention-to-treat (ITT)

$$Y_i = \alpha + \beta Treat_i + \delta Control_i + \varepsilon_i \tag{1}$$

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, sex, education, wealth, and phone ownership.

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.

$$Exposed_i = \eta + \theta Treat_i + \pi\, Control_i + \upsilon_i \tag{2}$$

$$Y_i = \alpha + \beta \widehat{Exposed}_i + \delta\, Control_i + \varepsilon_i \tag{3}$$

[13] 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.

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

$$Y_i = \alpha + \beta Treat_i + \gamma Trait_i + \theta Trait_i * Treat_i + \delta\ Control_i\ + \varepsilon_i \qquad (4)$$

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

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 A3.2. 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[14]), 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[15]. If several household members met the inclusion criteria, one was randomly chosen as respondent. This yielded a sample of 2,006 individuals[16].

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%[17], which is high for a telephone survey, but lower than we expected from the planned

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[14] We set the upper age limit of 70 to ensure that the respondent is able to complete the interview. Refer to appendix A3.2 for a detailed list and reasoning for each in- and exclusion criterion.

[15] 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 3.3).

[16] 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.

[17] 1,409 respondents could be re-interviewed, but due to missing information on the month of screening 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.

in-person endline data collection. The endline sample is hence slightly smaller than was deemed necessary in the power calculation (see appendix A3.2).

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%. Compared to the same age group who owns 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).

Treatment and control group were balanced across all key variables of interest at baseline, except for phone ownership (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, but respondents who were lost to follow-up seem to be to a higher proportion female, less educated and 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).

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.

According to the message delivery reports, 97% of treatment group individuals received at least one full cycle of intervention messages before one of the Posbindu dates. For 84% of our sample, we have also self-reported measures of exposure[18]: 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

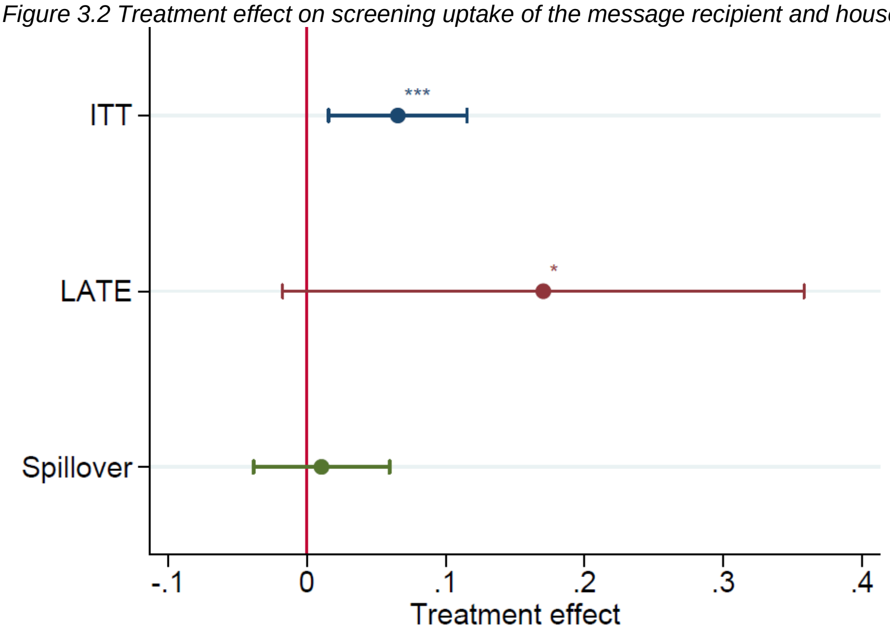
[18] As the questions about message content were asked only in the very end of the interview, the estimation sample for the LATE excludes 204 respondents who terminated the interview before this question. Respondents in this subsample are to a higher proportion male, to a lesser proportion phone owner,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

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 (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

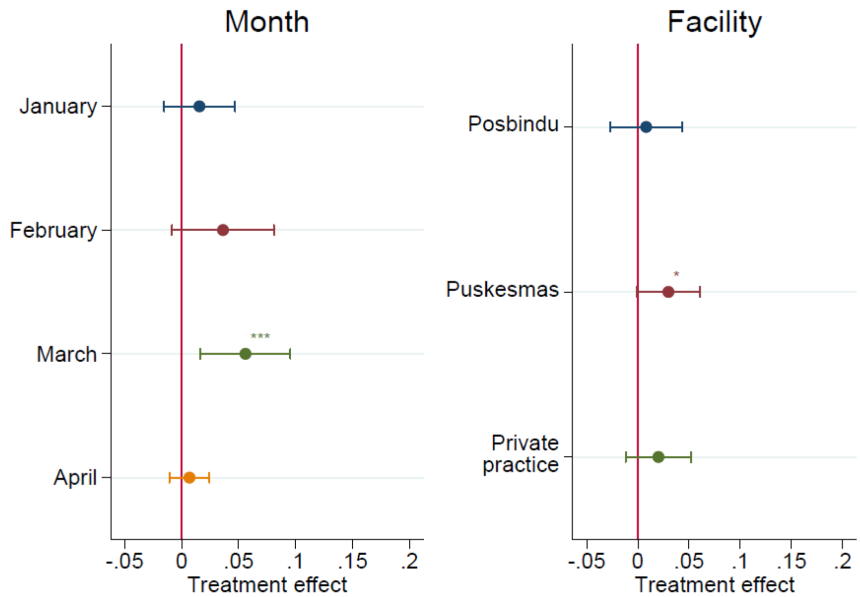


*Point estimates of the treatment coefficient from equation 1 (ITT), the instrumented treatment coefficient from equation 3 (LATE) for the message recipient and other household members (ITT), controlling for age, gender, wealth and phone ownership; see Table A 3.12 for tabular display with and without covariates; displayed with 95% 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 95% 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

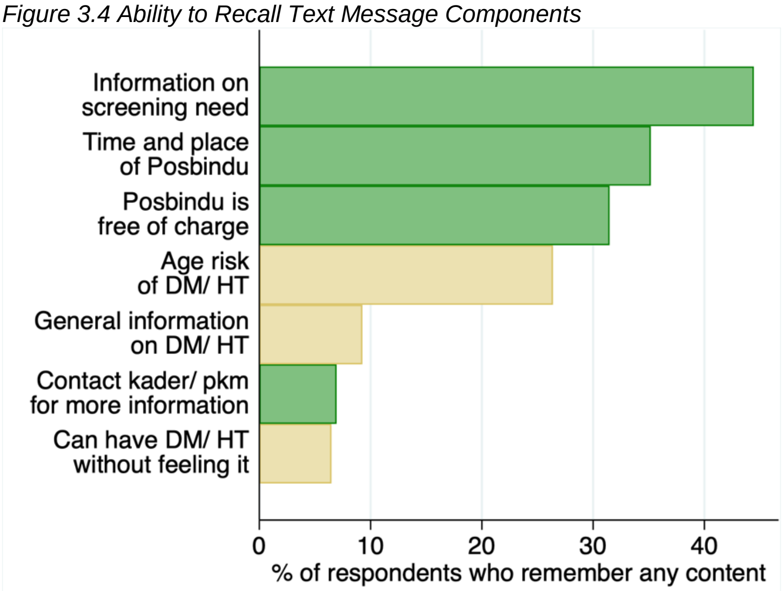
	(1) SMS knowledge	(2) SMS knowledge	(3) General disease knowledge	(4) General disease knowledge
Treated	-0.0009	-0.0029	-0.0365	-0.0570
	(0.0609)	(0.0610)	(0.0616)	(0.0597)
Covariates	No	Yes	No	Yes
Observations	1088	1088	1042	1042

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 being told 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 the Posbindu program 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 a weak correlation between screening and willingness to take risks and patience in our study setting. 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 Treatment 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.

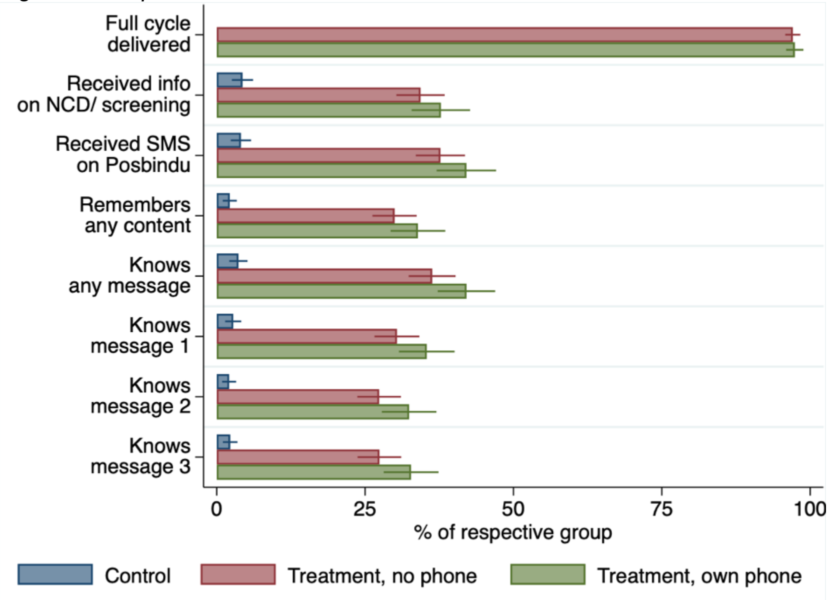
<u>Treatment exposure</u>

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



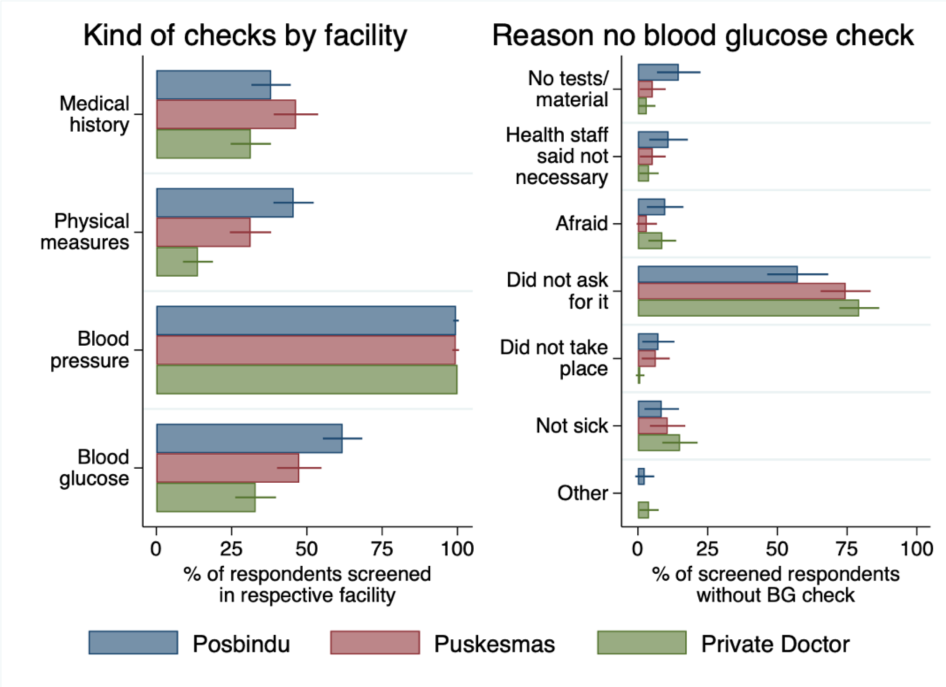
"Full cycle delivered" is based on the provider delivery reports, the remaining indicators are based on the respondent's self-report at endline; "Knows any content" indicates whether the respondent could name any message content when asked in an open-ended question (compare Figure 3.4); "Knows any message"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

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



<u>Cost estimation</u>

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 a community-based 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 Mekonnen 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, 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. 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 misperceptions on screening recommendations 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.

Chapter 4

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

with: Eliana Chavarría, Farah Diba, Maja E. Marcus, Marthoenis, Anna Reuter, Sebastian Vollmer

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 behaviour, 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 behaviour 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 behaviour are relatively high. Knowledge is the largest explanatory driver of protective health behaviour, 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.

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4.1 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; 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.

4.2 Background

4.2.1 Country Background: 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).

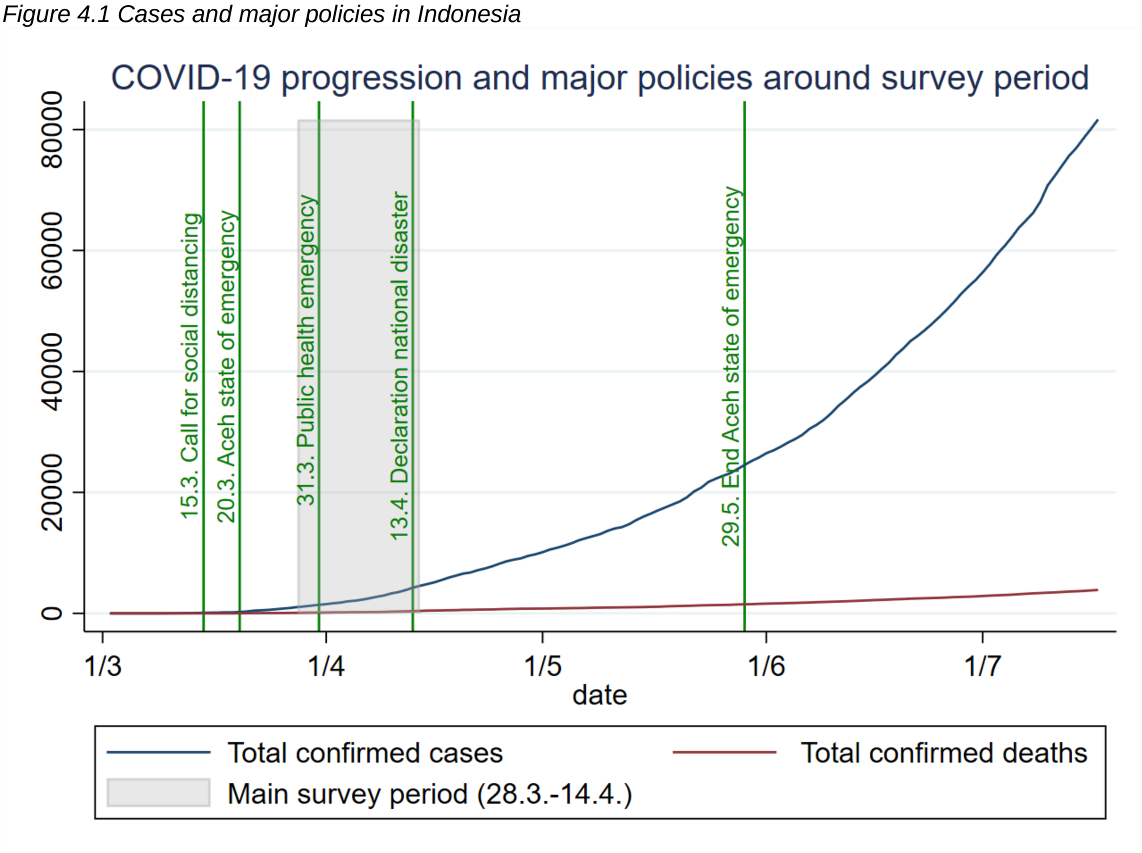
In the late 2000s, Aceh was faced with multiple challenges in the health sector (Evans 2010). An exceptionally high share of the burden of disease fell on the poor and rural population (Evans 2010). In 2009, the provincial government introduced a new health insurance scheme which provided free basic 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.

4.2.2 Country Background: 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 4.1. 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 2020b). By the end of the collection period, the pandemic was declared a national disaster (President of Indonesia 2020a), 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 4.1 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 2020c). When having a cough, cold, and shortness of breath, the recommendation was to immediately contact a health facility (Ministry of Health 2020a). 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).

4.2.3 Conceptual Background: 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.

Knowledge

One major determinant of the adoption of protective health measures is information (Dupas 2011b). 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 2011b; 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 delivery (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).

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 2011b; 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 and 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 (La Cruz-Sánchez and Aguirre-Gómez 2014).

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[19] (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; Tsutsui et al. 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; Tsutsui et al. 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).

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

4.3 Methods

4.3.1 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[20] 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 (Figure A 4.1), 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 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 section A4.1. A disaggregation of the number of contacted, eligible and participating households can be found in Table A 4.1. 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

[20] 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.

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 section A4.2. 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 (appendix section A4.5 for the questionnaire and Table A 4.2 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)[21]. 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; Falk et al. 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).

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

[21] 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.

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.

4.3.2 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 Figure A 4.2. 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.

Determinants of Knowledge

First, we estimate the determinants of pandemic knowledge:

$$KNOWLEDGE_i = \alpha + \beta SOCIOECON_i + \gamma INFO_i + \varepsilon_i \quad (1)$$

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.

Determinants of Uptake

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

$$UPTAKE_i = \alpha + \beta SOCIOECON_i + \delta KNOWLEDGE_i + \theta PREF_i + \varepsilon_i \quad (2)$$

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 (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 (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.

4.4 Results

4.4.1 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 4.1. 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 4.3, 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.

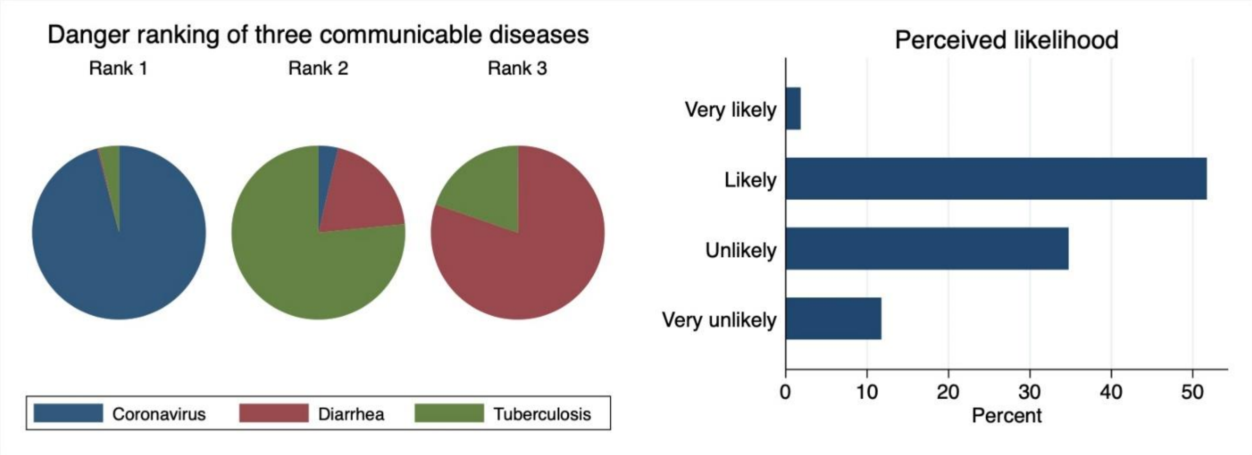
Table 4.1 Basic sample characteristics

	Mean	SD	N
Age	49.88	8.00	1,112
50 or older	0.46	0.50	1,112
Other member 50 or older	0.41	0.49	1,112
Sex	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 4.2). Also, more than half of the respondents think it is likely they will experience

COVID-19 (see Figure 4.2). 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.[22]

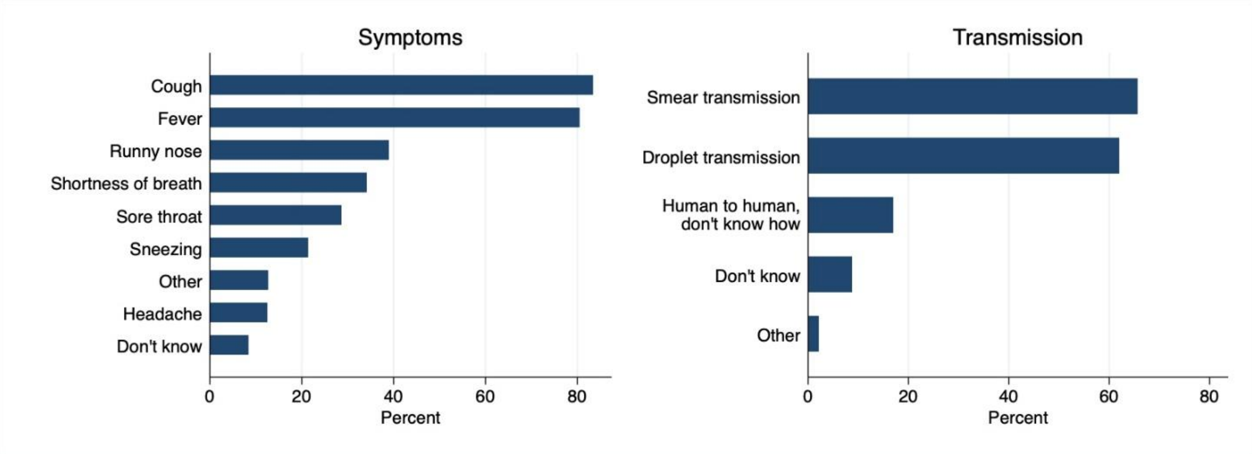
Figure 4.2 Perceived severity and likelihood



Most respondents could name at least one of the common symptoms of COVID-19. As depicted in Figure 4.3, 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 4.3). 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 4.4).

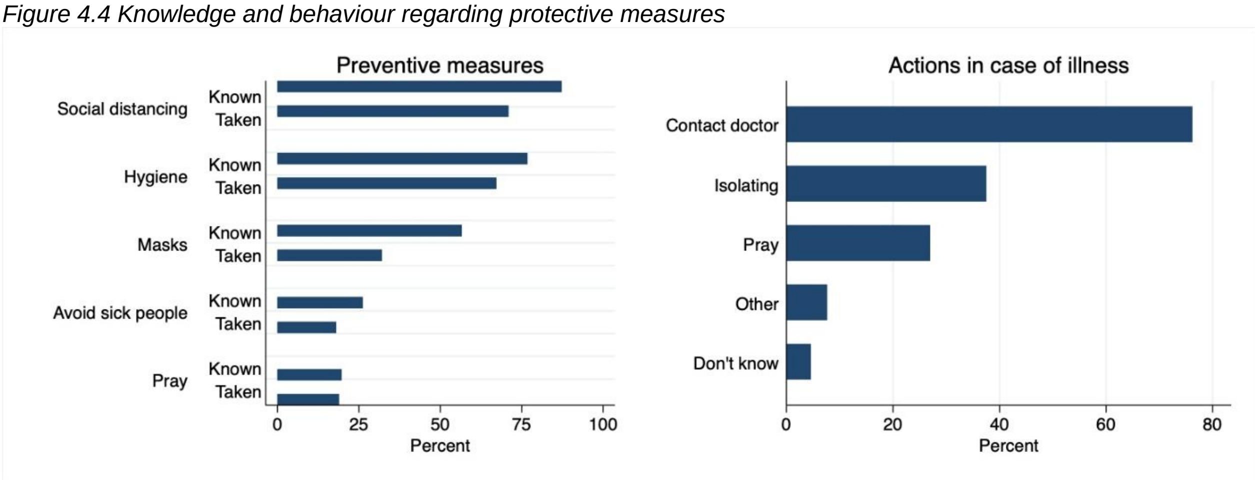
[22] Even though the question was deemed appropriate during pre-testing, four days into the data collection, enumerators reported that this question caused distress in some respondents, who had just lost their livelihood. Hence, we excluded it immediately thereafter.

Figure 4.3 Knowledge on symptoms and transmission.



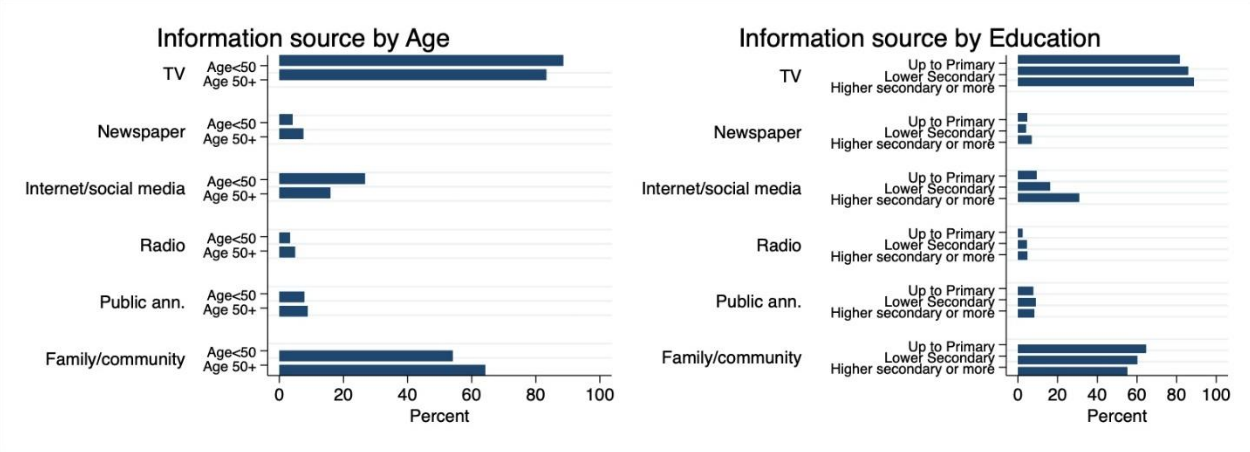
Social distancing and hygiene measures are widely known to the sample (87% and 77% respectively, Figure 4.4). Yet, there appears to be a gap between knowledge and uptake of these measures. For masks, this knowledge-uptake gap is especially sizeable: While 57% of the sample state masks can help to prevent 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 4.5 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 4.4 Knowledge and behaviour regarding protective measures



As depicted in Figure 4.5, 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 4.6). 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 4.5 Information sources by group



4.4.2 Determinants of Knowledge

The results of estimating equation 1 on the disease knowledge outcomes can be found in Table 4.2. 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 4.2 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)
Other 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. 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. A base model with socioeconomic variables only is depicted in Table A 4.8. Logit and probit models are depicted in Table A 4.10.*

Table 4.3 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 4.3 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)
Other 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. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. A base model with socioeconomic variables only is depicted in Table A 4.8. Logit and probit models are depicted in Table A 4.11.*

4.4.3 Determinants of Protective Behavior

Table 4.4 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 p.p. 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 4.4 Determinants of preventive behaviour

	(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)
Other 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)
Droplet transmission	0.030		0.039*
	(0.026)		(0.022)
Smear transmission	0.056**	0.001	
	(0.026)	(0.019)	
Social dist.	0.740***		
	(0.022)		
Hygiene		0.866***	
		(0.015)	
Wear masks			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. 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 base model with socioeconomic variables only is depicted in Table A 4.9. Logit and probit models are depicted in Table A 4.12.*

Finally, Table 4.5 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 4.5 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)
Other 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)
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 risks 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 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 4.9. Logit and probit models are depicted in Table A 4.13.*

4.5 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 4.7).

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 2011b; 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 2020a). 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.

4.6 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.

Chapter 5

The Effect of Personalized Health Information on Preventive Behavior amongst COVID-19 Risk Groups: a Randomized Experiment in Pakistan

With Sheraz Ahmad Khan, Zohaib Khan, Muhammad Jawad Noon, Andreas Landmann, Sebastian Vollmer

Abstract

Avoiding a COVID-19 infection remains crucial for population groups that are at higher risk to experience a complicated disease course and live in settings with limited access to healthcare services. Our telephone survey with low-income households in Pakistan from April to October 2020 shows that gaps in knowledge and practice of individual preventive practices prevailed. Using a randomized experiment, we evaluated whether a more targeted and personalized SMS information campaign exploiting health insurance records could contribute to narrowing this gap. We find that the intervention helped the at-risk population to adhere to higher levels of handwashing in the time between the first and second wave of infections, and all message recipients were more than twice as likely to use tele-medical services compared to the control group.

Study pre-registration: This study is registered in the AEA RCT Registry and the unique identifying number is: "AEARCTR-0006307”

5.1 Introduction

Avoiding a COVID-19 infection is particularly important in settings with fragile health systems that are not equipped to attend to a high number of patients with a complicated disease course. To contribute to the adoption of individual preventive measures against COVID-19, the Government of Pakistan has issued detailed recommendations for preventive actions for its population and spread this information through various channels. Our telephone survey with low-income households in the province Khyber Pakhtunkhwa revealed that in early stages of the pandemic (April-June 2020) general COVID-19 awareness was high, but gaps in prevention knowledge and uptake prevailed. Contrary to the expectation that individuals with a higher risk for a severe disease progression have higher returns to prevention, we did not find higher levels of preventive knowledge and practice in households with a household member who belongs to a group with elevated risk. According to official guidelines of the Government of Pakistan, main risk group indicators are age above 60 or a chronic pre-condition, i.e. cardio-vascular diseases, respiratory diseases, cancer, diabetes or hypertension.

Based on these findings, and in collaboration with the local public health service, we designed a text messaging campaign with the aim to reduce knowledge gaps and to increase preventive behavior in the population at risk. Implementing the intervention through the local public health insurance allowed a more targeted and personalized intervention that could be a viable complement to other information campaigns. The effectiveness of the intervention was tested via a randomized controlled trial. The intervention consisted of a set of six informative text messages, which were sent to a random subset of the health insurance beneficiaries over the course of five consecutive days in August and September 2020. We assess two main and two supplementary hypotheses: First, we test whether the intervention had an effect on the adoption of preventive practices (number of preventive practices, handwashing, wearing masks and using telemedicine) in the whole sample. Secondly, we consider the sub-samples of households with and without a member in the risk group separately to see whether the intervention is more effective in the risk group as they might become more aware of their higher individual return to adopting preventive measures. To further explain these main hypotheses, we test two secondary hypotheses: Within the risk group, we test whether making the individual risk more salient via risk personalization can make the messages more effective. Lastly, we examine whether the main effects are driven by improved knowledge about individual risk and prevention practices.

We find that the intervention increased the reported uptake of individual preventive practices. More specifically, it increased the uptake of handwashing by 6 percentage points, which is an 18% increase relative to the control group uptake of 47%, and telemedicine usage in case of a health need by 5 percentage points, compared to 2% usage in the control group. No such effect could be detected for wearing masks. The effect on the number of preventive practices and handwashing is driven by households with a member who belongs to the COVID-19 risk group. In the risk group alone, handwashing uptake increased by 9 percentage points, while no effect can be detected in the non-risk group. We find evidence for higher telemedicine treatment effects among risk group households who have received messages with a light risk personalization. As we do not detect changes in knowledge after the intervention, this does not seem to be the main channel for the observed impact. Apart from the experimental outcomes, we show descriptively the potential of scaling up the intervention using the enrollment and claims data of the health insurance program.

The role of information and awareness has long been acknowledged in the uptake of preventive health behavior, which remained widely under-used in LMICs before the pandemic (Kremer et al. 2019). Information provision has the potential to boost it either by providing new information and updating beliefs (e.g. Dupas (2011b), Brown et al. (2017), Madajewicz et al. (2007)), or making existing information more salient via reminders (e.g. Busso et al. (2015), Pop-Eleches et al. (2011)). With increasing mobile-phone coverage, phone-based interventions (Aker 2017) and text messages in particular have been widely used as means to provide both functions. Systematic reviews like Hall et al. (2015) on health behavior in general, Armanasco et al. (2017) on preventive health or a multi-arm study on vaccination uptake in the US Milkman et al. (2021) show overall small but meaningful effects of text messaging interventions and provide best practices for message design.
As mobile-phone based interventions are low-cost tools, they have been widely adopted by governments and NGOs during the COVID-19 pandemic, which also led to an upsurge in experimental impact evaluations that are related to ours. Early in the pandemic, Banerjee et al. (2020) found that broadcasted SMS with links to celebrity-endorsed videos increased the uptake of handwashing and reporting of COVID-19 symptoms. An increase in handwashing was also detected for a more generic prevention information intervention via SMS in Peru in June 2020 (Boruchowicz et al. 2020). None of these interventions had an effect on social distancing. Another messaging intervention during the peak of the first wave in the Indian state of Bihar did not lead to more handwashing either (Bahety et al. 2021).

Our study has two main contributions to the literature: First, we contribute to the literature on solutions to shield COVID-19 risk groups. Such evidence remains scarce for LMICs, which have lower health system capacities and rarely have the opportunities to target risk groups directly like for instance in the United Kingdom or other high-income countries (Burd and Coleman 2020). By including both age-based and precondition-based risk factors, we take a population-based perspective in contrast to other studies that focus on specific disease groups such as people with diabetes (Dizon-Ross et al. 2020). Moreover, we extend the list of preventive practices by the use of telemedicine which is particularly relevant for the risk group. Secondly, we contribute to the text messaging literature more broadly as relying on health insurance enrollment and claims data allows us to combine scalability and personalization of the intervention. On the one hand, scalability is possible via broadcasting by telecommunication providers like in (Banerjee et al. 2020), but in a non-emergency context when the information is not relevant to everyone this poses the risk of an overflow of information and less attention to relevant messages. On the other hand, personalization has been found to enhance the effectiveness of such interventions (Head et al. 2013), which was in the past often done via a pre-intervention contact, and makes the intervention more costly and less scalable. Targeting and personalizing messages through sparse but potentially sufficient information in administrative data could therefore combine the strengths of both approaches. Birth registers as used for contacting, but not personalizing in India (Bahety et al. 2021), city records in Peru (Boruchowicz et al. 2020) or NGO records in Bangladesh (Siddique et al. 2020) have similar advantages, but cover more geographically limited areas or specific population groups. With increasingly digitized health systems additional applications beyond COVID-19 are likely to emerge.

5.2 Context

5.2.1 Policy and societal context

Our study is set in the Pakistani province Khyber Pakhtunkhwa (KP). Even before the pandemic, Pakistan's and particularly KP's health systems were fragile (Asian Development Bank 2019). More recently, the provincial government of KP has implemented several reforms such as the Social Health Protection Initiative providing free inpatient health insurance (Government of KPK 2010). Nevertheless, a review of the provision of higher level inpatient care conducted in fall 2019 flagged substantial gaps in the availability of material, trained staff and management capacities (Asian Development Bank 2019), which are essential in caring for patients with a complicated COVID-19 disease course. From the onset of the pandemic, KP recorded high infection rates and a high case fatality rate compared to the other provinces (Anser et al. 2020). The high case fatality rate could be a consequence of a larger share of undetected cases or worse treatment of detected cases.

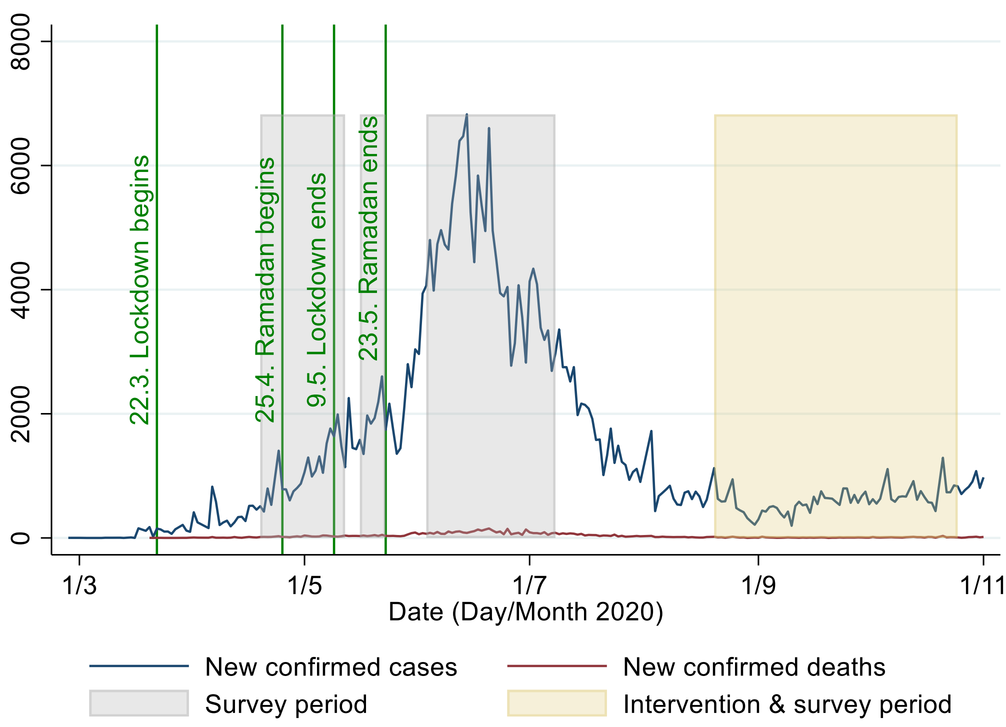
In response to the outbreak of the pandemic, the federal government of Pakistan issued the *The National Action Plan for The Corona Virus Disease* (Ministry of Health 2020b). Cell-broadcasting of text and voice messages on preventive measures and symptoms was an integral part of this strategy. The initial plan did not include risk-group specific policies, but paved the way for targeted recommendations, which were published shortly after (Government of Pakistan 2020). For the elderly and people with certain preconditions (cardio-vascular, respiratory diseases, cancer, diabetes and hypertension), recommendations stressed the adherence to common preventive practices to avoid an infection. Special attention was given to care for preconditions as poorly controlled preconditions intensify the risk of a complicated disease course and the use of tele-medical services where possible. The recommendations also stressed that caregivers and other household members should apply more caution.

Considering Pakistan's demographic situation with a rather low life expectancy at birth (67 years) and only 4.3% of the population over the age of 65 (World Bank 2021), the share of the population in the risk group for a complicated COVID-19 disease course is estimated to be lower than the global average (around 17% according to Clark et al. (2020)). Considering the low health system capacity to cater even to a low number of severe cases in combination with a culture of large multi-generational households aggravates the burden. Our survey data with KP's low-income population shows that around two thirds of households have at least one member that is in the risk group (Table A 5.19). 60% of households have a member over the age of 60, and 26% of households have a member with one of the five preconditions. Among the preconditions hypertension is most common, followed by diabetes and other cardio-vascular conditions, while respiratory diseases were only reported in 2% and cancer in 1% of households.

5.2.2 State of COIVD-19 knowledge, practice and information campaign exposure

As depicted in Figure 5.1, the trial is embedded in a larger study, was preceded by three survey waves during an earlier stage of the pandemic and is itself set in the time between the first and second wave of the COVID-19 pandemic in Pakistan.

Figure 5.1 Study timeline



Pakistan-wide daily new COVID-19 cases and deaths as well as major events (case and death data from (Hale et al. 2020)), see Table A 5.1 for details.

The rapid response survey generated initial insights into the target population's knowledge, attitudes and behavior pertaining to the COVID-19 pandemic[23]. We found that from the beginning of the survey period, there was a high general awareness of COVID-19 and its severity in our study region, but also substantial knowledge gaps about specific preventive practices that did not narrow over time. Only half of the respondents could name both fever and cough as symptoms of COVID-19, 80% knew that SARS-Cov-2 can be transmitted through physical contact but only 40% knew that it can also be transmitted via air droplets (Figure A 5.8). Social distancing was widely known as preventive method, wearing masks was initially only known by about half of respondents and also hygiene measures such as handwashing were only named by less than half of the respondents. Around 60% of respondents were aware of old age being a risk factor, only 20% mentioned any precondition as a risk factor and over 30% falsely mentioned children as a risk group. It stands out that respondents with at-risk household members do not display substantially different knowledge or preventive practice compared to respondents without a household member in the risk group (Table A 5.20).

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[23] See appendix A5.2 for a description of the data collection, which is very similar to the post-intervention survey, and more detailed results.

The majority of respondents relied on other people and television for information on COVID-19. Internet and newspaper only play a considerable role among people with higher education (Figure A 5.6). Around 75% of the 250 interviewees in the last weeks of pre-intervention data collection confirmed that they had received some information on COVID-19 through their mobile phone. Out of those, around half report to have received information on a daily basis. Around the same number of respondents report to have received government SMS, but with a lower frequency (Figure A 5.7).

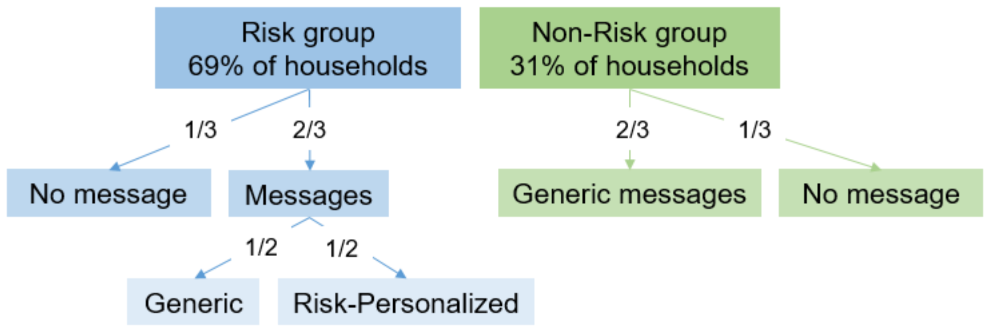
5.3 Experimental details

5.3.1 Experimental set-up

We test as primary hypotheses whether the intervention had any effect on the uptake of preventive practices (hypothesis 1) and whether this effect was larger in the risk group (hypothesis 2). As secondary hypotheses, we test the effect of personalized messages within the risk group (hypothesis 3), and whether effects work through an increase in knowledge (hypothesis 4). These main analyses follow the registered pre-analysis plan (Khan et al. 2020).

The experimental design is depicted in Figure 5.2. The sample can be divided into households with and without a household member in the risk group. Two thirds of the sample received an intervention and one third did not receive any intervention. In the risk group, there are two treatment arms: half of the treated households received a risk-personalized intervention and half received generic messages. In the non-risk group, all treated households received generic messages.

Figure 5.2 Experimental design

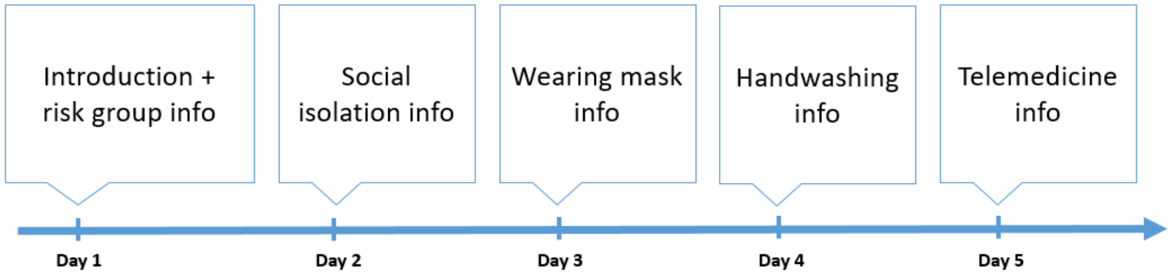


5.3.2 Intervention

The intervention was an information campaign of the Social Health Protection Initiative (SHPI) in the province of Khyber Pakhtunkhwa. It consisted of a set of six informative text messages that were sent to the selected recipients over the course of five days. The information content reinforced the government of Pakistan's specific recommendations for COVID-19 risk groups (Government of Pakistan 2020), which reflected the current state of knowledge on COVID-19 risk groups and prevention. As depicted in Figure 5.3, on the first day, an introductory message was sent before the first information message on risk groups. On each of the following days, one information message on either social distancing, wearing masks, handwashing, or using telemedicine before visiting a doctor was sent. In addition to the main information content, each message contained elements that have previously been found to enhance the effectiveness of such interventions. First, the sender mask of the message was "Sehat Insaf Card", which is the name of the SHPI's health insurance program that all recipients are beneficiaries of and can therefore be considered a well-trusted sender of health-related messages. Second, the main cardholder, who is likely also the main decision-maker in the household, was addressed by name, which is a second trust-building element as well as a means to increase relevance. Third, on every day, the recipient was provided with a telephone number that s/he could call in case of further questions. On most days, this was the number of a helpline that normally consults (potential) health insurance beneficiaries on enrollment and card usage related queries and would either provide the caller with basic information or re-direct him/her to a telemedicine helpline in case of a medical query. The information message on telemedicine directly contained the telemedicine helpline number. All messages were sent in Urdu language with Latin script (as listed in Table A 5.2) as the majority of the study population was either literate in Urdu language themselves or had another family member who could read the message to them (see Table A 5.4). Each message also contained the call to "tell your family" about this message as it was directed towards the main cardholder but relevant for all household members.

In addition to this general message specification, a subgroup of those with at least one household member in the risk group received a more personalized version of the risk group information message. Personalization was reached by listing risks first that were known to be present within the household. All risk groups that were not specific to the respective family were then listed with decreasing frequency. The distribution of messages in the respective order was then also applied to the groups that received a generic risk message to ensure comparability of the groups except for the personalization.

Figure 5.3 Intervention timeline



The messages were sent through the Telenor bulk messaging portal by the helpline company ICU healthcare, which provides an infrastructure to launch awareness campaigns for the SHPI and is part of the research team. Selection into the sample and treatment allocation was only known to the research team. As there was no explicit baseline data collection, participants were fully blinded to treatment assignment prior to the intervention and were unaware of the existence of a treatment and a control group. Those who were interviewed before, consented to being contacted by us again, but did not receive any specific information on text messages. The interviewers of the post-intervention survey were also unaware of treatment allocation and posed the same questions to all respondents.

We see that around 40-50% of treatment group respondents remember receiving our messages, and examine barriers to receiving and reading the messages in section 5.4.3.

5.3.3 Data

Sample selection

The sampling frame for the trial consists of the list of households that were enrolled in the Sehat Sahulat Program up until 2019 as provided by the SHPI. Eligibility to enrollment for the program is restricted to the poorest 69% of the population based on the household poverty score that was collected as part of the PMT census in 2010. Between 2015 and 2019, 1.5 million out of the 2.4 million eligible households have been enrolled in the insurance. Appendix Table A 5.3 displays that the enrolled households (or their designated main cardholders) are on average less wealthy, slightly older, to a higher proportion male and married than the general eligible population. As this study contains a mobile-phone based intervention, the sampling frame was restricted to the almost 0.6 million households for whom there is a unique phone number in the records[24]. Within the household, we aimed to interview the main insurance card holder, which was successful in over 75% of the interviews (Table A 5.4). A household was excluded if the main cardholder was not member of the household anymore.

[24] For the majority of the remaining (66%), there is either no phone number in the records or a clearly wrong number (e.g. not sufficient or too many digits).

The intervention sample is derived from a combination of households who were already interviewed during a previous survey round and an additional draw from the sampling frame (see Figure A 5.1 for a graphic display of the composition of the sample from the sampling frame until the estimation sample). The previous interview as well as the additional intervention sample were selected following the same procedure. The main part of the sample was then drawn from the list of households with unique phone numbers, stratified by district to ensure representativeness of all regions of the province based on the proportion of their enrolled population. Furthermore, households with previous insurance claims that are likely to indicate an increased risk for a complicated COVID-19 infection were over-sampled to gain sufficient observations from this population group that usually only comprises of 5% of households. Finally, 1,769 households with a previous interview and complete information on self-reported risk were included in the intervention sample, as well as 27,229 households without a previous interview.

Randomization

Treatment assignment was done just before the launch of the intervention by the authors at the individual level by assigning random numbers with the function *runiform* in Stata 15. Treatment was first assigned in the previously interviewed sample. In the risk group, one third of households were randomly allocated to the control group, one third to the personalized and one third to the generic treatment arm. The distribution of exact risk messages (the order of the mentioned risk groups) was determined by the prevalence of risk groups in the personalized treatment arm and then applied to the generic treatment group in both samples. In the additional sample, we randomly allocated two thirds to the treatment group again mirroring the distribution of risk messages in the personalized group.

Analysis sample, balance and attrition

The sample in the post-intervention survey comprises of 2,382 respondents, among which 306 respondents are from the previous interview sample and 2,077 from the additional sample (Figure A 5.1). The sample characteristics are displayed in Table A 5.4. Treatment and control group characteristics were balanced at randomization (Table A 5.5), and among post-intervention survey respondents except for a slightly higher age in the control group (Table A 5.6). As displayed in appendix Table A 5.7 to Table A 5.11, there is no differential attrition between treatment and control group. It needs to be mentioned that there are detectable differences along the sparse administrative data characteristics between the attrited and the interviewed (Table A 5.8) in the additional sample, but not among previously interviewed respondents (Table A 5.9).

Conducting a survey during a pandemic made some deviations from the survey protocol necessary. We present the results from a restricted sample that is closer to the intended protocol. This restricted sample includes all respondents who were interviewed up to one week after the intended interview date (for the treatment group, this is two weeks after the end of the intervention) and excludes the last week of data collection. As outlined in appendix section A5.2, we had intended to interview message recipients around one week after receiving the last intervention message. The second deviation was an extension of the data collection period. We had intended to complete the data collection within one month to keep contextual factors such as the progression of the pandemic rather constant, but only reached the stopping rule (reaching the intended sample size) after two months of data collection. It stands out that in the last week of interviews, the sample characteristics are not as clearly balanced between treatment and control group as in the remaining survey period (Figure A 5.2, Figure A 5.3). In addition, the end of the data collection period falls into a time of the beginning of the second pandemic wave.

5.3.4 Estimation strategy

Following the experimental design with random treatment assignment, we use OLS regression models to compare the outcomes of treatment and control households in an intention-to-treat analysis. The outcome measures, risk group indicators, treatment and control variables are defined as follows, and as specified in the pre-analysis plan (Khan et al. 2020).

Outcome measurement

The main outcome is uptake of preventive practices, which is measured in two ways. First, a count index captures the number of different practices that were mentioned in the messages (physical distancing, handwashing, wearing masks, telemedicine usage). Secondly, we use the individual binary indicators for the uptake of handwashing, wearing masks and telemedicine usage. The uptake of handwashing and wearing masks is self-reported in an unaided recall question. Though measured in the same way, the individual physical distancing indicator is not included as uptake was already very high in the pre-intervention survey. Telemedicine usage is also measured as a survey-based indicator derived from a question about calling a doctor or telemedicine helpline for a health need in the family during the previous month. Consequently, the sample for the telemedicine usage outcome only includes the 21% of the sample who reported to have had any health need in the household during the previous month. Additionally, we pre-registered an alternative measure of telemedicine usage capturing the number of calls to the telemedicine helpline during two months after the intervention as derived from the helpline's call records. As too few calls from the study population could be identified in the records[25], these are only studied descriptively.

The secondary outcome is knowledge about risk groups and preventive practices. Both indicators are measured using unaided recall questions of which COVID-19 risk groups and preventive practices the respondent can name. For both risk groups and preventive practices, we derive a count index, which captures the number of correctly named elements that were part of the messages (0-2 for risk groups and 0-4 for preventive practices).

Risk group definition

Every household that reports[26] to have at least one member over the age of 60 and/ or a member with a relevant precondition (cardiovascular or respiratory disease, cancer, diabetes or hypertension) is defined as a risk group household. As only one member of the household is the respondent, this information is collected from him/ her representing the household.

Treatment

Treatment is measured by assignment. For hypotheses 1 (prevention uptake), 2 (risk group heterogeneity) and 4 (knowledge) it takes value 1 if we sent the intervention to the household and 0 otherwise. For hypothesis 3 (personalization), the treatment variable takes value 1 if the risk group household was sent a personalized risk message and value 0 if it was sent a generic risk message.

Control variables

The main specification does not include any covariates. In an alternative specification, we add the respondent's age in years, an indicator for being female, three categories of completed education (up to primary as reference, secondary and tertiary) as reported in the survey. As a measure of wealth, we use the proxy means test (pmt) score, which is a continous wealth measure that was calculated for each household in a census in 2010, and reported in the insurance data as the poverty line for health insurance eligibility is also based on this score.

Regression specification

We estimate the intention-to-treat effect on practice and knowledge outcomes (hypotheses 1 and 4) using the following framework:

$$(1)\ Y_i = \alpha + \beta treat_i + \varepsilon_i \ \ (+\theta\ C_i)$$

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[25] As the helpline did not record each caller's national identification number for privacy reasons, only households that called the helpline with the same telephone number that is noted in their health insurance enrollment data could be identified.

[26] For the subset of households that was already interviewed in a pre-intervention survey wave, we use the risk group information from the first interview in case it differs at endline as this influenced the randomization. Results do not change when using the endline risk group information.

Y_i is the respective outcome variable (i.e. preventive practice index, binary indicators of mask wearing, handwashing and telemedicine usage, risk and prevention knowledge indices) for household *i*. In addition to the basic specification that regresses the respective outcome on a treatment dummy $treat_i$ (assigned to receive the intervention), we also estimate a second specification that includes basic control variables C_i (age, gender, education, wealth):

$$(2)\ Y_i = \alpha + \beta treat_i + \gamma risk_i + \delta(treat_i * risk_i) + \varepsilon_i \quad (+\theta C_i)$$

To test for the difference in the treatment effect between risk and non-risk group (hypothesis 2), equation 2 is used to estimate the interaction effect between the binary risk group indicator $risk_i$ and the same treatment indicator as above.

$$(3)\ Y_i = \alpha + \beta personalized_i + \varepsilon_i$$

The treatment effect of the personalized messages (hypothesis 3) is estimated using equation 3 to compare the outcomes of personalized against generic message recipients among the treated in the risk group. The probability of receiving a personalized message by assignment in the previously interviewed sample differs from receiving a personalized message by chance in the additional sample. Therefore, the estimates of each risk group are re-weighted using a propensity score that reflects the likelihood of receiving a personalized message depending on the kind of risk group and whether the households was part of the previously interviewed or the additional sample.

As a robustness check, p-values of the primary hypotheses (H1 and H2) are adjusted for multiple hypotheses testing using the Benjamini-Hochberg method (Benjamini and Hochberg 1995).

5.4 Results

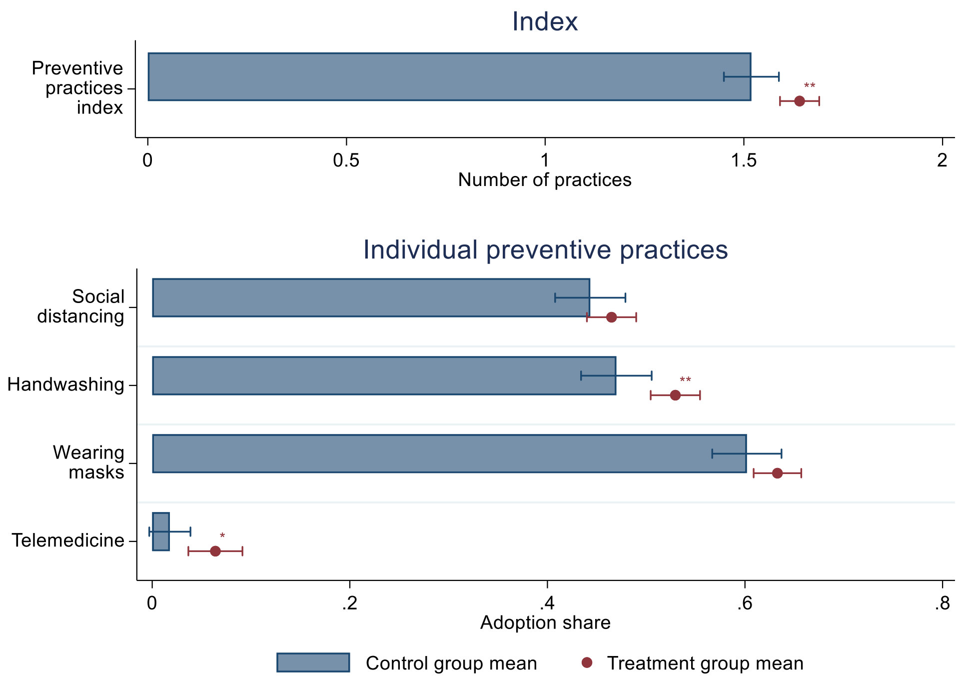
5.4.1 Treatment effect on the uptake of preventive practices

Main results

We find that the intervention increased the uptake of preventive practices. Figure 5.4 shows that control group respondents practice on average 1.5 out of the four preventive practices that were mentioned in the messages, which increases by around 0.12 (8%) in the treatment group. Out of the individual practices, most control group respondents (60%) report to adhere to regular mask-wearing, 47% to handwashing, slightly less continue to practice social distancing, and out of those who had an illness in the household in the previous month only 2% made use of telemedicine. The average treatment group uptake is higher in all index elements, but it is only significantly distinguishable from control group uptake for handwashing and telemedicine usage. For handwashing, the treatment effect is around 6 percentage points (13% increase relative to the control group), and a 5 percentage points increase in telemedicine usage when ill almost triples the control group uptake (Table A 5.12). The main effect on the preventive practices index and handwashing uptake is robust to multiple hypothesis testing adjustments, but the adjusted q-value of the treatment effect on telemedicine usage increases to above 0.1 (Table A 5.17).

Considering the call record of the telemedicine helpline that was mentioned in the messages, only 23 calls can be attributed to the intervention sample, and all are from the treatment group. Most callers ask about the messages, and two of them ask for advice regarding a specific health complaint. All these calls were made directly after receiving the intervention, and we do not detect any longer-term effects over the following three months (until November 2020). This shows that the effect on the uptake of telemedicine is not driven by calling the helpline, but rather by calling health workers or health facilities directly.

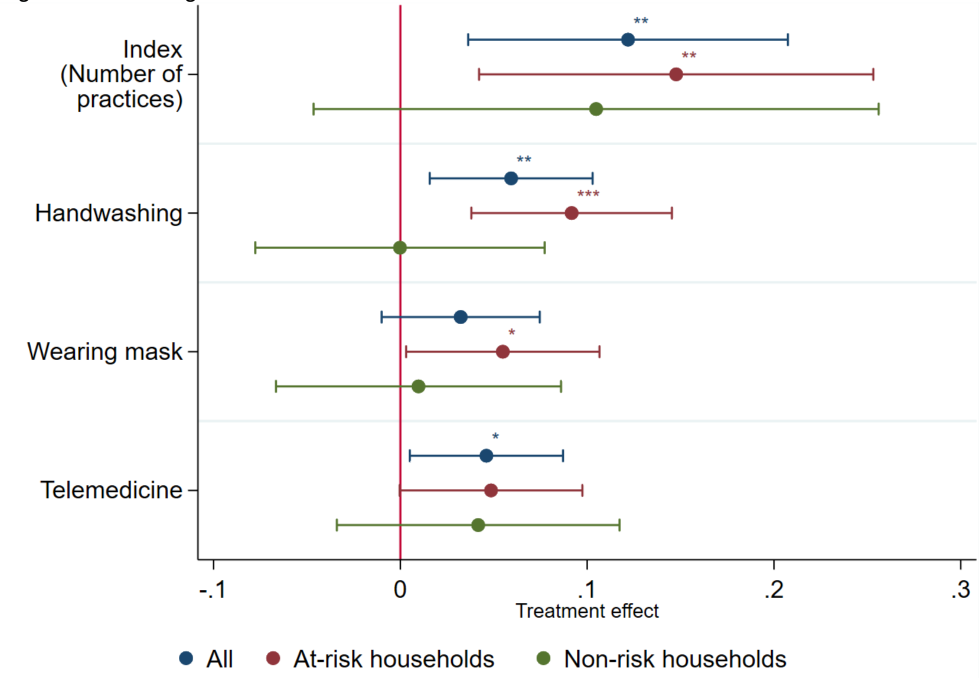
Figure 5.4 Treatment effect on preventive practice uptake



*Control group (bars) and treatment group (dots) means of main outcomes with 90% confidence intervals. Stars indicate the p-value of regressing the respective practice indicator on the binary treatment indicator following equation 1, * p < 0.1, ** p < 0.05, *** p < 0. Refer to Table A 5.12 for tabular display.*

Estimating the heterogeneous treatment effect for households with and without a member in the risk group shows that the effect on handwashing uptake is significantly higher in risk group households. This difference is not robust to multiple hypothesis testing (Table A 5.18) and the specification with control variables (Table A 5.13). Nevertheless, Figure 5.5 and Table A 5.14 show that respondents from risk group households (red) drive the whole sample treatment effect for the prevention index and handwashing, while no treatment effect can be detected in the non-risk sample (green) alone. In the risk group only, regular handwashing to prevent the spread of COVID-19 increased by over 9 percentage points and mask wearing increased by around 5 percentage points. The uptake of telemedicine is similar across risk and non-risk group.

Figure 5.5 Heterogeneous treatment effect across at-risk and non-risk households



*Treatment coefficients from estimating equation 1 in the complete sample, and for at-risk and non-risk households separately. Stars indicate the p-value of regressing the respective practice indicator on the binary treatment indicator following equation 1, * p < 0.1, ** p < 0.05, *** p < 0. See Table A 5.12 and Table A 5.14 for the tabular display.*

Further explorative analyses

When looking at the uptake of preventive practices over time starting in the pre-intervention period, we see that on average the number of preventive practices adopted by the control group, and handwashing and social distancing in particular, decreased in the intervention period (Figure A 5.4)[27]. This might be due to the progression of the pandemic, which meant high case numbers in the pre-intervention period and low case numbers during the intervention period (Figure 5.1). Consequently, the treatment effect on handwashing uptake comes from the treated maintaining higher levels of prevention, while control group uptake decreases. A similar development cannot be detected for knowledge, which remains stable or increases in the case of mask-wearing (Figure A 5.5).

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[27] Telemedicine usage in case of a health need was not measured in the pre-intervention period, and can therefore not be compared over time.

5.4.2 Mechanisms

Personalization

We find that receiving a personalized message rather than a generic one increases the likelihood to call a doctor or telemedicine helpline before visiting a health facility by 7 percentage points (Table 5.1). For the other preventive practices, we cannot detect a significant difference in the treatment effect between recipients of personalized and generic messages.

Table 5.1 Personalization treatment effects on preventive practices (hypothesis 3, treated risk group only)

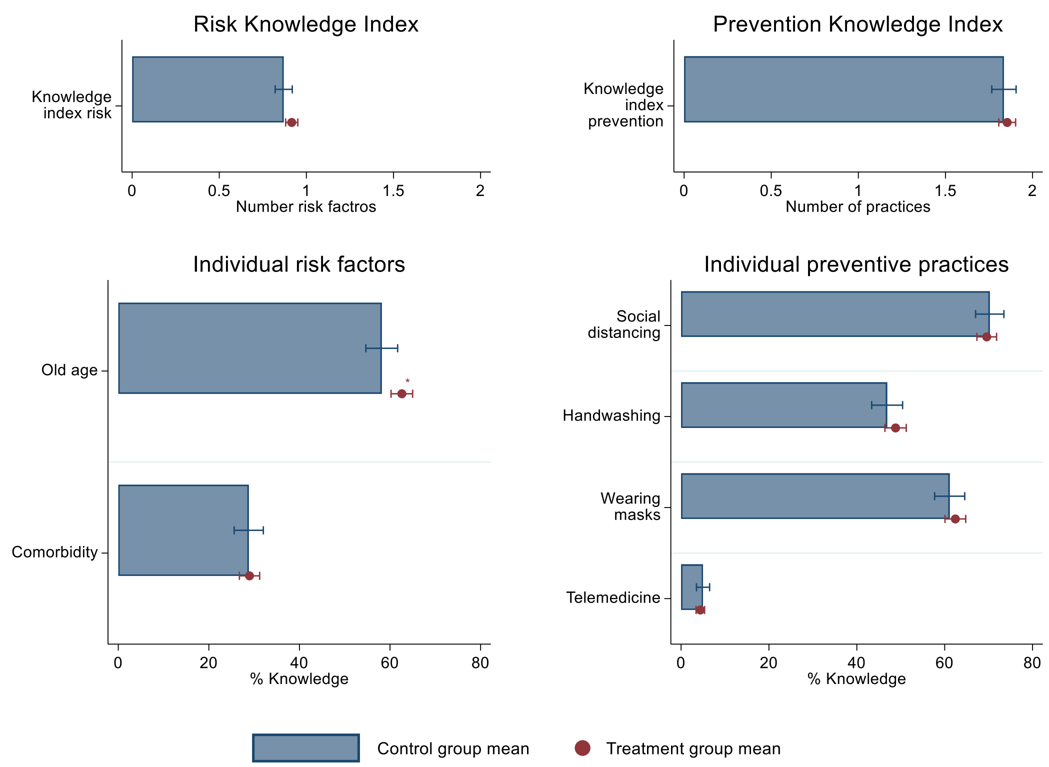
	Preventive practices index	Handwashing	Wearing masks	Telemedicine if sick
Personalized vs generic treatment	-0.0023	0.0460	-0.0354	0.0728*
	(0.0787)	(0.0401)	(0.0382)	(0.0392)
Observations	706	706	706	168

*Estimation results of equation 3 with the respective preventive practice on the binary personalization indicator, re-weighted taking personalization probability into account. Sample is restricted to the treatment group with at least one risk group member in the household. Personalization entails listing the household-specific risk factor first in the risk message. The preventive practices index is a count-index ranging from 0 to 4 counting whether the respondent mentioned to practice handwashing, social distancing or mask wearing on a regular basis and/ or using telemedicine in case of a health need. Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01.*

Knowledge

We do not find that the increases in the uptake of preventive practices are mainly driven by closing information gaps in risk and prevention knowledge (hypothesis 4). As depicted in Figure 5.6, around 58% of the control group respondents knew that old age implies a higher risk and only 29% knew a relevant precondition. Different from the patterns in prevention uptake, the best known preventive practice was social distancing (70%), followed by wearing masks (61%) and handwashing (47%). We see neither an effect of the intervention on the aggregate risk and prevention knowledge indices nor on the individual items of the prevention knowledge index. Due to the precision of these estimates and the robustness of the null effect across specifications (Table A 5.15, Table A 5.16), we rule out that the intervention increased prevention and risk knowledge sufficiently to explain the effect on prevention uptake.

Figure 5.6 Treatment effect on risk and prevention knowledge



*Control group (bars) and treatment group (dots) means of main outcomes with 90% confidence intervals. Stars indicate the p-value of regressing the respective knowledge indicator on the binary treatment indicator following equation 1, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Refer to Table A 5.15, Table A 5.16 for tabular display.*

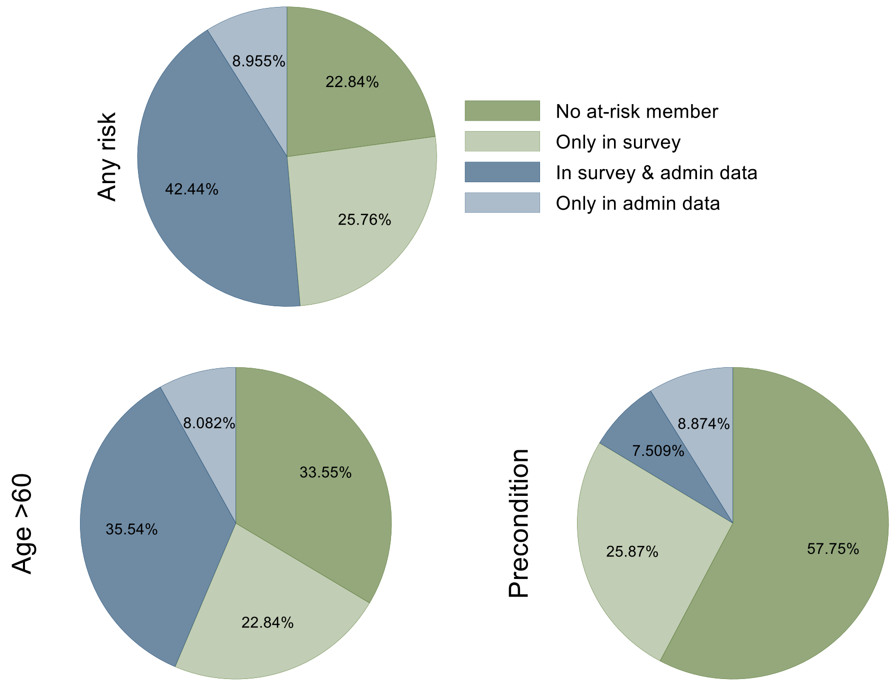
5.4.3 Scale-up potential

As we find the intervention to be effective, we further examine its scale-up potential. The intervention could be scaled up in the same way as it was implemented for this study, except for the risk group targeting and personalization, for which we relied on survey-based information. As we see that targeting and potentially also risk-personalization are effective components of the intervention, we first assess the scale-up potential of the intervention through administrative data alone. Secondly, it is inherent to low-touch text messaging interventions that only a subset of assigned message recipients is exposed to the intervention. Therefore, we examine descriptively factors that hinder message recipients from receiving, reading and understanding the messages to understand how the effectiveness of the intervention can be improved.

Risk group identification in the administrative data

Age and precondition risk group information can also be derived from the health insurance enrollment and claims data. Age can be identified in the enrollment data via the age of the main cardholder, but not the age of all family members. Preconditions can be derived from the insurance claims data. Each of these claims is recorded with one of 829 treatment categories, which allow to identify previous treatments which point towards a precondition that might increase the risk for a complicated COVID-19 progression. By design of the health insurance scheme, these treatments only include inpatient or maternity related care and therefore do not include all potentially relevant preconditions. As depicted in Figure 5.7, 58% of the households who were either interviewed in the pre-intervention or the intervention period reported to have a member above the age of 60, and 61% of these could have been identified from the age of the main cardholder in the enrollment data alone. This share could even be increased with access to full household member lists. The identification of the precondition-based risk group does not look as promising: Around one third of households have a member with a relevant precondition according to the survey data, but only around 23% of these could have been identified through the claims on the main cardholder's id, and a similar share is potentially wrongly identified in the claims data. Even with access to full household claim data, mis-targeting would be substantial.

Figure 5.7 Identification of COVID-19 risk factors in the interview and administrative data

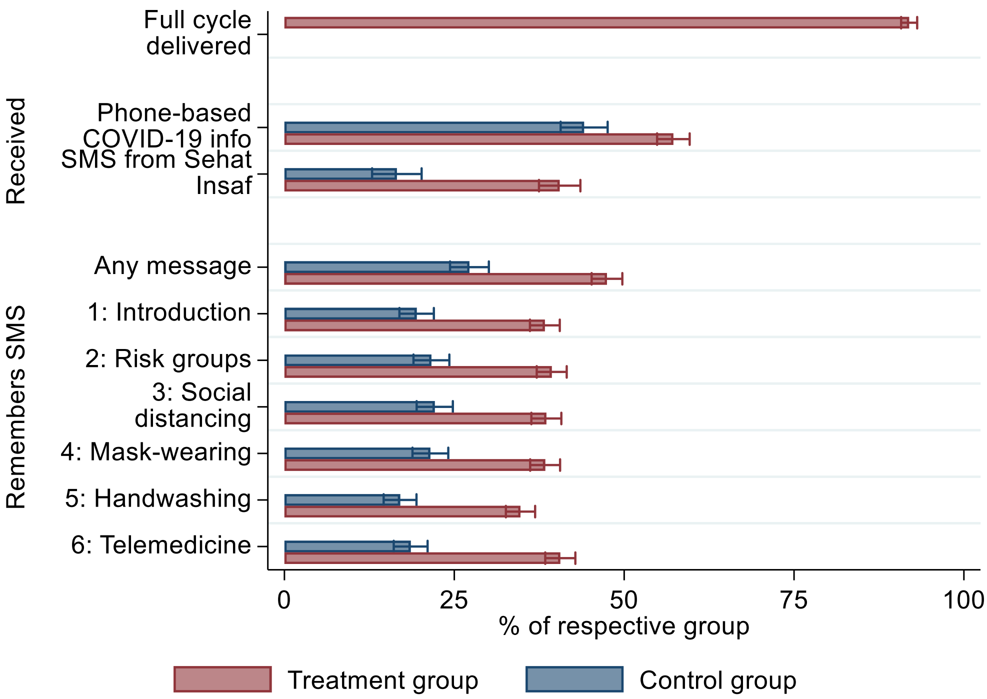


Shares on all interviewed households (during pre-intervention and intervention period) who are identified as having at least one at-risk member in the survey and/ or administrative data. "Any risk" captures all households who have at least one member over the age of 60 and/ or with a relevant precondition.

Intervention exposure

Around 90% of messages were correctly delivered to interview respondents (Figure 5.8). This share could be further improved if databases were updated more frequently (less invalid numbers) and network coverage improved (less failed deliveries to correct numbers). 40 to 50% of respondents report to remember specific messages that we sent. As we know that the government, telecommunication companies, NGOs and others sent out more general messages throughout the pandemic, it is not surprising that also some people in the control group report to remember specific messages. The share in the treatment group is around twice as high for all messages. As the intervention was sent out in a geographically sparse manner throughout the province, it is very unlikely that this is an indication of spillovers, but rather that the respondent cannot distinguish messages that s/he has received from other sources from our messages.

Figure 5.8 Different measures of message receipt shares in the interviewed sample



Treatment and control group means of each binary message receipt indicator with 90% confidence intervals; "Full cycle delivered" is taken from the provider's delivery reports; the remaining indicators are survey-based: "Phone-based COVID-19 info" and "SMS from Sehat Insaf" are based on closed-ended questions whether the respondent remembers receiving any SMS on COVID-19 during the previous 3 weeks and who sent this message; the indicators in the "Remembers SMS" block are based on whether the respondent remembers to have seen the message after being read out loud by the interviewer.

The ability to understand the messages poses an (expected) barrier to being exposed to and reacting to the messages. Less than half of respondents report to be literate in Urdu themselves, but almost 80% of households have at least one member who can read Urdu. Additionally, around 23% of respondents report that they did not even understand the message when it was read to them by an enumerator.

It is possible that messages were not trusted or the recipient did not pay attention to them. From the qualitative interviews after the pilot intervention (appendix section A5.2), we know that messages from the health ministry or the health insurance program are generally perceived as trustworthy and mentioning the name of the recipient was also named as a reason for paying attention to the messages. Respondents further stated that the messages were rather perceived as official messages than advertisement.

5.5 Discussion and Conclusion

In settings with fragile health systems and limited vaccination rollout, such as our study region in Pakistan, avoiding a COVID-19 infection with individual preventive practices remains key, especially for those at higher risk of experiencing a severe disease course. Our randomized experiment shows that a personalized and targeted text messaging campaign delivered to health insurance beneficiaries can be a complimentary measure to increase uptake of preventive practies. The intervention increased the uptake of handwashing by 6 percentage points, an 18% increase relative to the control group. This effect is driven by the at-risk population for whom handwashing uptake increased by 9 percentage points. In the whole sample, the intervention increased the uptake of tele-medical services by 5 percentage points, which almost tripled control group uptake of 2%. Within the risk group, making the household-specific risk more salient via light risk-personalization in the messages makes the intervention more effective for telemedicine usage. The treatment effect on handwashing uptake is comparable in size and direction to (Banerjee et al. 2020)'s celebrity-endorsed text and video message broadcasting intervention at an earlier stage of the pandemic in India. Such an effect could not be replicated by Bahety et al. (2021) with a generic, pure text messaging intervention during the peak of the first wave in India.

We do not find evidence for increased knowledge as channel for these effects. This is in line with other text-messaging interventions that do not detect any updates in knowledge early in the pandemic (Banerjee et al. 2020) or during the peak of the first wave in India (Bahety et al. 2021). We suspect that our text message campaign rather narrows the knowledge-action gap by making existing information more salient and helping message recipients to form habits. Message personalization possibly facilitated this.

Our study is subject to several limitations. First, we rely on self-reported outcomes that are susceptible to social desirability. We address this concern by using only unaided recall questions for outcome measurement and ensuring blinding of interviewers and participants to treatment allocation. To keep the interview as short as possible, the response rate high and retain comparability to the pre-intervention survey, we opted to not include additional measurements. Comparing our results to Bahety et al. (2021) gives confidence in the validity of the outcome. They also use the open question as main specification, but test in addition a direct elicitation, asking about the community rather than the individual and a list experiment. Second, it is inherent to telephone surveys that the sample that is reached and willing to give an interview is different from the general population, especially in low-income settings. As opposed to random digit dialing or mere lists of telephone numbers, we can leverage household characteristics from the insurance database to get an idea of what sections of the population our sample adequately represents. Finally, deviations from the planed survey protocol due to pandemic conditions led to a sample size that was lower than we intended based on power calculations. Since the primary treatment effect is robust in the pooled sample as well as in the risk group alone, this is mostly an issue for the effects on risk personalization.

All in all, our personalized and targeted SMS campaign can be an effective complement to ongoing efforts to shield COVID-19 risk groups in Khyber Pakhtunkhwa. It increased the uptake of individual preventive practices, particularly in households that have a member that is at higher risk of experiencing a severe disease course. The intervention was successful in making existing knowledge more salient and encouraged continued adoption. There is potential in scaling up text messaging interventions that make use of the sparse individual information in health insurance records.

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Appendices

A2 Appendix for chapter 2

Table A 2.1 Timeline health insurance schemes and relevant legislation

1934	**Implementation of the first public health insurance for civil servants of “European Status” under Dutch colonial legislation (Saatsregeling 1/1934)**
1938	Extension of public health insurance to all civil servants and their families on a voluntary basis
1945	Indonesia gains independence
1960	Law 9/1960: The Basic Health Law adopted
1968	Implementation of mandatory health insurance for civil servants (Askes)
1969-90	Implementation of 1st version of the health fund and experiments with community-based health insurance
1977	Law and implementation of social security program for formal sector workers
1992	Creation of Jamsostek including mandatory health insurance for formal sector employees Introduction of JPKM HMO systems
1994	Introduction of Health Cards
1997/98	Asian Financial Crisis and Creation of a Social Safety Net (JPS)
2000	Constitutional reform amending the right to medical care and social protection into the 1945 constitution
2001	Decentralization Laws
2004	Law 40/2004: groundwork for social security system (SJSN law)
2004/05	Implementation of the social health insurance Askeskin
2008	Scale-up and renaming of social health insurance to be Jamkesmas
2007	Launch of the Family Hope Program (PKH)
2011	Law 24/2011 to build health insurance administration agency BPJS Establishment of Jampersal as extension to Jamkesmas
2012	National Social Security Councol (DJSN) formulates a roadmap for the implementation of a national health insurance
2014	BPJS and JKN start operating
2019	Goal to have reached UHC

Sources: (Rokx et al. 2012), (Pisani et al. 2017), (Vidyattama et al. 2014), (Johar 2009; Suryahadi et al. 2014), (DJSN 2012)

Figure A 2.1 Public health insurance schemes before and after 2014

Target group	Poor/ Near-poor	(retired) civil servants, military and veterans	Formal sector employees	Informal Sector workers / self-employed
Before January 1st 2014				
Scheme	***Jamkesmas***	***Askes/ Asabri***	***Jamsostek***	No specific scheme, only voluntary private and company insurances
Funding	Fixed premium of 6,500 IDR per member per month contributed by the central government from general taxation	Employees pay 2% of basic pay and government pays 1%	Employers pay 3-6% of the salary depending on the employee's marital status; but a maximum of 1m IDR per month	
Benefit	Comprehensive; drugs within formulary covered			
	No cost-sharing	Cost-sharing available for services outside basic benefits package		
Facility type	All Puskesmas, public hospitals and selected private hospitals	Mostly contracted public health centers and hospitals		
Provider payment mechanism	Puskesmas: capitation based Hospital: case-mix (INA-CBG)	- Special fee schedules for civil servants - Extra billing depending on negotiated fees		
Jamkesda *(in specific provinces or districts with varying target groups)*				
Funding	From province/ district budget			
Benefits	Varied province/ district			
From January 1st 2014: ***BPJS Health*** *(all target groups)*				
Funding	Fixed premiums: 19,225 IDR contributed by the central government from general taxation	Salary-based contributions of 5% of the monthly salary, of which 4% are paid by employers and 1% by employees		Fixed monthly premium contribution of 25,500 IDR / 42,500 IDR / 59.500 IDR
Benefits	Comprehensive			
Facility type	All Puskesmas			
	Class 3 hospital beds in public and selected private hospitals	May be entitled for class 2 or 3 hospital beds in public and selected private hospitals depending on premium levels		
Provider payment	Puskesmas: capitation based Hospital: case-mix system (INA-CBG)			

Adapted from (Clearstate 2015), depicts premium levels at the time of the reform in 2014.

Table A 2.2 Changes in district composition in SUSENAS: list of changes in 2015-17 district list to align with 2011-14 data

District ID* in 2015-17	District ID in 2011-14	District name in 2015-17	District name in 2011-14
District ID changed (Province split)**			
6501	6406	Kab. Malinau***	Kab. Malinau
6502	6407	Kab. Bulungan	Kab. Bulungan
6504	6408	Kab. Nunukan	Kab. Nunukan
6503	6410	Kab. Tana Tidung	Kab. Tana Tidung
6571	6473	Kota Tarakan	Kota Tarakan
District ID and name changed (District split)			
1612	1603	Kab. Penukal Abab Lematang Ilir	Kab. Muara Enim
1613	1605	Kab. Musi Rawas Utara	Kab. Musi Rawas
1813	1801	Kab. Pesisir Barat	Kab. Lampung Barat
3218	3207	Kab. Pangandaran	Kab. Ciamis
5321	5303	Kab. Malaka	Kab. Kupang
6411	6402	Kab. Mahakam Hulu	Kab. Kutai Barat
7211	7201	Kab. Banggai Laut	Kab. Banggai Kepulauan
7212	7203	Kab. Morowali Utara	Kab. Morowali
7412	7403	Kab. Konawe Kepulauan	Kab. Konawe
7411	7404	Kab. Kolaka Timur	Kab. Kolaka
7606	7604	Kab. Mamuju Tengah	Kab. Mamuju
8208	8203	Kab. Pulau Taliabu	Kab. Kepulauan Sula
9111	9105	Kab. Manokwari Selatan	Kab. Manokwari
9112	9105	Kab. Pegunungan Arfak	Kab. Manokwari

** district ID consists of the province ID and a district identifier; ** the province North Kalimantan (65) split from the province East Kalimantan (64) and is treated as one for this analysis; “Kab”=regency (rural district) and “Kota”=municipality (urban district)*

Table A 2.3 Definition of outcome, exposure and control variables across survey waves

	Description	Variable construction across survey waves
Outcomes		
Inpatient care usage	Dummy variables for use of inpatient care in any of the following facility types Recall period: 1 year Sample: all households Level of observation: household member	- 2011-14: frequencies of visits to each facility were recorded; dummy takes value 1 if at least one visit indicated and 0 if none - 2015-17: visits directly recorded as dummy, no manipulation necessary
	Total inpatient	Recorded in separate survey question in all waves and equals the usage of at least one of the following facilities once
	Public	Aggregated from at least one of public hospital or public health center used
	Public hospital	
	Public health center (Puskesmas)	
	Private	Aggregated from at least one of private hospital or private practice used
	Private hospital	
	Private practice	Aggregated from the sub-options doctor's practice or joint clinic and other health worker's practice (e.g. midwife or nurse)
Outpatient care usage	Dummy variables for use of outpatient care in any of the following facility types Recall period: 1 month Sample: all household members who report an illness during the previous month Level of observation: household member	- 2011-14: Illness during the last month is specified as one of: fever, cough, flu, difficulty breathing, diarrhea, headache, toothache or other Frequencies of visits to each facility were recorded; dummy takes value 1 if at least one visit indicated and 0 if none - 2015-17: Illness during the last month is recorded as a dummy naming the above categories only as examples Visits directly recorded as dummy, no manipulation necessary
	Total outpatient	Recorded in separate survey question in all waves and equals the usage of at least one of the following facilities once
	Public	Aggregated from at least one of public hospital or public health center used
	Public hospital	
	Public health center (Puskesmas)	- 2011-14: the option is only "Puskesmas" - 2015-17: Aggregated from the explicitly separate options "Puskesmas/ Pustu" and community-based programs "UKBM"
	Private	Aggregated from at least one of private hospital or private practice used
	Private hospital	
	Private practice	Aggregated from the sub-options doctor's practice or joint clinic and other health worker's practice (e.g. midwife or nurse)
Health expenditure	Real quarterly expenditure in IDR collected in 16 distinct categories throughout all years and aggregated as below Deflated using IMF's Consumer Price Index with base year 2010 Level of observation: household	- 2011-12: expenditure and core module cannot be matched at the household level and can therefore only be used in the district-level analysis - 2011-2014: monthly recall of the previous three months individually; all three reported monthly expenditures are aggregated to form quarterly expenditure - 2015-16: one year recall period; divided by four for average quarterly expenditure
	Total	Sum of all 16 health expenditures
	Treatment	Sum of all public and private treatment expenditure

	Treatment public	Sum of treatment costs in public hospitals and public health centers (puskesmas, pustu, polindes, posyandu)
	Treatment private	Sum of treatment costs in private hospitals and private doctors or other health worker practices (midwife, nurse)
	Medication	Sum of expenditure for prescription drugs, non-prescription and traditional medication and glasses, artificial leg or wheelchair
	Prevention	Sum of expenditure for pregnancy examination, immunization, medical check-ups, contraception and other costs (e.g. vitamins, food supplements, fitness)
Exposure		
Health insurance membership	Dummy variable of having at least one household member enrolled in public health insurance at the time of the interview Level of observation: household	- 2011-14: collected at the household level - 2015-17: collected at the individual level, aggregated to having at least one household member in one of the schemes
	Any health insurance	Aggregate indicator for having at least one household member in any public subsidized of self-paid health insurance scheme
	Subsidized health insurance	Includes Jamkesmas, health fund (2011-12), Jampersal (2013-14), Jamkesda (2013-17), JKN PBI (in 2015-16, the survey does not differentiate between the subsidized and self-paid arm in JKN, so that all is counted towards subsidized)
	Self-paid health insurance	Includes Askes, Jamsostek, company insuance (2011-12 and 2015-17), JKN non-PBI (2017)
Household level control variables		
Living in a urban area	Dummy variable as defined in SUSENAS based on administrative level 4 category (rural or urban village)	
Per capita household expenditure	Monthly average in IDR, deflated using IMF's Consumer Price Index with base year 2010	
Access to electricity	Dummy variable indicating whether the household either uses electricity for cooking or has electric light	
House ownership	Dummy variable indicating whether the building the household resides in is owned by a household member	
Asset index	Compiled following the DHS asset index methodology	Includes assets that are recorded in all waves: owning a gas cylinder, refrigerator, air conditioner, water heater, landline telephone, mobile phone, computer, motorbike, boat, motorboat, car, TV, land, improved drinking water, improved latrine, finished floor, finished roof, finished wall, per capita floor area, having a domestic worker, owning the dwelling, renting the dwelling, access to electricity, using clean cooking fuel
Membership in other social protection programs	Dummy variable indicating whether the household or any of its members is the beneficiary of any other public social protection program	This includes: rice subsidy (Raskin), poor student support, cash transfer programs (condidtioal PKH in 2013-14; unconditional BLSM in 2016), other social insurance (veteran, pension, work accident, unemployment), receiving business credit as part of a community empowerment program
Individual level control variables		
Gender	Dummy variable indicating whether the respective household member is female	

Age	Continuous variable	
Education	Categorical variable indicating the highest completed level of education Sample: household members above the age of 5 Aggregated categories: no formal education, primary, junior secondary, senior secondary, higher	Primary: public (SD/ SDLB), Islamic (Ibtidayah), package A Junior Secondary: public (SMP/ SMPLB), Islamic (Tsanawiyah), package B Senior secondary: public (SMA / SMLB), Islamic (Aliyah), vocational (SMK), package C Higher: D1-D4, S1-S3
Occupation	Categorical variable of sector of main employment during the past week	2011-14 and 17: more detailed categories, which are aggregated to match the categories from 2015-16: Agriculture (rice and crops, horticulture, plantation, fisheries, livestock, forestry); Mining and quarrying; Processing industry; electricity and gas (includes waste and water management in 2017); construction / building; Trading, hotel and restaurant; transportation, warehousing, information and communication; finance and insurance; services (education, health, administration, real estate, technical services, arts and entertainment)

Table A 2.4 Selected individual and household characteristics by year

	2011	2013	2015	2017
Individual characteristics				
Age in years	28.7315	29.4137	29.8578	30.3440
	(19.4047)	(19.6399)	(19.8009)	(20.0021)
Female share	0.5037	0.5025	0.5025	0.5024
	(0.5000)	(0.5000)	(0.5000)	(0.5000)
Share with primary education or less	0.4834	0.4743	0.4574	0.4314
	(0.4997)	(0.4993)	(0.4982)	(0.4953)
Married share	0.4812	0.4852	0.4857	0.4847
	(0.4996)	(0.4998)	(0.4998)	(0.4998)
Share with any illness in previous month	0.2931	0.2794	0.3035	0.2862
	(0.4552)	(0.4487)	(0.4598)	(0.4520)
Number of individuals	1,118,239	1,094,179	1,097,719	1,132,749
Household characteristics				
Share living in urban area	0.4954	0.4973	0.5015	0.5308
	(0.5000)	(0.5000)	(0.5000)	(0.4991)
Number of household members	3.8501	3.8277	3.7914	3.7669
	(1.6756)	(1.6612)	(1.6172)	(1.6519)
Monthly p.c. expenditure in IDR	599,882	675,654	711,635	800,563
	(731,632)	(780,469)	(825,914)	(769,783)
Share with access to electricity	0.9483	0.9653	0.9754	0.9814
	(0.2214)	(0.1830)	(0.1550)	(0.1351)
Share with own house	0.7877	0.8008	0.8263	0.7961
	(0.4089)	(0.3994)	(0.3789)	(0.4029)
Floor area in m^2	67.8170	70.7536	74.1781	78.0332
	(56.2399)	(53.1329)	(57.2550)	(58.0490)
Share enrolled in any social security program	0.5663	0.5952	0.5963	0.5512
	(0.4956)	(0.4909)	(0.4906)	(0.4974)
Number of households	285,307	284,063	285,908	297,276

Standard deviations in parentheses below mean (accounting for sampling weights); every other year is displayed for convenience.

Table A 2.5 Health insurance membership patterns across years and schemes

	2011	2013	2015	2017
Any health insurance	0.4449	0.4901	0.5712	0.6676
	(0.4970)	(0.4999)	(0.4949)	(0.4711)
Subsidized	0.2722	0.3311	0.4580	0.4388
	(0.4451)	(0.4706)	(0.4982)	(0.4962)
Self-paid	0.1755	0.1470	0.1330	0.2574
	(0.3804)	(0.3541)	(0.3395)	(0.4372)
Private	0.0214		0.0164	0.0192
	(0.1446)		(0.1271)	(0.1372)

Shares of households that have at least one member in the respective scheme; shares account for sampling weights; standard deviation in parentheses; Self-paid schemes include Askes, Jamsostek, company insurance, JKN non-PBI (in 2017); Subsidized schemes include Jamkesmas, Jampersal, Health fund, JKN (in 2015 all and in 2017 only PBI); every other year is displayed for convenience.

Figure A 2.2 Share of insured households in 2013 by district

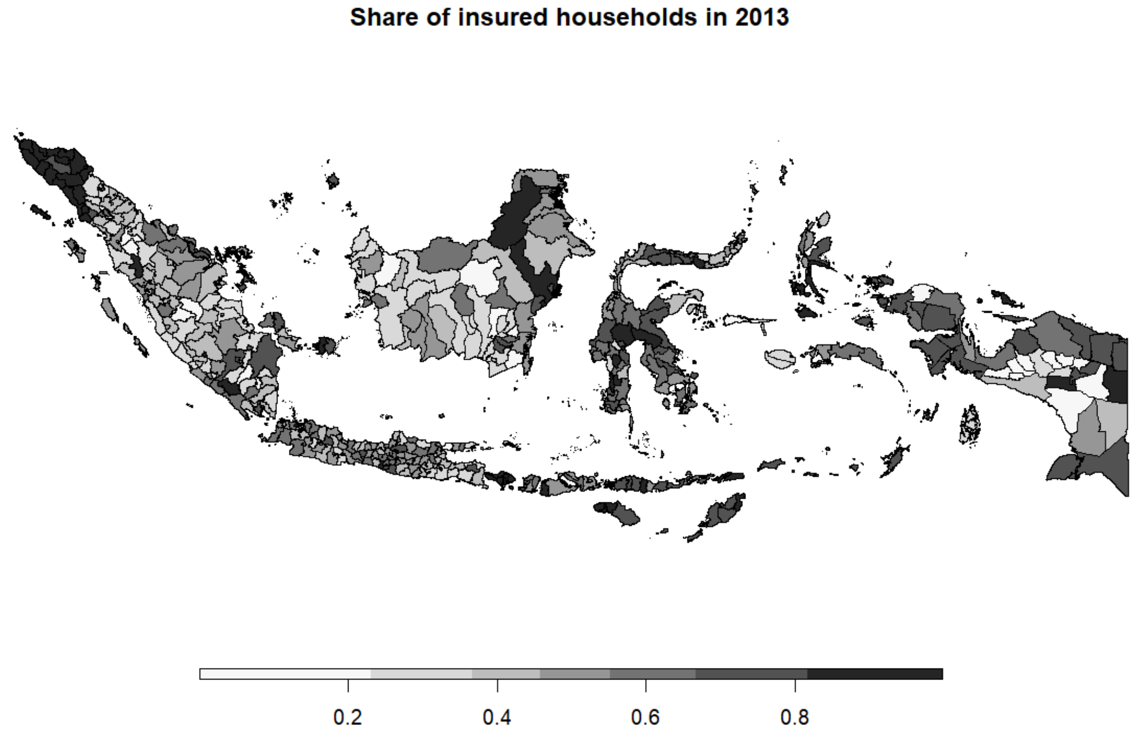


Figure A 2.3 Difference between 2017 and 2013 share of insured household per district (post-reform change)

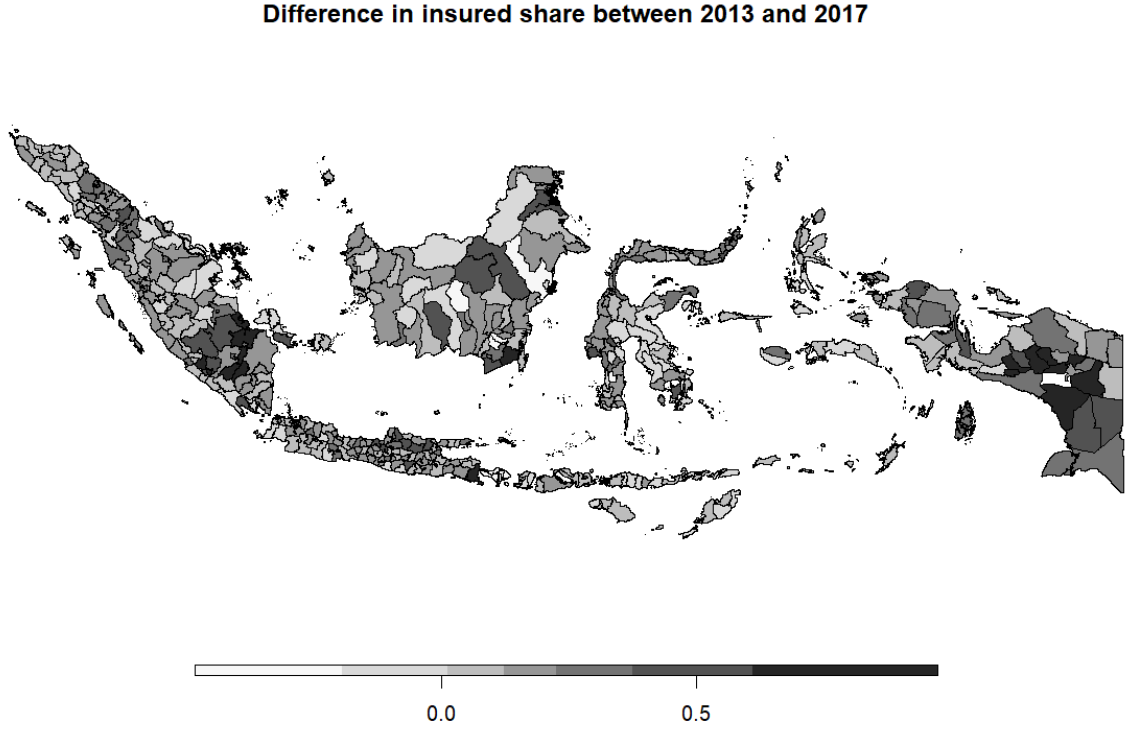


Table A 2.6 Health facility usage patterns across years

	2011	2013	2015	2017
Inpatient (share of all individuals, during the previous year)				
Any	0.0210	0.0233	0.0361	0.0419
	(0.1433)	(0.1510)	(0.1865)	(0.2003)
Any public	0.0117	0.0131	0.0199	0.0229
	(0.1076)	(0.1138)	(0.1398)	(0.1497)
Public hospital	0.0089	0.0101	0.0154	0.0177
	(0.0940)	(0.0998)	(0.1230)	(0.1320)
Puskesmas	0.0029	0.0033	0.0047	0.0055
	(0.0542)	(0.0575)	(0.0687)	(0.0737)
Any private	0.0094	0.0104	0.0165	0.0196
	(0.0964)	(0.1014)	(0.1275)	(0.1385)
Private hospital	0.0075	0.0082	0.0126	0.0152
	(0.0863)	(0.0902)	(0.1114)	(0.1225)
Private practice	0.0018	0.0022	0.0038	0.0043
	(0.0426)	(0.0468)	(0.0616)	(0.0652)
Outpatient (share of individuals who reported any illness during the previous month)				
Any	0.4580	0.4887	0.5596	0.4632
	(0.4982)	(0.4999)	(0.4964)	(0.4986)
Any public	0.1824	0.1792	0.2027	0.1849
	(0.3861)	(0.3835)	(0.4020)	(0.3882)
Public hospital	0.0247	0.0281	0.0384	0.0341
	(0.1553)	(0.1653)	(0.1923)	(0.1815)
Puskesmas	0.1608	0.1561	0.1667	0.1536
	(0.3674)	(0.3629)	(0.3727)	(0.3606)
Any private	0.2872	0.3229	0.3454	0.2927
	(0.4524)	(0.4676)	(0.4755)	(0.4550)
Private hospital	0.0191	0.0235	0.0303	0.0299
	(0.1370)	(0.1515)	(0.1713)	(0.1702)
Private practice	0.2645	0.2970	0.3083	0.2577
	(0.4411)	(0.4569)	(0.4618)	(0.4374)

Shares of individuals using the respective health facility in the respective year; shares account for sampling weights; standard deviation in parentheses; every other year is displayed for convenience.

Figure A 2.4 Share of individuals using inpatient care during the past year by district

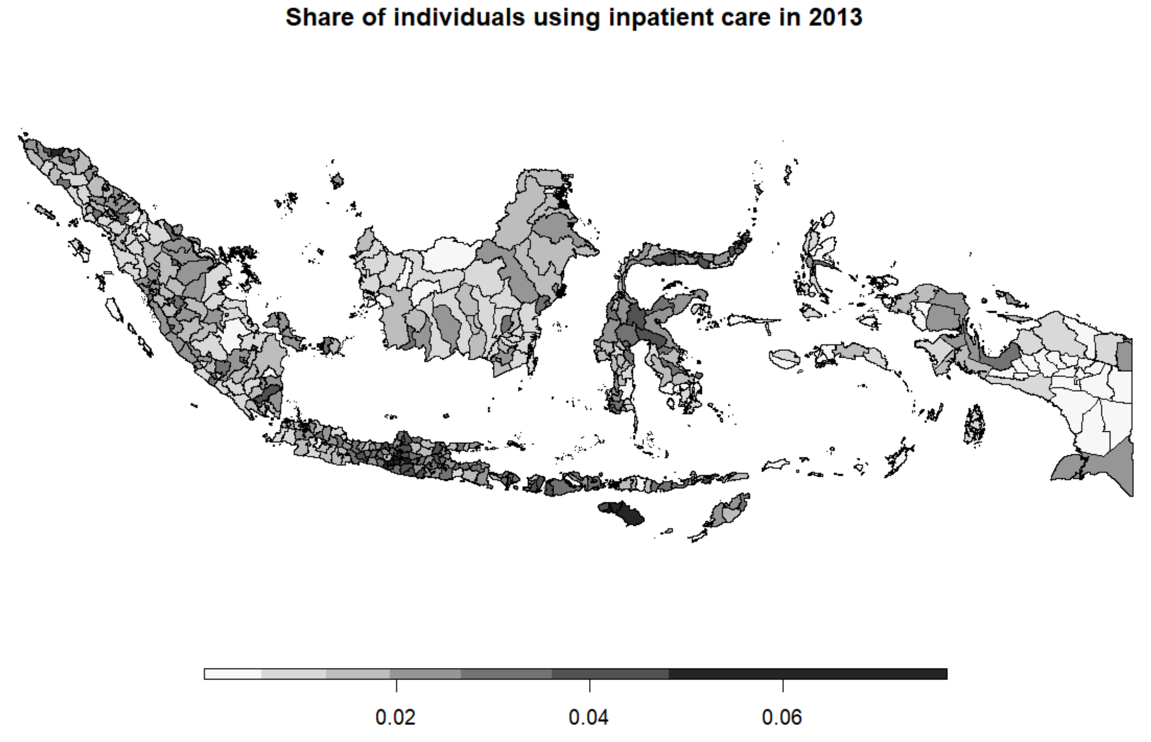


Figure A 2.5 Difference between 2017 and 2013 share of individuals using inpatient care during the past year per district (post-reform change)

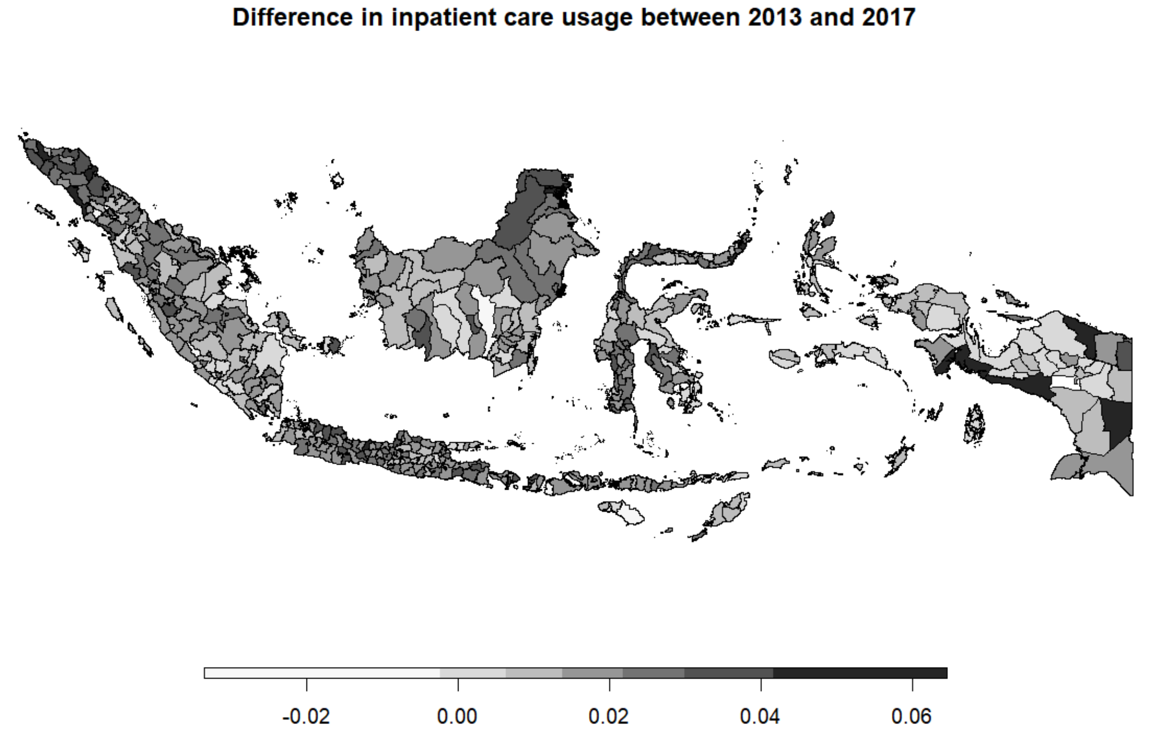


Figure A 2.6 Share of sick individuals using outpatient care during the past month by district

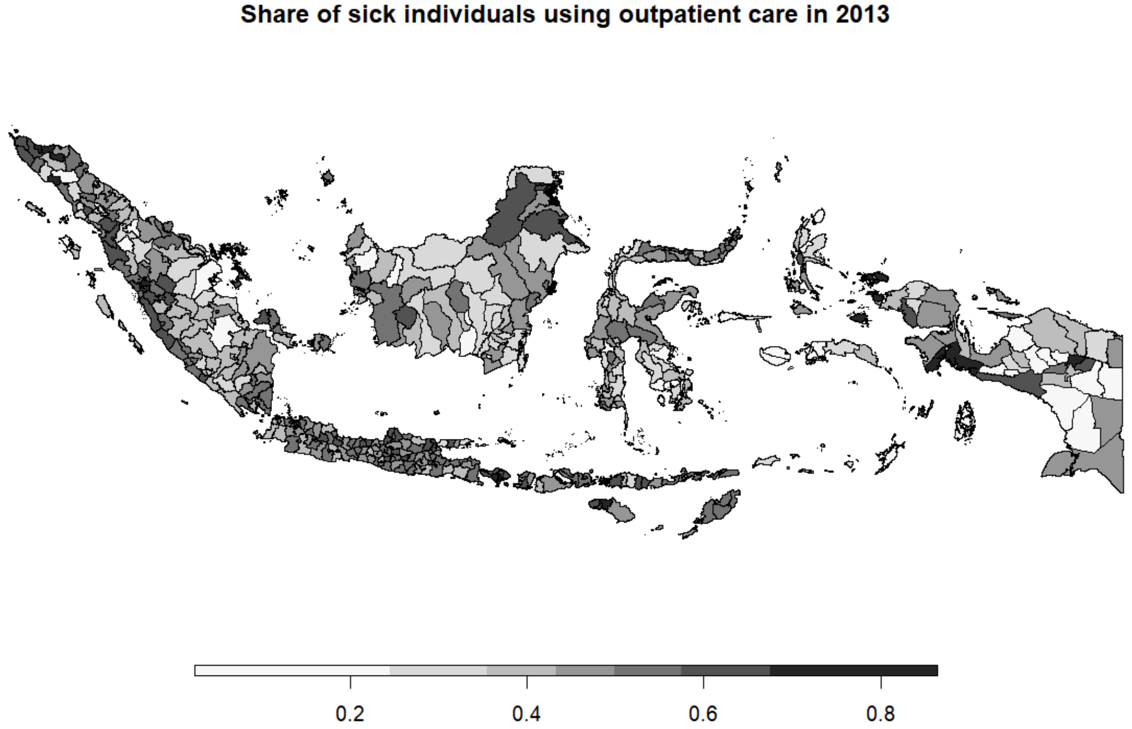


Figure A 2.7 Difference between 2017 and 2013 share of sick individuals using outpatient care during the past month per district (post-reform change)

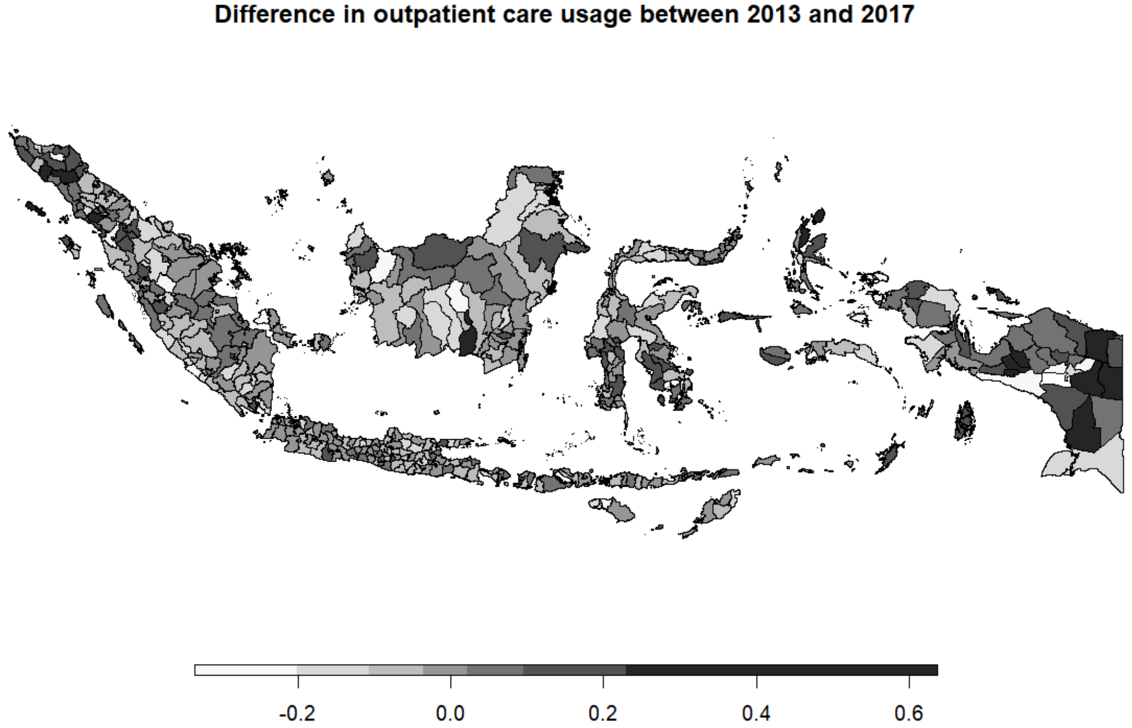


Table A 2.7 Quarterly health expenditure in IDR across years

	2013	2014	2015	2016
Total	237,031	239,306	187,202	198,841
	(1,607,873)	(1,559,447)	(939,641)	(951,688)
Treatment	165,637	166,976	139,195	141,263
	(1,495,171)	(1,452,433)	(863,899)	(838,023)
Public treatment	54,527	53,944	47,000	52,257
	(797,227)	(810,300)	(431,914)	(459,754)
Private treatment	111,110	113,032	92,195	89,006
	(1,253,515)	(1,192,907)	(721,238)	(677,013)
Medication	25,962	26,150	13,648	21,655
	(207,306)	(238,575)	(112,783)	(133,133)
Prevention	28,069	28,452	19,749	20,041
	(114,280)	(109,201)	(87,545)	(80,371)
Share of total health in household expenditure	0.019	0.019		
	0.008	0.008		
Share of households with catastrophic health expenditure (>15%)	0.022	0.023		
	0.015	0.015		

Means of quarterly household health expenditure; means account for sampling weights; deflated to 2010 prices using the IMF CPI; standard deviation in parentheses; total is the sum of all expenditure categories; treatment is the sum of treatment in private and public health facilities; the remaining categories are aggregated from 16 more detailed health expenditure categories.

Figure A 2.8 Mean quarterly household health expenditure in 2013 by district in thousand IDR

Mean quarterly household health expenditure in 2013

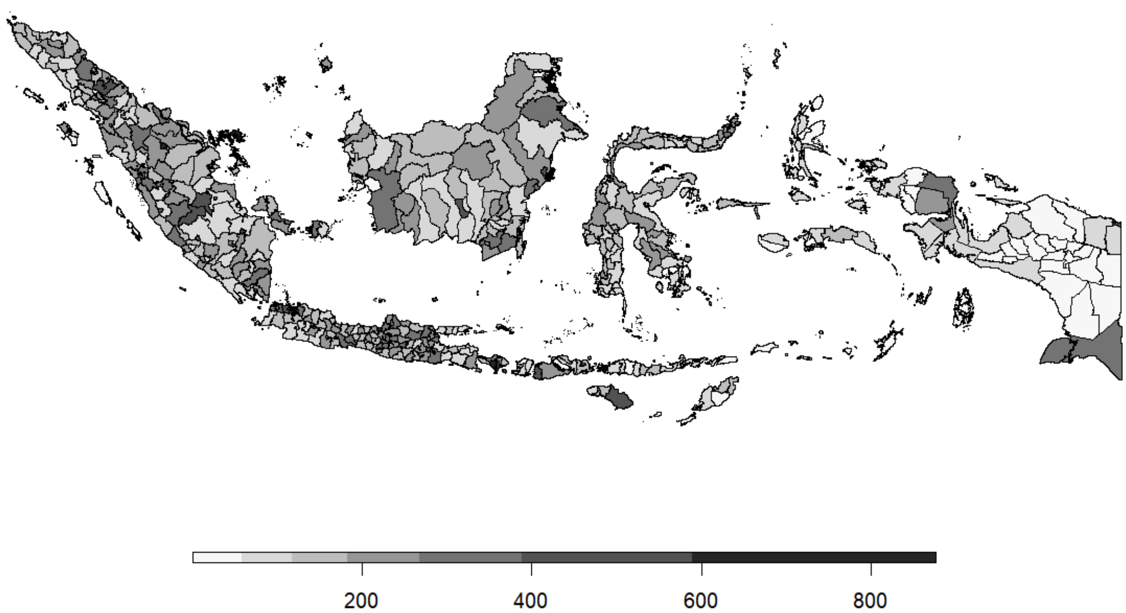


Figure A 2.9 Difference between 2017 and 2013 Mean quarterly household health expenditure per district in thousand IDR (post-reform change)

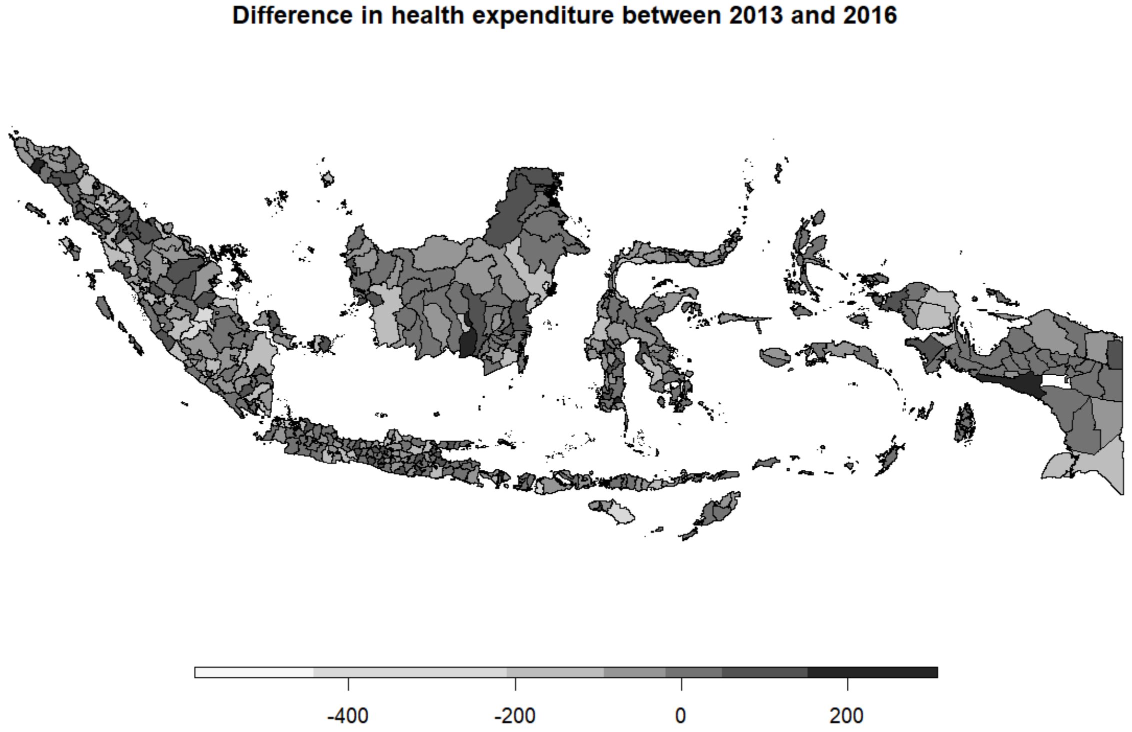


Table A 2.8 District-level estimation: disaggregated inpatient care usage proportions

	Total Inpatient	Public	Public Hospital	Puskesmas	Private	Private Hospital	Private Practice
Insurance coverage	-0.000663	-0.00351**	-0.00245	-0.000836	0.00305**	0.00159	0.00150***
	(0.0024)	(0.0018)	(0.0015)	(0.0008)	(0.0013)	(0.0012)	(0.0006)
2014	0.000228	-0.000259	-0.000124	-0.0000865	0.000513	0.000561	-0.0000334
	(0.0008)	(0.0006)	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0002)
2015	0.00864***	0.00364***	0.00270***	0.000906*	0.00533***	0.00330***	0.00193***
	(0.0013)	(0.0011)	(0.0009)	(0.0005)	(0.0007)	(0.0006)	(0.0003)
2016	0.00956***	0.00434***	0.00268**	0.00159***	0.00558***	0.00344***	0.00214***
	(0.0016)	(0.0013)	(0.0012)	(0.0006)	(0.0009)	(0.0008)	(0.0004)
2017	0.0123***	0.00472***	0.00309**	0.00171**	0.00797***	0.00522***	0.00270***
	(0.0020)	(0.0015)	(0.0014)	(0.0007)	(0.0012)	(0.0010)	(0.0005)
Coverage x 2014	0.00263*	0.00178	0.00135	0.000268	0.000990	0.000937	-0.0000121
	(0.0014)	(0.0012)	(0.0011)	(0.0006)	(0.0008)	(0.0007)	(0.0004)
Coverage x 2015	0.00554**	0.00637***	0.00563***	0.000571	-0.00109	0.000393	-0.00155***
	(0.0024)	(0.0019)	(0.0017)	(0.0008)	(0.0012)	(0.0010)	(0.0006)
Coverage x 2016	0.00480*	0.00647***	0.00637***	0.0000959	-0.00192	-0.000185	-0.00176***
	(0.0026)	(0.0022)	(0.0020)	(0.0010)	(0.0013)	(0.0012)	(0.0006)
Coverage x 2017	0.00515*	0.00807***	0.00790***	0.0000413	-0.00286*	-0.000507	-0.00236***
	(0.0030)	(0.0024)	(0.0021)	(0.0010)	(0.0016)	(0.0014)	(0.0007)
ymean	0.0302	0.0200	0.0159	0.00434	0.0105	0.00813	0.00236
r2	0.596	0.484	0.442	0.155	0.388	0.318	0.168
N	2484	2484	2484	2484	2484	2484	2484

*Estimation of equation 1 in SUSENAS 2013-17 with base year 2013; district clustered standard errors in parentheses; control variables: number of Puskesmas, urban fraction, district average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01*

Table A 2.9 District-level pre-trends: disaggregated inpatient care usage proportions

	Total Inpatient	Public	Public Hospital	Puskesmas	Private	Private Hospital	Private Practice
Insurance coverage	0.00236	0.000733	0.00135	-0.000753	0.00170	0.000346	0.00145***
	(0.0019)	(0.0016)	(0.0014)	(0.0007)	(0.0011)	(0.0009)	(0.0005)
2012	-0.00170**	-0.00102*	-0.000310	-0.000684**	-0.000651	-0.000643*	0.0000368
	(0.0008)	(0.0006)	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0002)
2013	0.00135	-0.0000615	0.000249	-0.000456	0.00148**	0.000751	0.000732***
	(0.0010)	(0.0008)	(0.0006)	(0.0003)	(0.0006)	(0.0005)	(0.0002)
Coverage x 2012	-0.000107	0.000134	-0.000728	0.000821	-0.000327	-0.0000283	-0.000333
	(0.0016)	(0.0013)	(0.0011)	(0.0006)	(0.0009)	(0.0008)	(0.0003)
Coverage x 2013	0.0000299	0.00186	0.00106	0.00120*	-0.00194*	-0.000812	-0.00107**
	(0.0018)	(0.0015)	(0.0013)	(0.0006)	(0.0011)	(0.0009)	(0.0004)
ymean	0.0191	0.0126	0.0100	0.00282	0.00665	0.00523	0.00139
r2	0.185	0.111	0.0979	0.0404	0.140	0.129	0.0563
N	1491	1491	1491	1491	1491	1491	1491

*Estimation of equation 1 in SUSENAS 2011-13 with base year 2011; district clustered standard errors in parentheses; control variables: urban fraction, district average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

Table A 2.10 p-values of the pairwise test for equality of the yearly insurance coverage interaction coefficients on inpatient care outcomes

	Coverage x 2013	Coverage x 2014	Coverage x 2015	Coverage x 2016	Coverage x 2017
Total					
Coverage x 2012	0.9259	0.1458	0.0306	0.0855	0.1117
Coverage x 2013		0.2415	0.0620	0.1332	0.1498
Coverage x 2014			0.1567	0.3708	0.3813
Coverage x 2015				0.6844	0.7674
Coverage x 2016					0.9391
Public					
Coverage x 2012	0.1701	0.1585	0.0010	0.0057	0.0021
Coverage x 2013		0.7721	0.0322	0.0674	0.0249
Coverage x 2014			0.0056	0.0269	0.0070
Coverage x 2015				0.9371	0.5532
Coverage x 2016					0.5458
Public hospital					
Coverage x 2012	0.1050	0.0805	0.0005	0.0013	0.0002
Coverage x 2013		0.6664	0.0225	0.0272	0.0060
Coverage x 2014			0.0028	0.0080	0.0013
Coverage x 2015				0.7230	0.2755
Coverage x 2016					0.5188
Puskesmas					
Coverage x 2012	0.4820	0.6332	0.9311	0.6528	0.5955
Coverage x 2013		0.3956	0.7778	0.4778	0.4324
Coverage x 2014			0.6562	0.8958	0.7780
Coverage x 2015				0.5536	0.4930
Coverage x 2016					0.8801
Private					
Coverage x 2012	0.0427	0.4233	0.4373	0.2271	0.1424
Coverage x 2013		0.0903	0.8314	0.8518	0.5758
Coverage x 2014			0.0427	0.0160	0.0109
Coverage x 2015				0.5197	0.2316
Private hospital					
Coverage x 2012	0.2340	0.5347	0.9688	0.7208	0.6672
Coverage x 2013		0.2557	0.6333	0.8647	0.9633
Coverage x 2014			0.4691	0.3072	0.2945
Coverage x 2015				0.6383	0.5331
Coverage x 2016					0.8567
Private practice					
Coverage x 2012	0.0845	0.5089	0.0495	0.0201	0.0081
Coverage x 2013		0.1339	0.5508	0.3907	0.1673
Coverage x 2014			0.0011	0.0003	0.0005
Coverage x 2015				0.6720	0.2381
Coverage x 2016					0.3445

p-values of pairwise post-estimation test of the respective coverage and year interaction coefficients from estimating equation 1 in SUSENAS 2011-2013 with base year 2011 and SUSENAS 2013-2017 with base year 2013 as displayed in Table A 2.8 and Table A 2.9.

Table A 2.11 Robustness check 1: Main inpatient care outcomes with different sets of district control variables

	No controls	Main specification	Main + sick proportion	Main + district size	Main with wealth quintiles
Total					
Coverage x	0.00299**	0.00263*	0.00283**	0.00263*	0.00306**
2014	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0015)
Coverage x	0.00534**	0.00554**	0.00628***	0.00553**	0.00516**
2015	(0.0024)	(0.0024)	(0.0022)	(0.0024)	(0.0024)
Coverage x	0.00532**	0.00480*	0.00686***	0.00478*	0.00530**
2016	(0.0026)	(0.0026)	(0.0024)	(0.0026)	(0.0026)
Coverage x	0.00556*	0.00515*	0.00832***	0.00513*	0.00578*
2017	(0.0030)	(0.0030)	(0.0028)	(0.0030)	(0.0030)
Public					
Coverage x	0.00235**	0.00178	0.00190*	0.00176	0.00196
2014	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0012)
Coverage x	0.00712***	0.00637***	0.00684***	0.00629***	0.00607***
2015	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Coverage x	0.00710***	0.00647***	0.00778***	0.00626***	0.00636***
2016	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Coverage x	0.00880***	0.00807***	0.0101***	0.00787***	0.00839***
2017	(0.0024)	(0.0024)	(0.0023)	(0.0024)	(0.0024)
Public hospital					
Coverage x	0.00182*	0.00135	0.00146	0.00134	0.00154
2014	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0011)
Coverage x	0.00606***	0.00563***	0.00602***	0.00557***	0.00521***
2015	(0.0016)	(0.0017)	(0.0016)	(0.0017)	(0.0017)
Coverage x	0.00694***	0.00637***	0.00745***	0.00622***	0.00626***
2016	(0.0020)	(0.0020)	(0.0019)	(0.0020)	(0.0020)
Coverage x	0.00845***	0.00790***	0.00956***	0.00776***	0.00811***
2017	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0022)
Puskesmas					
Coverage x	0.000409	0.000268	0.000293	0.000264	0.000278
2014	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Coverage x	0.000929	0.000571	0.000663	0.000548	0.000668
2015	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Coverage x	0.000182	0.0000959	0.000349	0.0000329	0.0000670
2016	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Coverage x	0.000274	0.0000413	0.000429	-0.0000214	0.000175
2017	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Private					
Coverage x	0.000729	0.000990	0.00107	0.00100	0.00124
2014	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Coverage x	-0.00211*	-0.00109	-0.000798	-0.00102	-0.00117
2015	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Coverage x	-0.00208	-0.00192	-0.00113	-0.00175	-0.00135
2016	(0.0013)	(0.0013)	(0.0012)	(0.0013)	(0.0013)
Coverage x	-0.00320*	-0.00286*	-0.00163	-0.00268*	-0.00254
2017	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)
Private hospital					
Coverage x	0.000682	0.000937	0.00101	0.000947	0.00122*
2014	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Coverage x	-0.000532	0.000393	0.000653	0.000447	0.000296
2015	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0011)

Coverage x 2016	-0.000310	-0.000185	0.000536	-0.0000398	0.000318
	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0012)
Coverage x 2017	-0.000829	-0.000507	0.000599	-0.000363	-0.000217
	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0014)
Private practice					
Coverage x 2014	-0.0000268	-0.0000121	-0.00000389	-0.0000101	-0.0000560
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Coverage x 2015	-0.00164***	-0.00155***	-0.00152***	-0.00154***	-0.00155***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Coverage x 2016	-0.00179***	-0.00176***	-0.00168***	-0.00173***	-0.00172***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Coverage x 2017	-0.00239***	-0.00236***	-0.00223***	-0.00233***	-0.00234***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)

Estimation results of interaction coefficients β_t from equation 1 with different sets of district- and time- specific control variables (vector C); main specification is equivalent to the tables above: urban fraction, average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; alternative specifications either add the proportion of individuals reporting an illness during the previous month or district size measured by the number of respondents per district, replace all wealth measures with shares of households in each national wealth quintile, or add no control variables; district clustered standard errors in parentheses; accounting for sampling weights.

Table A 2.12 Robustness check 2: Inpatient care outcomes with different reference periods

	Reference year: 2013	Reference year: 2011	Reference year: 2012	Pooled pre vs. pooled post
Total				
Coverage x 2012		-0.0000312		
		(0.0018)		
Coverage x 2013		0.00393*	0.00393*	
		(0.0023)	(0.0023)	
Coverage x 2014	0.00263*	0.00259	0.00245	
	(0.0014)	(0.0021)	(0.0018)	
Coverage x 2015	0.00554**	0.00545**	0.00546**	
	(0.0024)	(0.0026)	(0.0024)	
Coverage x 2016	0.00480*	0.00403	0.00425	
	(0.0026)	(0.0028)	(0.0026)	
Coverage x 2017	0.00515*	0.00471	0.00501	
	(0.0030)	(0.0033)	(0.0031)	
Coverage x post				0.00393*
				(0.0023)
Public				
Coverage x 2012		0.000417		
		(0.0013)		
Coverage x 2013		0.00161	0.000886	
		(0.0016)	(0.0013)	
Coverage x 2014	0.00178	0.00423**	0.00346**	
	(0.0012)	(0.0018)	(0.0015)	
Coverage x 2015	0.00637***	0.00887***	0.00826***	
	(0.0019)	(0.0023)	(0.0020)	
Coverage x 2016	0.00647***	0.00822***	0.00782***	
	(0.0022)	(0.0024)	(0.0022)	
Coverage x 2017	0.00807***	0.00970***	0.00931***	
	(0.0024)	(0.0027)	(0.0025)	
Coverage x post				0.00617***
				(0.0019)
Public hospital				
Coverage x 2012		-0.000545		
		(0.0011)		
Coverage x 2013		0.000807	0.00110	
		(0.0014)	(0.0011)	
Coverage x 2014	0.00135	0.00287**	0.00312**	
	(0.0011)	(0.0014)	(0.0012)	
Coverage x 2015	0.00563***	0.00737***	0.00761***	
	(0.0017)	(0.0019)	(0.0018)	
Coverage x 2016	0.00637***	0.00765***	0.00803***	
	(0.0020)	(0.0020)	(0.0020)	
Coverage x 2017	0.00790***	0.00894***	0.00945***	
	(0.0021)	(0.0024)	(0.0023)	
Coverage x post				0.00599***
				(0.0016)
Puskesmas				
Coverage x 2012		0.000942		
		(0.0006)		
Coverage x 2013		0.00115*	0.000148	
		(0.0007)	(0.0006)	
Coverage x 2014	0.000268	0.00160*	0.000591	
	(0.0006)	(0.0009)	(0.0007)	

Coverage x 2015	0.000571	0.00172*	0.000877	
	(0.0008)	(0.0010)	(0.0008)	
Coverage x 2016	0.0000959	0.000951	0.000178	
	(0.0010)	(0.0012)	(0.0009)	
Coverage x 2017	0.0000413	0.00101	0.000117	
	(0.0010)	(0.0011)	(0.0010)	
Coverage x post				0.000191
				(0.0009)
Private				
Coverage x 2012		-0.000541		
		(0.0010)		
Coverage x 2013		-0.00213*	-0.00149	
		(0.0011)	(0.0009)	
Coverage x 2014	0.000990	-0.00168	-0.000958	
	(0.0008)	(0.0011)	(0.0010)	
Coverage x 2015	-0.00109	-0.00384***	-0.00312**	
	(0.0012)	(0.0013)	(0.0013)	
Coverage x 2016	-0.00192	-0.00463***	-0.00389***	
	(0.0013)	(0.0016)	(0.0015)	
Coverage x 2017	-0.00286*	-0.00510***	-0.00431**	
	(0.0016)	(0.0018)	(0.0017)	
Coverage x post				-0.00246**
				(0.0011)
Private hospital				
Coverage x 2012		-0.000157		
		(0.0008)		
Coverage x 2013		-0.000914	-0.000688	
		(0.0010)	(0.0008)	
Coverage x 2014	0.000937	-0.000386	-0.000136	
	(0.0007)	(0.0011)	(0.0009)	
Coverage x 2015	0.000393	-0.00106	-0.000800	
	(0.0010)	(0.0012)	(0.0011)	
Coverage x 2016	-0.000185	-0.00161	-0.00132	
	(0.0012)	(0.0015)	(0.0013)	
Coverage x 2017	-0.000507	-0.00155	-0.00123	
	(0.0014)	(0.0016)	(0.0015)	
Coverage x post				-0.000633
				(0.0010)
Private practice				
Coverage x 2012		-0.000416		
		(0.0003)		
Coverage x 2013		-0.00119***	-0.000742*	
		(0.0005)	(0.0004)	
Coverage x 2014	-0.0000121	-0.00133***	-0.000837**	
	(0.0004)	(0.0004)	(0.0004)	
Coverage x 2015	-0.00155***	-0.00282***	-0.00235***	
	(0.0006)	(0.0005)	(0.0005)	
Coverage x 2016	-0.00176***	-0.00301***	-0.00255***	
	(0.0006)	(0.0006)	(0.0005)	
Coverage x 2017	-0.00236***	-0.00355***	-0.00305***	
	(0.0007)	(0.0007)	(0.0007)	
Coverage x post				-0.00181***
				(0.0005)

Estimation results of interaction coefficients β_t from equation 1 with differing reference years (and samples) using the main specification of covariates and accounting for sampling weights; district clustered standard errors in parentheses; reference year: 2013 is the main specification in SUSENAS 2013-2017 as displayed in Table A 2.8; reference year: 2011 is estimated *in SUSENAS 2011-2017 with reference year 2011; reference year: 2012 is estimated in SUSENAS 2012-2017 with reference year 2012; the last column displays the result of replacing the categorical year variable with a post-policy indicator variable in SUSENAS 2011-2017 (0=year 2011-2013, 1=2014-2017).*

Table A 2.13 District-level estimation: disaggregated outpatient care usage proportions

	Total Outpatient	Public	Public Hospital	Puskesmas	Private	Private Hospital	Private Practice
Insurance	0.0692**	0.0881***	-0.00372	0.0890***	-0.0200	-0.00632*	-0.0184
coverage	(0.0311)	(0.0284)	(0.0108)	(0.0245)	(0.0151)	(0.0033)	(0.0147)
2014	-0.0130	-0.0250***	-0.00624*	-0.0215***	0.00964	-0.00136	0.0101
	(0.0099)	(0.0082)	(0.0035)	(0.0080)	(0.0070)	(0.0020)	(0.0068)
2015	0.0829***	0.0327*	0.00518	0.0265*	0.00595	0.00487**	-0.00513
	(0.0198)	(0.0172)	(0.0072)	(0.0151)	(0.0116)	(0.0023)	(0.0110)
2016	0.0856***	0.0296*	0.00798	0.0165	0.0227*	0.00754**	0.00969
	(0.0193)	(0.0166)	(0.0088)	(0.0140)	(0.0127)	(0.0037)	(0.0118)
2017	-0.0472**	0.0229	0.00201	0.0177	-0.0695***	0.000211	-0.0728***
	(0.0219)	(0.0178)	(0.0065)	(0.0161)	(0.0136)	(0.0029)	(0.0132)
Coverage	0.0222	0.0250*	0.00947	0.0193	0.00102	0.00267	-0.000560
x 2014	(0.0170)	(0.0141)	(0.0067)	(0.0136)	(0.0119)	(0.0031)	(0.0116)
Coverage	-0.0201	-0.00321	0.0158	-0.0203	0.0105	-0.000339	0.0133
x 2015	(0.0299)	(0.0260)	(0.0106)	(0.0231)	(0.0175)	(0.0035)	(0.0167)
Coverage	-0.0287	-0.00128	0.0185	-0.0130	-0.00827	0.00190	-0.00536
x 2016	(0.0298)	(0.0257)	(0.0123)	(0.0221)	(0.0186)	(0.0050)	(0.0173)
Coverage	0.0262	-0.0235	0.00927	-0.0292	0.0510***	0.00635*	0.0456**
x 2017	(0.0305)	(0.0257)	(0.0105)	(0.0234)	(0.0184)	(0.0037)	(0.0180)
ymean	0.498	0.239	0.0437	0.201	0.262	0.0194	0.237
r2	0.331	0.182	0.135	0.116	0.149	0.0753	0.153
N	2484	2484	2484	2484	2484	2484	2484

*Estimation of equation 1 in SUSENAS 2013-17 (subsample that reported illness during previous month) with base year 2013; district clustered standard errors in parentheses; control variables: number of Puskesmas, urban fraction, district average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

Table A 2.14 District-level pre-trends: disaggregated outpatient care usage proportions

	Total Outpatient	Public	Public Hospital	Puskesmas	Private	Private Hospital	Private Practice
Insurance	0.0400	0.00607	0.0000631	0.00486	0.0393**	0.00119	0.0393**
coverage	(0.0347)	(0.0341)	(0.0108)	(0.0336)	(0.0172)	(0.0043)	(0.0167)
2012	0.00245	-0.0161**	0.00203	-0.0163**	0.0209***	0.00201	0.0194***
	(0.0101)	(0.0075)	(0.0023)	(0.0076)	(0.0071)	(0.0016)	(0.0069)
2013	0.0231*	-0.00876	0.00309	-0.00986	0.0371***	0.00527***	0.0336***
	(0.0122)	(0.0100)	(0.0032)	(0.0101)	(0.0087)	(0.0020)	(0.0085)
Coverage	-0.00594	0.0237	-0.00159	0.0235	-0.0347***	-0.00177	-0.0325**
x 2012	(0.0200)	(0.0154)	(0.0053)	(0.0155)	(0.0131)	(0.0028)	(0.0127)
Coverage	0.0103	0.0325*	0.00483	0.0275	-0.0296*	-0.00437	-0.0268*
x 2013	(0.0221)	(0.0185)	(0.0063)	(0.0190)	(0.0152)	(0.0033)	(0.0150)
ymean	0.443	0.213	0.0320	0.186	0.241	0.0152	0.223
r2	0.146	0.0560	0.0638	0.0461	0.146	0.0502	0.134
N	1491	1491	1491	1491	1491	1491	1491

*Estimation of equation 1 in SUSENAS 2011-13 (subsample that reported illness during previous month with base year 2011; district clustered standard errors in parentheses; control variables: urban fraction, district average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

Table A 2.15 p-values of the pairwise test for equality of the yearly insurance coverage interaction coefficients on outpatient care outcomes

	Coverage x 2013	Coverage x 2014	Coverage x 2015	Coverage x 2016	Coverage x 2017
Total					
Coverage x 2012	0.3724	0.2515	0.7314	0.5708	0.4155
Coverage x 2013		0.6629	0.4884	0.3708	0.7114
Coverage x 2014			0.1828	0.1033	0.8979
Coverage x 2015				0.7101	0.0929
Coverage x 2016					0.0217
Public					
Coverage x 2012	0.5893	0.9753	0.3432	0.3884	0.1290
Coverage x 2013		0.7013	0.2835	0.3164	0.1092
Coverage x 2014			0.2897	0.3163	0.0554
Coverage x 2015				0.8972	0.4355
Coverage x 2016					0.3037
Public hospital					
Coverage x 2012	0.3183	0.0975	0.1137	0.1067	0.3342
Coverage x 2013		0.6267	0.4004	0.3379	0.7407
Coverage x 2014			0.5880	0.4736	0.9821
Coverage x 2015				0.7904	0.5489
Coverage x 2016					0.4711
Puskesmas					
Coverage x 2012	0.8133	0.7558	0.1027	0.1704	0.0751
Coverage x 2013		0.6884	0.1362	0.2071	0.0977
Coverage x 2014			0.1029	0.1757	0.0446
Coverage x 2015				0.6666	0.7308
Coverage x 2016					0.4117
private					
Coverage x 2012	0.6780	0.0314	0.0383	0.2401	0.0004
Coverage x 2013		0.1317	0.1152	0.4021	0.0040

Coverage x 2014			0.4971	0.6083	0.0033
Coverage x 2015				0.1843	0.0112
Coverage x 2016					0.0001
Private hospital					
Coverage x 2012	0.4078	0.3730	0.9336	0.6296	0.1099
Coverage x 2013		0.2493	0.6119	0.4196	0.0805
Coverage x 2014			0.2630	0.8613	0.2540
Coverage x 2015				0.5294	0.0209
Coverage x 2016					0.2666
Private practice					
Coverage x 2012	0.6359	0.0452	0.0281	0.1924	0.0008
Coverage x 2013		0.1793	0.0992	0.3623	0.0072
Coverage x 2014			0.3056	0.7821	0.0058
Coverage x 2015				0.1663	0.0433
Coverage x 2016					0.0006

p-values of pairwise post-estimation test of the respective coverage and year interaction coefficients from estimating equation 1 in SUSENAS 2011-2013 with base year 2011 and SUSENAS 2013-2017 with base year 2013 as displayed in Table A 2.13 and Table A 2.14.

Table A 2.16 Robustness check 1: Outpatient care outcomes with different sets of control variables

	No controls	Main specification	Main + sick proportion	Main + district size	Main with wealth quintiles
Total					
Coverage x	0.0214	0.0222	0.0208	0.0221	0.0206
2014	(0.0167)	(0.0170)	(0.0171)	(0.0170)	(0.0170)
Coverage x	-0.0178	-0.0201	-0.0252	-0.0205	-0.0213
2015	(0.0297)	(0.0299)	(0.0290)	(0.0299)	(0.0299)
Coverage x	-0.0316	-0.0287	-0.0430	-0.0299	-0.0351
2016	(0.0302)	(0.0298)	(0.0293)	(0.0298)	(0.0305)
Coverage x	0.0297	0.0262	0.00437	0.0250	0.0307
2017	(0.0307)	(0.0305)	(0.0296)	(0.0305)	(0.0306)
Public					
Coverage x	0.0218	0.0250^{*}	0.0238^{*}	0.0249^{*}	0.0247^{*}
2014	(0.0142)	(0.0141)	(0.0142)	(0.0141)	(0.0140)
Coverage x	-0.00187	-0.00321	-0.00748	-0.00371	0.000528
2015	(0.0262)	(0.0260)	(0.0252)	(0.0260)	(0.0262)
Coverage x	-0.00602	-0.00128	-0.0131	-0.00260	-0.00626
2016	(0.0271)	(0.0257)	(0.0249)	(0.0258)	(0.0273)
Coverage x	-0.0261	-0.0235	-0.0416^{*}	-0.0248	-0.0226
2017	(0.0259)	(0.0257)	(0.0249)	(0.0256)	(0.0258)
Public hospital					
Coverage x	0.00907	0.00947	0.00908	0.00945	0.0101
2014	(0.0068)	(0.0067)	(0.0067)	(0.0067)	(0.0068)
Coverage x	0.0159	0.0158	0.0144	0.0157	0.0149
2015	(0.0104)	(0.0106)	(0.0105)	(0.0106)	(0.0107)
Coverage x	0.0178	0.0185	0.0145	0.0182	0.0166
2016	(0.0122)	(0.0123)	(0.0123)	(0.0122)	(0.0124)
Coverage x	0.00976	0.00927	0.00308	0.00895	0.00883
2017	(0.0106)	(0.0105)	(0.0106)	(0.0105)	(0.0107)
Puskesmas					
Coverage x	0.0167	0.0193	0.0185	0.0192	0.0186
2014	(0.0134)	(0.0136)	(0.0138)	(0.0136)	(0.0132)
Coverage x	-0.0182	-0.0203	-0.0234	-0.0207	-0.0154
2015	(0.0234)	(0.0231)	(0.0226)	(0.0231)	(0.0233)
Coverage x	-0.0166	-0.0130	-0.0215	-0.0141	-0.0162
2016	(0.0233)	(0.0221)	(0.0215)	(0.0221)	(0.0237)
Coverage x	-0.0322	-0.0292	-0.0423^{*}	-0.0303	-0.0280
2017	(0.0233)	(0.0234)	(0.0232)	(0.0233)	(0.0233)
Private					
Coverage x	0.00247	0.00102	0.000743	0.00103	0.000406
2014	(0.0116)	(0.0119)	(0.0119)	(0.0119)	(0.0120)
Coverage x	0.0120	0.0105	0.00952	0.0106	0.00678
2015	(0.0173)	(0.0175)	(0.0175)	(0.0175)	(0.0175)
Coverage x	-0.00682	-0.00827	-0.0111	-0.00804	-0.00923
2016	(0.0184)	(0.0186)	(0.0188)	(0.0186)	(0.0184)
Coverage x	0.0565^{***}	0.0510^{***}	0.0467^{**}	0.0513^{***}	0.0554^{***}
2017	(0.0184)	(0.0184)	(0.0185)	(0.0185)	(0.0184)
Private hospital					
Coverage x	0.00224	0.00267	0.00261	0.00269	0.00301
2014	(0.0030)	(0.0031)	(0.0030)	(0.0031)	(0.0031)
Coverage x	-0.00113	-0.000339	-0.000557	-0.000187	-0.000249
2015	(0.0034)	(0.0035)	(0.0035)	(0.0035)	(0.0035)

Coverage x 2016	0.00142	0.00190	0.00130	0.00231	0.00175
	(0.0051)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Coverage x 2017	0.00560	0.00635*	0.00543	0.00676*	0.00617*
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0037)
Private practice					
Coverage x 2014	0.000764	-0.000560	-0.000775	-0.000573	-0.00122
	(0.0112)	(0.0116)	(0.0116)	(0.0116)	(0.0117)
Coverage x 2015	0.0153	0.0133	0.0125	0.0132	0.00949
	(0.0164)	(0.0167)	(0.0167)	(0.0167)	(0.0166)
Coverage x 2016	-0.00384	-0.00536	-0.00757	-0.00555	-0.00621
	(0.0172)	(0.0173)	(0.0175)	(0.0173)	(0.0172)
Coverage x 2017	0.0514***	0.0456**	0.0422**	0.0454**	0.0501***
	(0.0179)	(0.0180)	(0.0181)	(0.0180)	(0.0180)

Estimation results of interaction coefficients β_t from equation 1 with different sets of district- and time- specific control variables (vector C); main specification is equivalent to the tables above: urban fraction, average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; alternative specifications either add the proportion of individuals reporting an illness during the previous month or district size measured by the number of respondents per district, replace all wealth measures with shares of households in each national wealth quintile, or add no control variables; district clustered standard errors in parentheses; accounting for sampling weights.

Table A 2.17 Robustness check 2: Outpatient care outcomes with different reference periods

	Reference year: 2013	Reference year: 2011	Reference year: 2012	Pooled pre vs. pooled post
Total				
Coverage x 2012		-0.0122		
		(0.0202)		
Coverage x 2013		-0.00115	0.0115	
		(0.0231)	(0.0205)	
Coverage x 2014	0.0222	0.0239	0.0361	
	(0.0170)	(0.0268)	(0.0237)	
Coverage x 2015	-0.0201	-0.0150	-0.00109	
	(0.0299)	(0.0290)	(0.0297)	
Coverage x 2016	-0.0287	-0.0246	-0.0100	
	(0.0298)	(0.0288)	(0.0311)	
Coverage x 2017	0.0262	0.0266	0.0406	
	(0.0305)	(0.0274)	(0.0298)	
Coverage x post				-0.0337
				(0.0288))
Public				
Coverage x 2012		0.0181		
		(0.0165)		
Coverage x 2013		0.0211	0.00538	
		(0.0204)	(0.0190)	
Coverage x 2014	0.0250*	0.0489**	0.0313	
	(0.0141)	(0.0228)	(0.0206)	
Coverage x 2015	-0.00321	0.0262	0.00691	
	(0.0260)	(0.0261)	(0.0247)	
Coverage x 2016	-0.00128	0.0266	0.00933	
	(0.0257)	(0.0267)	(0.0266)	
Coverage x 2017	-0.0235	0.00577	-0.0141	
	(0.0257)	(0.0245)	(0.0249)	
Coverage x post				-0.0216
				(0.0243)
Public hospital				
Coverage x 2012		-0.000258		
		(0.0056)		
Coverage x 2013		0.00112	0.000515	
		(0.0072)	(0.0080)	
Coverage x 2014	0.00947	0.0127	0.0118	
	(0.0067)	(0.0093)	(0.0089)	
Coverage x 2015	0.0158	0.0184*	0.0182*	
	(0.0106)	(0.0101)	(0.0093)	
Coverage x 2016	0.0185	0.0241*	0.0222*	
	(0.0123)	(0.0129)	(0.0124)	
Coverage x 2017	0.00927	0.0132	0.0120	
	(0.0105)	(0.0094)	(0.0083)	
Coverage x post				0.00943
				(0.0100)
Puskesmas				
Coverage x 2012		0.0169		
		(0.0164)		
Coverage x 2013		0.0182	0.00439	
		(0.0201)	(0.0180)	
Coverage x 2014	0.0193	0.0390*	0.0236	
	(0.0136)	(0.0229)	(0.0198)	

Coverage x 2015	-0.0203	0.00599	-0.0118	
	(0.0231)	(0.0248)	(0.0226)	
Coverage x 2016	-0.0130	0.00917	-0.00519	
	(0.0221)	(0.0233)	(0.0224)	
Coverage x 2017	-0.0292	-0.00483	-0.0223	
	(0.0234)	(0.0227)	(0.0238)	
Coverage x post				-0.0298
				(0.0217)
Private				
Coverage x 2012		-0.0333**		
		(0.0130)		
Coverage x 2013		-0.0303**	0.00217	
		(0.0151)	(0.0124)	
Coverage x 2014	0.00102	-0.0292*	0.00453	
	(0.0119)	(0.0159)	(0.0130)	
Coverage x 2015	0.0105	-0.0196	0.0166	
	(0.0175)	(0.0174)	(0.0171)	
Coverage x 2016	-0.00827	-0.0386**	-0.00326	
	(0.0186)	(0.0186)	(0.0183)	
Coverage x 2017	0.0510***	0.0160	0.0526***	
	(0.0184)	(0.0174)	(0.0178)	
Coverage x post				0.00707
				(0.0157)
Private hospital				
Coverage x 2012		-0.00149		
		(0.0027)		
Coverage x 2013		-0.00601*	-0.00485	
		(0.0035)	(0.0032)	
Coverage x 2014	0.00267	-0.00360	-0.00260	
	(0.0031)	(0.0029)	(0.0028)	
Coverage x 2015	-0.000339	-0.00693**	-0.00569*	
	(0.0035)	(0.0031)	(0.0030)	
Coverage x 2016	0.00190	-0.00451	-0.00356	
	(0.0050)	(0.0047)	(0.0048)	
Coverage x 2017	0.00635*	-0.000143	0.00102	
	(0.0037)	(0.0037)	(0.0036)	
Coverage x post				0.00117
				(0.0032)
Private practice				
Coverage x 2012		-0.0308**		
		(0.0125)		
Coverage x 2013		-0.0264*	0.00372	
		(0.0148)	(0.0121)	
Coverage x 2014	-0.000560	-0.0270*	0.00463	
	(0.0116)	(0.0154)	(0.0124)	
Coverage x 2015	0.0133	-0.0125	0.0212	
	(0.0167)	(0.0167)	(0.0164)	
Coverage x 2016	-0.00536	-0.0310*	0.00198	
	(0.0173)	(0.0181)	(0.0174)	
Coverage x 2017	0.0456**	0.0150	0.0493***	
	(0.0180)	(0.0173)	(0.0175)	
Coverage x post				0.00857
				(0.0148)

Estimation results of interaction coefficients β_t from equation 1 with differing reference years (and samples) using the main specification of covariates and accounting for sampling weights; district clustered standard errors in parentheses; reference year: 2013 is the main specification in SUSENAS 2013-2017 as displayed in Table A 2.13; reference year: 2011 is estimated *in SUSENAS 2011-2017 with reference year 2011; reference year: 2012 is estimated in SUSENAS 2012-2017 with reference year 2012; the last column displays the result of replacing the categorical year variable with a post-policy indicator variable in SUSENAS 2011-2017 (0=year 2011-2013, 1=2014-2017).*

Table A 2.18 District-level estimation: disaggregated health expenditure outcomes (in IDR)

	Total health expenditure	Treatment	Public treatment	Private treatment	Medication	Prevention
Insurance	10035.6	2675.7	11040.5	-8364.8	2506.8	569.7
coverage	(22841.0309)	(19012.8067)	(10496.3023)	(14130.4434)	(4234.7465)	(2688.4089)
2014	-1317.5	330.4	-601.9	932.3	-3826.2	-426.8
	(9972.1706)	(8849.4062)	(5349.8780)	(7077.1207)	(3792.2278)	(847.2268)
2015	-33879.8***	-19562.8*	-1579.0	-17983.8**	-10007.5***	-7064.6***
	(11700.7714)	(10163.3324)	(4977.0031)	(8427.9351)	(2232.3792)	(1213.6384)
2016	-34807.4**	-25731.9**	3946.8	-29678.6***	-1319.5	-11051.4***
	(14555.5208)	(12665.3975)	(6300.5251)	(10100.3605)	(2833.3535)	(1571.6002)
Coverage	1538.4	809.5	4695.1	-3885.6	8358.2	-2290.6
x 2014	(18278.4377)	(16487.9917)	(9977.8782)	(12452.8172)	(7827.3273)	(1532.6223)
Coverage	-38776.7**	-17215.9	-11594.6	-5621.2	-8238.1**	-2413.3
x 2015	(18534.7886)	(16479.8945)	(9020.3421)	(13605.4186)	(4036.3701)	(2247.9042)
Coverage	-44679.8**	-22134.6	-19468.7*	-2665.8	-11060.3**	881.5
x 2016	(22192.4975)	(20000.4249)	(10626.1041)	(16014.2519)	(4297.7851)	(2585.6530)
ymean	175274.5	122414.3	49310.5	73103.8	21287.1	18978.1
r2	0.253	0.139	0.0631	0.117	0.236	0.298
N	1987	1987	1987	1987	1987	1987

*Estimation of equation 1 in SUSENAS 2013-16 with base year 2013; district clustered standard errors in parentheses; control variables: number of Puskesmas, urban fraction, district average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

Table A 2.19 District-level pre-trends: disaggregated health expenditure outcomes (in IDR)

	Total health expenditure	Treatment	Public treatment	Private treatment	Medication	Prevention
Insurance	11684.2	9729.8	55.45	9674.3	-6958.1*	-654.2
coverage	(23054.2842)	(21205.4053)	(12093.9729)	(16456.5300)	(4126.0379)	(2550.7168)
2012	7864.3	11978.0	9172.4	2805.6	-2901.8*	-972.0
	(9819.5500)	(9053.3455)	(6211.3136)	(6753.5594)	(1721.5884)	(1453.3789)
2013	312.9	14703.7	-2819.2	17522.9**	-4511.9**	-617.7
	(11631.1102)	(10628.9139)	(6425.7322)	(8322.5629)	(2073.6429)	(1040.6291)
Coverage	-18387.4	-32475.6**	-9668.8	-22806.7*	10370.0***	1176.8
x 2012	(18072.2991)	(15864.6548)	(10621.6466)	(12889.8462)	(3522.4418)	(3817.5608)
Coverage	-2251.8	-17371.6	7627.6	-24999.1*	6326.1	1887.7
x 2013	(20771.2627)	(19025.1209)	(10787.8218)	(14808.6285)	(3986.9142)	(1917.6499)
ymean	181799.6	120638.6	48857.0	71781.6	25502.2	21167.4
r2	0.147	0.115	0.0323	0.124	0.0784	0.0842
N	1491	1491	1491	1491	1491	1491

*Estimation of equation 1 in SUSENAS 2011-13 with base year 2011; district clustered standard errors in parentheses; control variables: urban fraction, district average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

Table A 2.20 p-values of the pairwise test for equality of the yearly insurance coverage interaction coefficients on health expenditure outcomes

	Coverage x 2013	Coverage x 2014	Coverage x 2015	Coverage x 2016
Total				
Coverage x 2012	0.9024	0.2692	0.8572	0.7396
Coverage x 2013		0.4014	0.8344	0.7438
Coverage x 2014			0.0593	0.0637
Coverage x 2015				0.7691
Treatment				
Coverage x 2012	0.3928	0.1409	0.4635	0.6744
Coverage x 2013		0.5211	0.9578	0.9128
Coverage x 2014			0.2718	0.2162
Coverage x 2015				0.7623
Public treatment				
Coverage x 2012	0.1289	0.2897	0.9349	0.5314
Coverage x 2013		0.8867	0.2854	0.1424
Coverage x 2014			0.1109	0.0267
Coverage x 2015				0.2517
Private treatment				
Coverage x 2012	0.8739	0.2755	0.3042	0.3603
Coverage x 2013		0.3462	0.3915	0.4174
Coverage x 2014			0.8923	0.9354
Coverage x 2015				0.8566
Private				
Coverage x 2012	0.8739	0.2755	0.3042	0.3603
Coverage x 2013		0.3462	0.3915	0.4174
Coverage x 2014			0.8923	0.9354
Coverage x 2015				0.8566
Medication				
Coverage x 2012	0.3520	0.8031	0.0009	0.0003
Coverage x 2013		0.8117	0.0352	0.0143

Coverage x 2014			0.0599	0.0211
Coverage x 2015				0.2931
Prevention				
Coverage x 2012	0.8467	0.5898	0.6778	0.8397
Coverage x 2013		0.3130	0.4701	0.9532
Coverage x 2014			0.8336	0.1599
Coverage x 2015				0.0870

p-values of pairwise post-estimation test of the respective coverage and year interaction coefficients from estimating equation 1 in SUSENAS 2011-2013 with base year 2011 and SUSENAS 2013-2016 with base year 2013 as displayed in Table A 2.18 and Table A 2.19.

Table A 2.21 Robustness check 1: Health expenditure outcomes with different sets of control variables

	No controls	Main specification	Main + sick proportion	Main + district size	Main with wealth quintiles
Total					
Coverage x	5754.3	1538.4	1893.2	1219.3	10205.5
2014	(19165.9270)	(18278.4377)	(18152.1000)	(18259.3739)	(20324.3078)
Coverage x	-48165.3**	-38776.7**	-37138.7**	-40104.7**	-48938.8**
2015	(19621.2075)	(18534.7886)	(18494.8107)	(18472.7702)	(20531.8229)
Coverage x	-39801.4*	-44679.8**	-38702.7*	-46726.6**	-37078.8
2016	(22727.3083)	(22192.4975)	(22096.1873)	(22164.9813)	(23240.8284)
Treatment					
Coverage x	2904.7	809.5	1146.5	632.9	6282.3
2014	(16519.2932)	(16487.9917)	(16249.1277)	(16480.1407)	(17677.2650)
Coverage x	-24719.9	-17215.9	-15659.9	-17950.7	-24749.8
2015	(16554.3635)	(16479.8945)	(16395.3921)	(16457.8616)	(17767.7262)
Coverage x	-19276.6	-22134.6	-16457.0	-23267.3	-18617.1
2016	(19820.9282)	(20000.4249)	(19864.7220)	(20005.9085)	(20325.3969)
Public treatment					
Coverage x	4982.5	4695.1	4846.1	4640.5	6435.6
2014	(9672.2881)	(9977.8782)	(9905.9929)	(9975.0791)	(10149.3491)
Coverage x	-14380.6	-11594.6	-10897.3	-11821.8	-14146.6
2015	(8768.7011)	(9020.3421)	(8968.4245)	(9006.4270)	(9194.3233)
Coverage x	-19937.2*	-19468.7*	-16924.3	-19818.9*	-16626.5
2016	(10308.1674)	(10626.1041)	(10514.6993)	(10600.2861)	(10815.2445)
Private treatment					
Coverage x	-2077.8	-3885.6	-3699.6	-4007.6	-153.3
2014	(12426.6985)	(12452.8172)	(12350.0557)	(12450.2068)	(13347.3464)
Coverage x	-10339.3	-5621.2	-4762.5	-6128.9	-10603.2
2015	(13322.7024)	(13605.4186)	(13569.1319)	(13590.5911)	(14381.0921)
Coverage x	660.6	-2665.8	467.3	-3448.4	-1990.7
2016	(15889.6336)	(16014.2519)	(15971.9272)	(16040.6442)	(15770.6350)
Medication					
Coverage x	8206.9	8358.2	8371.9	8329.4	9426.1
2014	(7696.4024)	(7827.3273)	(7820.9048)	(7827.1403)	(7865.9059)
Coverage x	-10034.1**	-8238.1**	-8174.9**	-8357.7**	-9528.1**
2015	(4011.9183)	(4036.3701)	(4021.1697)	(4022.7569)	(4092.8882)
Coverage x	-11246.0**	-11060.3**	-10829.7**	-11244.7***	-10047.9**
2016	(4370.9349)	(4297.7851)	(4283.1241)	(4289.1190)	(4435.5218)
Prevention					
Coverage x	-1238.7	-2290.6	-2312.1	-2347.8	-1420.5
2014	(1506.6512)	(1532.6223)	(1538.6991)	(1532.8709)	(1613.8758)
Coverage x	-2189.3	-2413.3	-2512.6	-2651.6	-3008.5
2015	(2412.7207)	(2247.9042)	(2252.9733)	(2234.6850)	(2390.7912)
Coverage x	1507.9	881.5	519.4	514.2	1937.9
2016	(2783.8780)	(2585.6530)	(2613.4191)	(2563.3839)	(2691.5902)

Estimation results of interaction coefficients β_t from equation 1 with different sets of district- and time- specific control variables (vector C); main specification is equivalent to the tables above: urban fraction, average per capita household expenditure, categories of main sector of employment in the district, proportion with access to electricity, house ownership, primary education and membership in other social protection programs; alternative specifications either add the proportion of individuals reporting an illness during the previous month or district size measured by the number of respondents per district, replace all wealth measures with shares of households in each national wealth quintile, or add no control variables; district clustered standard errors in parentheses; accounting for sampling weights.

Table A 2.22 Robustness check 2: Health expenditure outcomes with different reference periods

	Reference year: 2013	Reference year: 2011	Reference year: 2012	Pooled pre vs. pooled post
Total				
Coverage x 2012		-17716.4		
		(17835.5985)		
Coverage x 2013		-3658.8	11119.2	
		(20020.8223)	(18621.6969)	
Coverage x 2014	1538.4	-2332.9	12409.9	
	(18278.4377)	(20762.7801)	(21469.2472)	
Coverage x 2015	-38776.7**	-39501.5**	-21757.4	
	(18534.7886)	(17487.2827)	(17481.9426)	
Coverage x 2016	-44679.8**	-46899.1**	-30750.4	
	(22192.4975)	(18227.6198)	(20175.0244)	
Coverage x post				-42752.8**
				(17811.9004)
Treatment				
Coverage x 2012		-32849.1**		
		(15630.6744)		
Coverage x 2013		-13529.6	17218.4	
		(17751.8123)	(17220.4545)	
Coverage x 2014	809.5	-13079.1	17158.3	
	(16487.9917)	(16742.7284)	(17389.9938)	
Coverage x 2015	-17215.9	-27526.8*	5822.9	
	(16479.8945)	(15216.7080)	(15686.4763)	
Coverage x 2016	-22134.6	-33251.9**	-1721.2	
	(20000.4249)	(15661.7807)	(17935.4522)	
Coverage x post				-21316.4
				(14758.4738)
Public treatment				
Coverage x 2012		-8488.9		
		(10560.5714)		
Coverage x 2013		7340.8	15491.1	
		(10065.8692)	(11064.3807)	
Coverage x 2014	4695.1	10003.6	18089.8	
	(9977.8782)	(11513.5344)	(12047.6736)	
Coverage x 2015	-11594.6	-4246.1	4057.2	
	(9020.3421)	(8183.0062)	(9722.0417)	
Coverage x 2016	-19468.7*	-13492.6	-5743.3	
	(10626.1041)	(10016.0229)	(11012.8296)	
Coverage x post				-18183.0*
				(9269.6417)
Private treatment				
Coverage x 2012		-24360.2**		
		(12385.7250)		
Coverage x 2013		-20870.4	1727.3	
		(14114.0430)	(13699.4537)	
Coverage x 2014	-3885.6	-23082.6*	-931.6	
	(12452.8172)	(12829.0878)	(12806.6726)	
Coverage x 2015	-5621.2	-23280.8*	1765.8	
	(13605.4186)	(13609.9576)	(12313.4008)	
Coverage x 2016	-2665.8	-19759.3*	4022.2	
	(16014.2519)	(10420.6857)	(13523.3615)	

Coverage x				-3133.4
post				(11314.2599)
Medication				
Coverage x		9627.6***		
2012		(3453.1737)		
Coverage x		4146.6	-5406.9	
2013		(3905.5115)	(4258.8350)	
Coverage x	8358.2	12454.3	3032.4	
2014	(7827.3273)	(8952.0780)	(9325.4327)	
Coverage x	-8238.1**	-4372.3	-14248.6***	
2015	(4036.3701)	(3265.1823)	(4335.7988)	
Coverage x	-11060.3**	-7379.1**	-17037.1***	
2016	(4297.7851)	(3585.8574)	(4685.0727)	
Coverage x				-13168.4**
post				(6397.4546)
Prevention				
Coverage x		318.3		
2012		(3745.8212)		
Coverage x		-70.05	-1021.2	
2013		(1888.6298)	(3602.1050)	
Coverage x	-2290.6	-1525.0	-2319.2	
2014	(1532.6223)	(1697.2082)	(3627.8327)	
Coverage x	-2413.3	-1220.6	-1496.2	
2015	(2247.9042)	(2149.1266)	(3835.1473)	
Coverage x	881.5	1642.0	1145.6	
2016	(2585.6530)	(2290.6510)	(3807.6100)	
Coverage x				558.8
post				(2275.2696)

Estimation results of interaction coefficients β_t from equation 1 with differing reference years (and samples) using the main specification of covariates and accounting for sampling weights; district clustered standard errors in parentheses; reference year: 2013 is the main specification in SUSENAS 2013-2016 as displayed in Table A 2.18; reference year: 2011 is estimated in SUSENAS 2011-2016 with reference year 2011; reference year: 2012 is estimated in SUSENAS 2012-2016 with reference year 2012; the last column displays the result of replacing the categorical year variable with a post-policy indicator variable in SUSENAS 2011-2016 (0=year 2011-2013, 1=2014-2016).

Table A 2.23 Health care usage probabilities across pre-reform insurance groups

	Outpatient (1 month, if sick)				Inpatient (1 year)			
	2011	2013	2015	2017	2011	2013	2015	2017
No previous health insurance								
Any	0.4311	0.4675	0.5368	0.4416	0.0162	0.0185	0.0290	0.0350
	(0.4952)	(0.4989)	(0.4986)	(0.4966)	(0.1261)	(0.1347)	(0.1679)	(0.1838)
Any public	0.1436	0.1439	0.1583	0.1515	0.0081	0.0092	0.0140	0.0176
	(0.3507)	(0.3510)	(0.3650)	(0.3585)	(0.0895)	(0.0957)	(0.1175)	(0.1313)
Public	0.2963	0.3345	0.3628	0.3021	0.0081	0.0093	0.0153	0.0180
hospital	(0.4566)	(0.4718)	(0.4808)	(0.4592)	(0.0896)	(0.0961)	(0.1228)	(0.1330)
Puskesmas	0.0152	0.0203	0.0242	0.0257	0.0056	0.0068	0.0099	0.0129
	(0.1225)	(0.1411)	(0.1538)	(0.1583)	(0.0748)	(0.0819)	(0.0990)	(0.1128)
Any private	0.0154	0.0222	0.0259	0.0257	0.0062	0.0072	0.0110	0.0131
	(0.1230)	(0.1473)	(0.1587)	(0.1584)	(0.0784)	(0.0847)	(0.1042)	(0.1137)
Private	0.1305	0.1276	0.1355	0.1277	0.0026	0.0027	0.0042	0.0048
hospital	(0.3369)	(0.3337)	(0.3422)	(0.3337)	(0.0506)	(0.0518)	(0.0648)	(0.0694)
Private	0.2769	0.3100	0.3294	0.2710	0.0019	0.0021	0.0042	0.0048
practice	(0.4475)	(0.4625)	(0.4700)	(0.4445)	(0.0434)	(0.0457)	(0.0645)	(0.0691)
Previous subsidized health insurance								
Any	0.4736	0.4954	0.5775	0.4809	0.0239	0.0251	0.0390	0.0436
	(0.4993)	(0.5000)	(0.4940)	(0.4996)	(0.1527)	(0.1564)	(0.1936)	(0.2043)
Any public	0.2470	0.2263	0.2692	0.2449	0.0169	0.0174	0.0264	0.0292
	(0.4313)	(0.4184)	(0.4435)	(0.4300)	(0.1289)	(0.1306)	(0.1603)	(0.1683)
Public	0.2429	0.2857	0.2967	0.2543	0.0072	0.0080	0.0131	0.0151
hospital	(0.4288)	(0.4518)	(0.4568)	(0.4355)	(0.0843)	(0.0892)	(0.1136)	(0.1218)
Puskesmas	0.0275	0.0269	0.0416	0.0362	0.0126	0.0128	0.0198	0.0218
	(0.1634)	(0.1616)	(0.1997)	(0.1869)	(0.1117)	(0.1122)	(0.1394)	(0.1460)
Any private	0.0116	0.0131	0.0181	0.0177	0.0054	0.0056	0.0095	0.0113
	(0.1071)	(0.1138)	(0.1335)	(0.1317)	(0.0731)	(0.0746)	(0.0972)	(0.1055)
Private	0.2240	0.2052	0.2312	0.2127	0.0046	0.0050	0.0068	0.0078
hospital	(0.4169)	(0.4038)	(0.4216)	(0.4092)	(0.0674)	(0.0703)	(0.0824)	(0.0878)
Private	0.2277	0.2693	0.2712	0.2305	0.0017	0.0024	0.0034	0.0038
practice	(0.4193)	(0.4436)	(0.4446)	(0.4212)	0.0239	0.0251	0.0390	0.0436
Previous self-paid health insurance								
Any	0.0313	0.0338	0.0488	0.0563	0.5135	0.5364	0.5787	0.4849
	(0.1741)	(0.1808)	(0.2154)	(0.2306)	(0.4998)	(0.4987)	(0.4938)	(0.4998)
Any public	0.0138	0.0150	0.0225	0.0240	0.1490	0.1568	0.1691	0.1403
	(0.1167)	(0.1214)	(0.1483)	(0.1530)	(0.3561)	(0.3636)	(0.3749)	(0.3473)
Public	0.0178	0.0191	0.0268	0.0333	0.3736	0.3925	0.4103	0.3561
hospital	(0.1321)	(0.1370)	(0.1614)	(0.1795)	(0.4838)	(0.4883)	(0.4919)	(0.4789)
Puskesmas	0.0126	0.0138	0.0209	0.0219	0.0539	0.0573	0.0756	0.0537
	(0.1114)	(0.1168)	(0.1430)	(0.1464)	(0.2258)	(0.2323)	(0.2643)	(0.2254)
Any private	0.0159	0.0173	0.0232	0.0295	0.0527	0.0596	0.0750	0.0713
	(0.1249)	(0.1303)	(0.1506)	(0.1691)	(0.2234)	(0.2367)	(0.2635)	(0.2573)
Private	0.0014	0.0013	0.0017	0.0022	0.0988	0.1052	0.0959	0.0890
hospital	(0.0371)	(0.0362)	(0.0413)	(0.0467)	(0.2984)	(0.3068)	(0.2944)	(0.2848)
Private	0.0018	0.0019	0.0034	0.0038	0.3201	0.3330	0.3321	0.2832
practice	(0.0424)	(0.0433)	(0.0584)	(0.0619)	(0.4665)	(0.4713)	(0.4710)	(0.4506)

Group-wise individual probability to use inpatient care during the previous year, outpatient care during the previous month if there was an acute illness; uncontrolled mean estimates over years accounting for sampling weights; standard deviations in parentheses; every other year is displayed for convenience.

Table A 2.24 Individual level estimation with binary insurance indicator: Inpatient care usage

	Total Inpatient	Public	Public Hospital	Puskesmas	Private	Private Hospital	Private Practice
Previously uninsured	-0.00778***	-0.00603***	-0.00503***	-0.00113***	-0.00194***	-0.00171***	-0.000208**
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Post reform	0.0149***	0.00838***	0.00662***	0.00177***	0.00679***	0.00552***	0.00128***
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Previously uninsured x post reform	-0.00347***	-0.00299***	-0.00277***	-0.000224*	-0.000473*	-0.00122***	0.000679***
	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0002)	(0.0001)
ymean	0.0286	0.0158	0.0121	0.00387	0.0130	0.0102	0.00283
r2	0.00985	0.00762	0.00630	0.00539	0.00852	0.00839	0.00235
N	7587345	7587345	7587345	7587345	7587345	7587345	7587345

*Estimation of equation 2 in SUSENAS 2011-17; reference categories of displayed coefficients: likely previous health insurance beneficiary, pre-reform (years 2011-2013) and their interaction; household clustered standard errors in parentheses; accounting for sampling weights; control variables: district fixed effects, individual age, gender, education, employment and household wealth quintile, living in urban indicator; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

Table A 2.25 Individual level estimation with binary insurance indicator: Outpatient care usage

	Total Outpatient	Public	Public Hospital	Puskesmas	Private	Private Hospital	Private Practice
Previously uninsured	-0.0376***	-0.0505***	-0.0125***	-0.0394***	0.00835***	-0.00536***	0.0131***
	(0.0018)	(0.0014)	(0.0005)	(0.0013)	(0.0017)	(0.0005)	(0.0016)
Post reform	0.0536***	0.0179***	0.00979***	0.00707***	0.0262***	0.00823***	0.0154***
	(0.0016)	(0.0013)	(0.0005)	(0.0012)	(0.0015)	(0.0006)	(0.0015)
Previously uninsured x post reform	0.00503**	-0.00357*	-0.00445***	0.000993	0.00791***	-0.00216***	0.00998***
	(0.0024)	(0.0018)	(0.0007)	(0.0017)	(0.0023)	(0.0007)	(0.0022)
ymean	0.496	0.185	0.0300	0.159	0.317	0.0253	0.287
r2	0.0409	0.0488	0.0185	0.0516	0.0586	0.0293	0.0539
N	2131234	2131234	2131234	2131234	2131234	2131234	2131234

*Estimation of equation 2 in SUSENAS 2011-17 (subsample that indicated illness in the previous month); reference categories of displayed coefficients: likely previous health insurance beneficiary, pre-reform (years 2011-2013) and their interaction; household clustered standard errors in parentheses; accounting for sampling weights; control variables: district fixed effects, individual age, gender, education, employment and household wealth quintile, living in urban indicator; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

Table A 2.26 Predicted margins of LPM and Probit models

	Outpatient (1 month)				Inpatient (1 year)			
	LPM		Probit		LPM		Probit	
	Pre-reform	Post-reform	Pre-reform	Post-reform	Pre-reform	Post-reform	Pre-reform	Post-reform
Total								
Previously insured	0.481	0.534	0.481	0.534	0.0246	0.0395	0.0246	0.0395
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Previously uninsured	0.443	0.502	0.443	0.502	0.0168	0.0283	0.0164	0.0284
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Public								
Previously insured	0.200	0.217	0.199	0.217	0.0147	0.0231	0.0147	0.0229
	(0.0010)	(0.0009)	(0.0010)	(0.0009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Previously uninsured	0.149	0.163	0.148	0.163	0.00865	0.0140	0.00839	0.0141
	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Public hospital								
Previously insured	0.0314	0.0412	0.0313	0.0407	0.0115	0.0181	0.0115	0.0179
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Previously uninsured	0.0189	0.0242	0.0183	0.0242	0.00645	0.0103	0.00612	0.0103
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Puskesmas								
Previously insured	0.173	0.180	0.172	0.179	0.00345	0.00522	0.00338	0.00520
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Previously uninsured	0.133	0.141	0.133	0.141	0.00232	0.00386	0.00242	0.00393
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Private								
Previously insured	0.295	0.321	0.295	0.321	0.0102	0.0170	0.0101	0.0169
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Previously uninsured	0.304	0.338	0.304	0.337	0.00822	0.0145	0.00816	0.0147
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Private hospital								
Previously insured	0.0236	0.0318	0.0231	0.0310	0.00811	0.0136	0.00808	0.0136
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Previously uninsured	0.0182	0.0243	0.0187	0.0252	0.00640	0.0107	0.00634	0.0109
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Private practice								
Previously insured	0.269	0.284	0.269	0.285	0.00200	0.00328	0.00197	0.00333
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Previously uninsured	0.282	0.307	0.282	0.307	0.00180	0.00375	0.00182	0.00375
	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Predicted margins of each combination of the interaction between the post-reform indicator and the indicator of being in the group with no pre-reform insurance coverage after estimating equation 2 in SUSENAS 2011-17 (for outpatient: subsample that indicated illness in the previous month) either as a linear probability model (specification as in Table A 2.24 and Table A 2.25) and the alternative specification as a probit model.

Table A 2.27 Household level estimation with binary insurance indicator: Real quarterly health expenditure (IDR)

	Total	Treatment	Public treatment	Private treatment	Medication	Prevention
Previously uninsured	-21190.1***	-17090.9***	-9815.4***	-7275.5***	-2281.0***	-1818.3***
	(2551.7001)	(2436.8165)	(1500.7946)	(1895.9617)	(318.2823)	(229.4601)
Post reform	-13324.5***	-9092.1***	-2268.1	-6824.0***	-2222.2***	-2010.2***
	(2198.2118)	(2092.4564)	(1407.4305)	(1525.7418)	(282.8525)	(184.2060)
Previously uninsured x post reform	7379.9***	5659.3**	2029.1	3630.2*	969.3***	751.3***
	(2808.1734)	(2683.1715)	(1622.6213)	(2112.1260)	(352.2161)	(238.4789)
ymean	65285.9	49950.8	16774.2	33176.6	7111.6	8223.5
r2	0.0185	0.0129	0.00375	0.0117	0.0124	0.0456
N	1092221	1092221	1092221	1092221	1092221	1092221

*Estimation of equation 3 in SUSENAS 2013-16; reference categories of displayed coefficients: likely previous health insurance beneficiary, pre-reform (years 2011-2013) and their interaction; standard errors in parentheses; accounting for sampling weights; control variables: district fixed effects, urban indicator, household wealth quintile, categories of household head's main sector of employment, education, number of household members, age structure, membership in other social protection programs; stars indicate levels of significance: *p<0.1; **p<0.05; ***p<0.01.*

A3 Appendix for chapter 3

A3.1 Wording of messages

Table A 3.1 Wording of messages

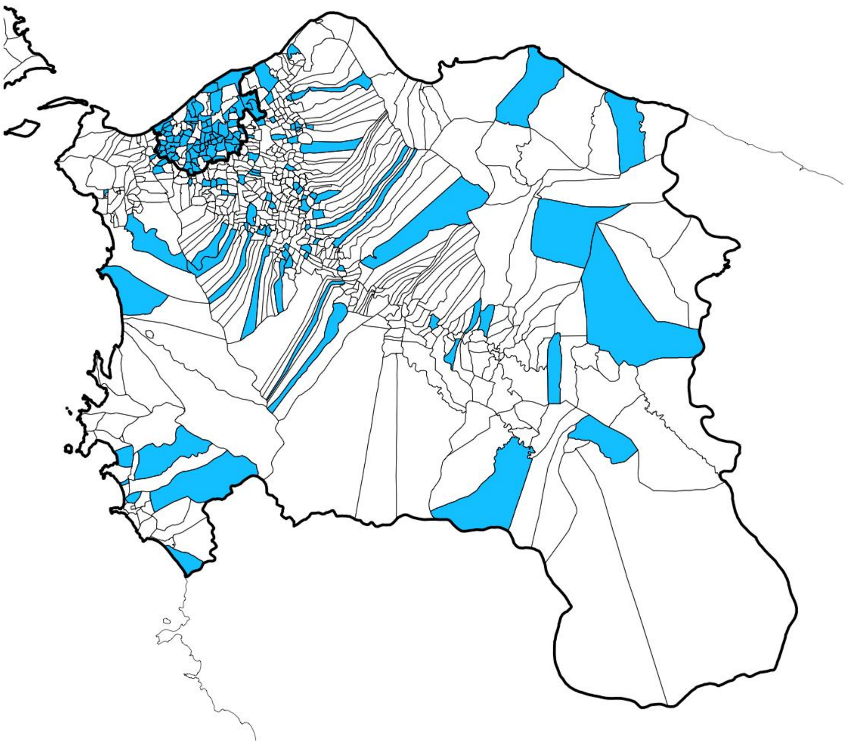
Message (English)	Message (Indonesian)	Sending date
Greetings [Mr/Ms] [name], do you know that diabetes does not always show symptoms but can be treated better if detected earlier. Check for FREE at POSBINDU [date]	Salam [Pak/Ibu] [name], tahukah Anda diabetes tdk selalu menunjukan gejala namun dapat 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

A3.2 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 Map of 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, 2010).
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

<table>
<tr><th></th><th>Total</th><th colspan="3">Of all contacts</th><th colspan="2">Of all consenting</th><th colspan="3">Of all eligible</th></tr>
<tr><td></td><td>Contacts</td><td>Empty houses</td><td>Refusal/ busy/ other</td><td>Consent</td><td>Eligible</td><td>Ineligible</td><td>Refusal</td><td>Incomplete</td><td>Complete</td></tr>
<tr><td>N</td><td>15,128</td><td>7,682</td><td>946</td><td>6,500</td><td>2,115</td><td>4,385</td><td>11</td><td>98</td><td>2,006</td></tr>
<tr><td></td><th colspan="9">Of all ineligible</th></tr>
<tr><td></td><td colspan="2">No member 40-70</td><td colspan="2">No member 40-70 present</td><td colspan="2">No phone access</td><td colspan="3">No member without diagnosis/ screening/care</td></tr>
<tr><td>N</td><td colspan="2">1,589</td><td colspan="2">414</td><td colspan="2">270</td><td colspan="3">2,112</td></tr>
</table>

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).

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[28]. 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 measurement and a 2.6 percentage point increase in blood glucose measurement.[29] 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

[28] 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.
[29] 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.

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.

<u>Calling procedure at endline</u>

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 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).

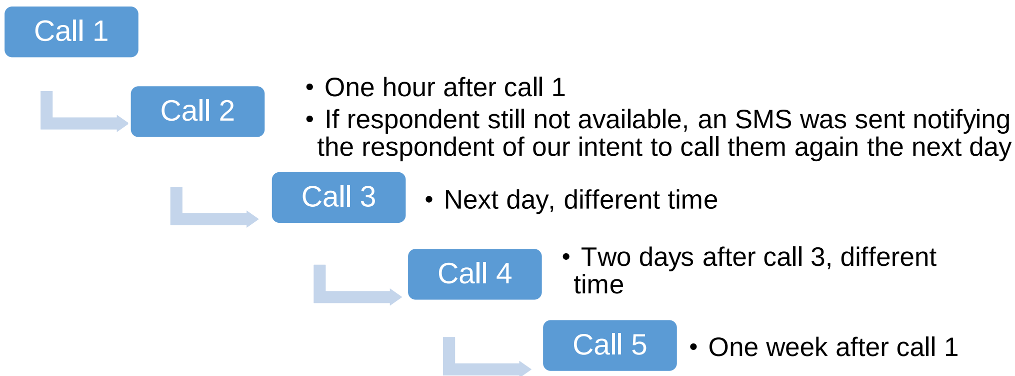


Figure A 3.2 Call Pattern at endline

A3.3 Variable definitions

Knowledge Indices

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.

A3.4 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.

A3.5 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:

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

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:

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

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:

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

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

A3.6 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

				Remembers content on:			
	Total treatment	Received message	LATE definition	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	(0.42)	(0.39)	(0.38)	(0.35)	(0.40)	(0.39)	(0.39)
Secondary	0.21	0.18	0.17	0.21	0.21	0.17	0.11
- Higher	(0.41)	(0.39)	(0.38)	(0.41)	(0.41)	(0.38)	(0.31)
Secondary	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	18.42	19.58***	19.76	20.07	19.10	19.87	20.00
knowledge	(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	0.29	0.28	0.25*	0.06***	0.15***	0.22	0.37
screened	(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.*

A4 Appendix for chapter 4

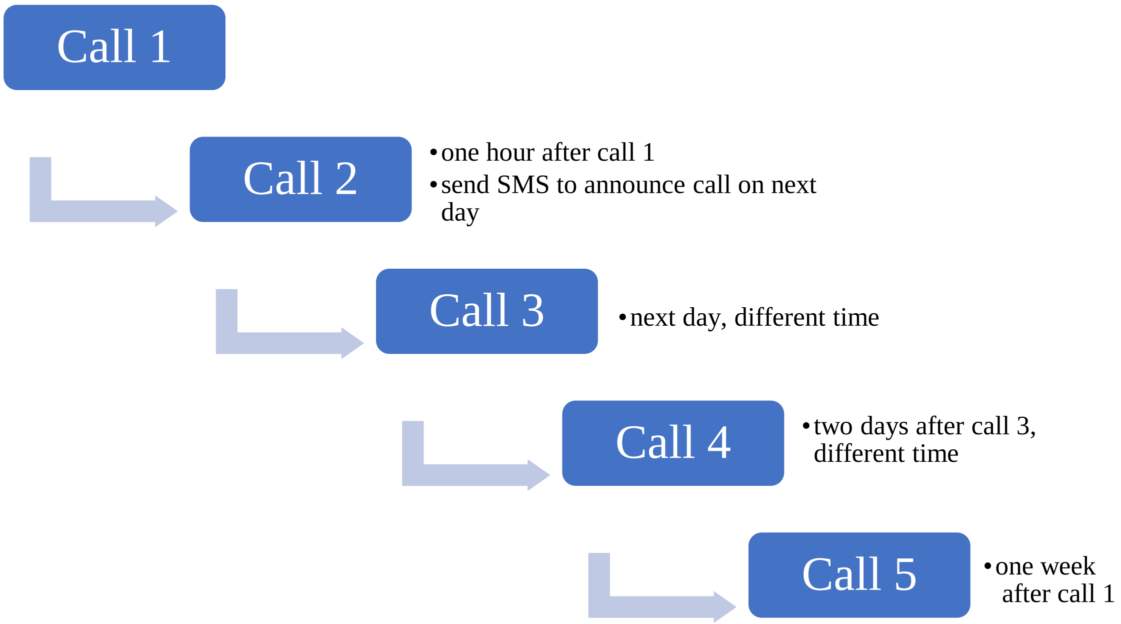
A4.1 Random walk scheme

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.
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.

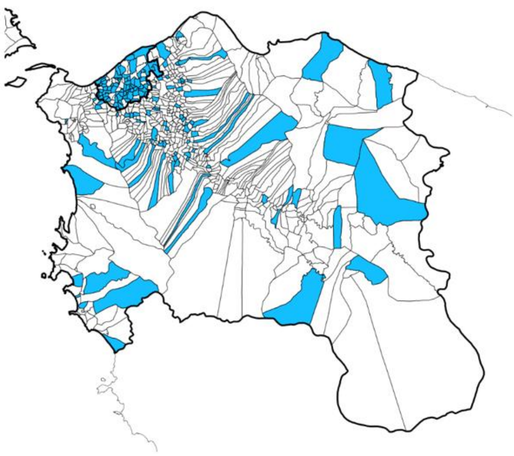
A4.2 Calling procedure

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).



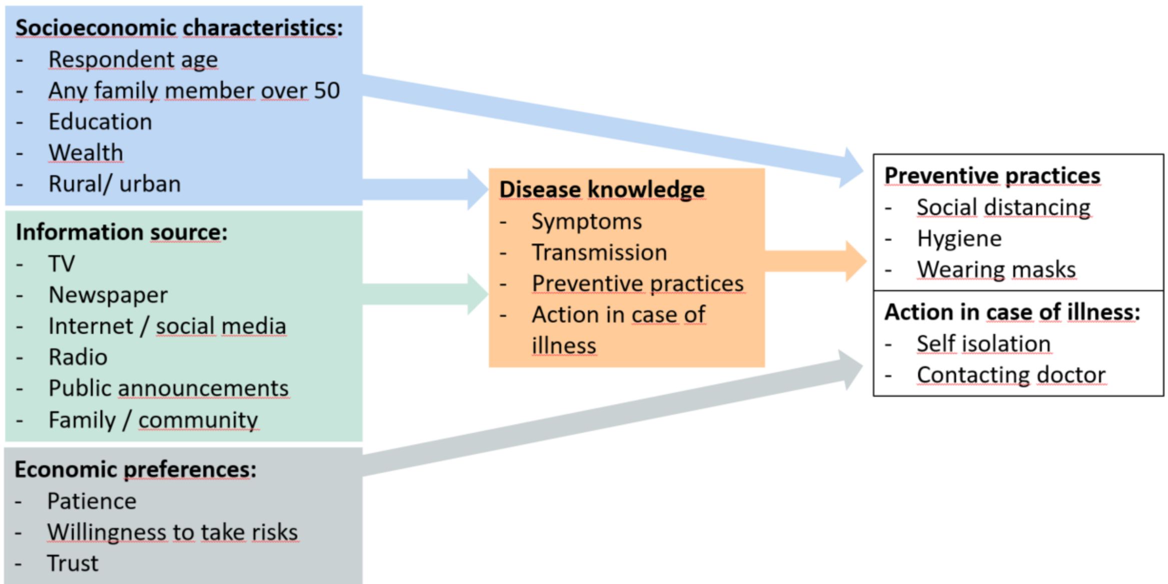
A4.3 Figures

Figure A 4.1 Map of sampled villages with administrative boundaries



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

Figure A 4.2 Overview of contributors to disease knowledge and practices that are tested in the regression analysis



A4.4 Tables

Table A 4.1 Overview of baseline contacts

	Total	**Of all contacts**			**Of all consenting**		**Of all eligible**		
	Contacts	Empty houses	Refusal/ busy/other	Consent	Eligible	Inelig.	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 4.2 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
$UPTAKE_i$	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

Table A 4.2 Variable Definitions ctd.

Vector name (as in equation)	**Variable Name** (as in output tables)	**Variable Definition**	**Questionnaire Number**
$UPTAKE_i$	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
	Female	0 - respondent is male 1 - respondent is female	A1
	Lower Secondary	Categorical variable:	A3
	Secondary and above	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
	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 4.2 Variable Definitions 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 4.3 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 4.4 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 4.5 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 (0.01)	0.81 (0.01)	0.77 (0.01)	0.87 (0.01)	0.57 (0.02)	0.57 (0.02)	0.35 (0.02)	0.72 (0.02)
Age								
- Younger than 50 (ref)	0.89 (0.01)	0.81 (0.02)	0.78 (0.02)	0.89 (0.01)	0.59 (0.02)	0.58 (0.03)	0.38 (0.02)	0.71 (0.02)
- 50 and older	0.85 (0.02)	0.81 (0.02)	0.75 (0.02)	0.86 (0.02)	0.53* (0.02)	0.54 (0.03)	0.32** (0.02)	0.73 (0.02)
Mem. age								
- Younger than 50 (ref)	0.87 (0.01)	0.81 (0.02)	0.77 (0.02)	0.87 (0.01)	0.57 (0.02)	0.60 (0.03)	0.35 (0.02)	0.69 (0.02)
- 50 and older	0.88 (0.02)	0.81 (0.02)	0.76 (0.02)	0.88 (0.02)	0.56 (0.02)	0.52** (0.03)	0.36 (0.02)	0.76*** (0.02)
Gender								
- Male (ref)	0.86 (0.02)	0.82 (0.02)	0.74 (0.02)	0.88 (0.02)	0.56 (0.02)	0.54 (0.03)	0.37 (0.02)	0.73 (0.02)
- Female	0.88 (0.01)	0.80 (0.02)	0.78 (0.02)	0.87 (0.02)	0.57 (0.02)	0.58 (0.02)	0.34 (0.02)	0.72 (0.02)
Wealth								
- Below median (ref)	0.86 (0.01)	0.79 (0.02)	0.73 (0.02)	0.88 (0.02)	0.49 (0.02)	0.51 (0.03)	0.34 (0.02)	0.67 (0.02)
- Above median	0.88 (0.02)	0.82 (0.02)	0.80** (0.02)	0.87 (0.02)	0.64*** (0.02)	0.61** (0.03)	0.36 (0.02)	0.77*** (0.02)
Area								
- Urban (ref)	0.86 (0.01)	0.77 (0.02)	0.73 (0.02)	0.85 (0.02)	0.52 (0.02)	0.49 (0.03)	0.28 (0.02)	0.74 (0.02)
- Rural	0.89 (0.02)	0.86*** (0.01)	0.82*** (0.02)	0.90** (0.02)	0.62*** (0.02)	0.65*** (0.03)	0.44*** (0.02)	0.69 (0.02)
Education								
- Up to primary (ref)	0.82 (0.02)	0.79 (0.03)	0.67 (0.03)	0.89 (0.02)	0.45 (0.03)	0.46 (0.05)	0.30 (0.03)	0.67 (0.03)
- Lower secondary	0.87* (0.03)	0.75 (0.03)	0.73 (0.03)	0.85 (0.02)	0.55** (0.03)	0.53 (0.04)	0.31 (0.03)	0.72 (0.03)
- Higher secondary or more	0.90*** (0.01)	0.84 (0.02)	0.83*** (0.02)	0.88 (0.02)	0.63*** (0.02)	0.62*** (0.03)	0.40*** (0.02)	0.74*** (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 4.6 Descriptive statistics: information source by group

	TV	Newspaper	Internet/ social media	Radio	Public announce–ment	Family/ community
Up to Primary (ref)	0.8161	0.0468	0.0936	0.0234	0.0769	0.6455
	(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 or more	0.8873***	0.0687	0.3081***	0.0475*	0.0827	0.5511***
	(0.0127)	(0.0110)	(0.0208)	(0.0089)	(0.0119)	(0.0204)
Younger than 50 (ref)	0.8856	0.0415	0.2670	0.0332	0.0779	0.5406
	(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 4.7 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 4.8. Estimates for the base model of equation 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 4.9. Estimates for the base model of equation 2

	(1) Does social dist.	(2) Does hygiene	(3) Wears masks	(4) Would isolate	(5) Would contact medical professional
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 4.10 Logit and probit estimates of Table 4.2

	(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 4.11 Logit and probit estimates of Table 4.3

	(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 4.12 Logit and probit estimates of Table 4.4

	(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 4.13 Logit and probit estimates of Table 4.5

	(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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

A4.5 Questionnaire and replication data

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.

Household characteristics are derived from SUSENAS 2017 (BPS 2018), willingness to take risk and patience are taken from the World Preference Survey (Falk et al. 2016), and the trust measure from the German Socioeconomic Panel (Kantar Public 2018). Questions on COVID-19 knowledge and behaviorare based on previous literature on pandemic knowledge and behavior (Balkhy et al. 2010; Ibuka et al. 2010).

A5 Appendix for chapter 5

A5.1 Tables and figures

Table A 5.1 Data collection and intervention timeline

		2020																															
		April				May				June				July				August				Sept.				October				Nov.			
Week	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Survey design and piloting	■	■	■	■																													
Pre-intervention survey (19.4.-11.5.; 16.5.-22.5.; 3.5.-8.7.))					■	■	■	■		■	■	■	■	■																			
Intervention piloting																■																	
Intervention sample selection, randomization & enrollment																			■														
Intervention (20.8.-20.9.)																				■	■	■	■	■									
Post-intervention survey (3.9.-25.10.)																						■	■	■	■	■	■	■					
Helpline outcome measurement																				■	■	■	■	■	■	■	■	■	■	■	■	■	

Table A 5.2 Wording of messages in English and Urdu

Message	English	Urdu
Introduction	Dear [name of main cardholder], Your health is important to us. We will be sending you important information by SMS regarding protection from corona virus. For more information contact Sehat Card helpline [insert number].	Mohtaram [name], Apki sehat hamaray liye ahem hai. Hum apko SMS ke zariye Coronavirus se bachao ke mutaliq ahem malomat faraham kren ge. Mazeed maloomaat ke liye Sehat Insaf Card helpline [insert numner] pe rabta kren.
Risk group information	Dear [name of main cardholder], Coronavirus disease is more dangerous and complicated in people above 60 years of age. Also, in people suffering from chronic conditions like diabetes, hypertension, cancer, heart or lung diseases. Practicing prevention can help protect your family.	Mohtaram [name], Coronavirus 60 saal se zaid umar k logon mai ziada khatarnak aur paicheeda sabit hota hai. Aur un logon mai bhi jo kisi aur daimi bemari jese k sugar, blood pressure, cancer, dil ya phaipharon k marz mai mubtala hain. Ehtyat krne se ap k ghar walo ki hifazat mumkin ha. Ehteyaat krne se aap ke ghar walo ki hifazat mumkin ha.
Social distancing information	Dear [name of main cardholder], Staying at home and keeping a distance from others reduces the risk of contracting coronavirus, also in those people who are at higher risk of complicated disease. Provide this information to your household members as well. For more information contact Sehat Card helpline [insert number].	Mohtram [name], Ghar pe rehnay aur doosron se fasla rakhnae se coronavirus lagne k imkanat kum ho jatay hain, un logon mai bhi jin mai paicheeda bemari ka khadsha ziada hai. Apne ghar walo ko bhi ye maloomat dain. Mazeed maloomat ke liye Sehat Card helpline [insert number] pe rabta kren
Wearing mask information	Dear [name of main cardholder], Keeping a 2-meter distance from others and wearing a mask outside home reduces the risk of contracting coronavirus, also in those people who are at higher risk of complicated disease. Tell this to your household members as well. For more information contact our helpline [insert number].	Muhtaram [name], Doosron se 2 meter ka fasla rakhne aur ghar se bahir mask pahen'nay se coronavirus lagne k imkanat kum ho jatay hain, un logon mai bhi jin mai paicheeda bemari ka khadsha ziada hai. Apne ghar walo ko bhi ye btayen. Mazeed maloomat ke liye hamari helpline [insert number] pe rabta kren
Handwashing information	Dear [name of main cardholder], Regular hand washing for at least 20 seconds reduces the risk of contracting coronavirus disease, also in those people who are at higher risk of complicated disease. Tell this to your household members as well. For more information contact Sehat Card helpline [insert number].	Mohtaram [name], Sabun se kum az kum 20 seconds k liye baqaidgi se hath dhonay se coronavirus lagne k imkanat kum hojatay hain, un logon mai bhi jin mai paicheeda bemari ka khadsha ziada hai. Apne ghar walo ko bhi ye btayen. Mazeed maloomat k liye Sehat Card helpline [insert numner] pe rabta kren.
Telemedicine information	Dear [name of main cardholder], In case of a health need, it is possible to have a free telephonic medical consultation before visiting a doctor. This can further protect you from contracting coronavirus. For free medical consultation, call PHA helpline [insert number]. Provide this information to your household members as well.	Mohtaram [name], Tabiat kharab honay ki surat mai doctor k pass janay se pehle phone pe muft tibi mashwara liya ja skta hai. Is tarah ap coronavirus se mazeed bach sktay hain. Muft tibi mashwaray k liye ap PHA telemedicine helpline [insert numner] pe rabta kren. Apne ghar walo ko bhi ye maloomaat dain

Table A 5.3 Differences in means of cardholder characteristics across datasets

	Entitlement	Enrollment	Unique phone
Wealth (PMT score)	18.8819	16.3941	16.6146
	(7.5178)	(6.1754)	(6.1575)
Age	58.6863	59.1794	59.3395
	(13.5752)	(12.9920)	(12.5503)
Female	0.2016	0.1880	0.1676
	(0.4012)	(0.3907)	(0.3735)
Married	0.9448	0.9533	0.9572
	(0.2283)	(0.2109)	(0.2025)
Region			
- North		0.3670	0.3892
		(0.4820)	(0.4876)
- Central		0.2860	0.2160
		(0.4519)	(0.4115)
- Hindko		0.1268	0.1588
		(0.3328)	(0.3655)
- South		0.2182	0.2360
		(0.4130)	(0.4247)
Claim history			
- Any		0.0519	0.0501
		(0.2219)	(0.2181)
- Covid risk		0.0481	0.0465
		(0.2140)	(0.2106)
N	2,371,685	1,480,841	585,657

Standard deviations below mean; a higher PMT score indicates more wealth; all differences between entitlement and enrollment as well as enrollment and households with a unique phone number are statistically significantly different from zero based on a ttest.

Figure A 5.1 Steps towards final estimation sample from previously interviewed and additionally sampled households

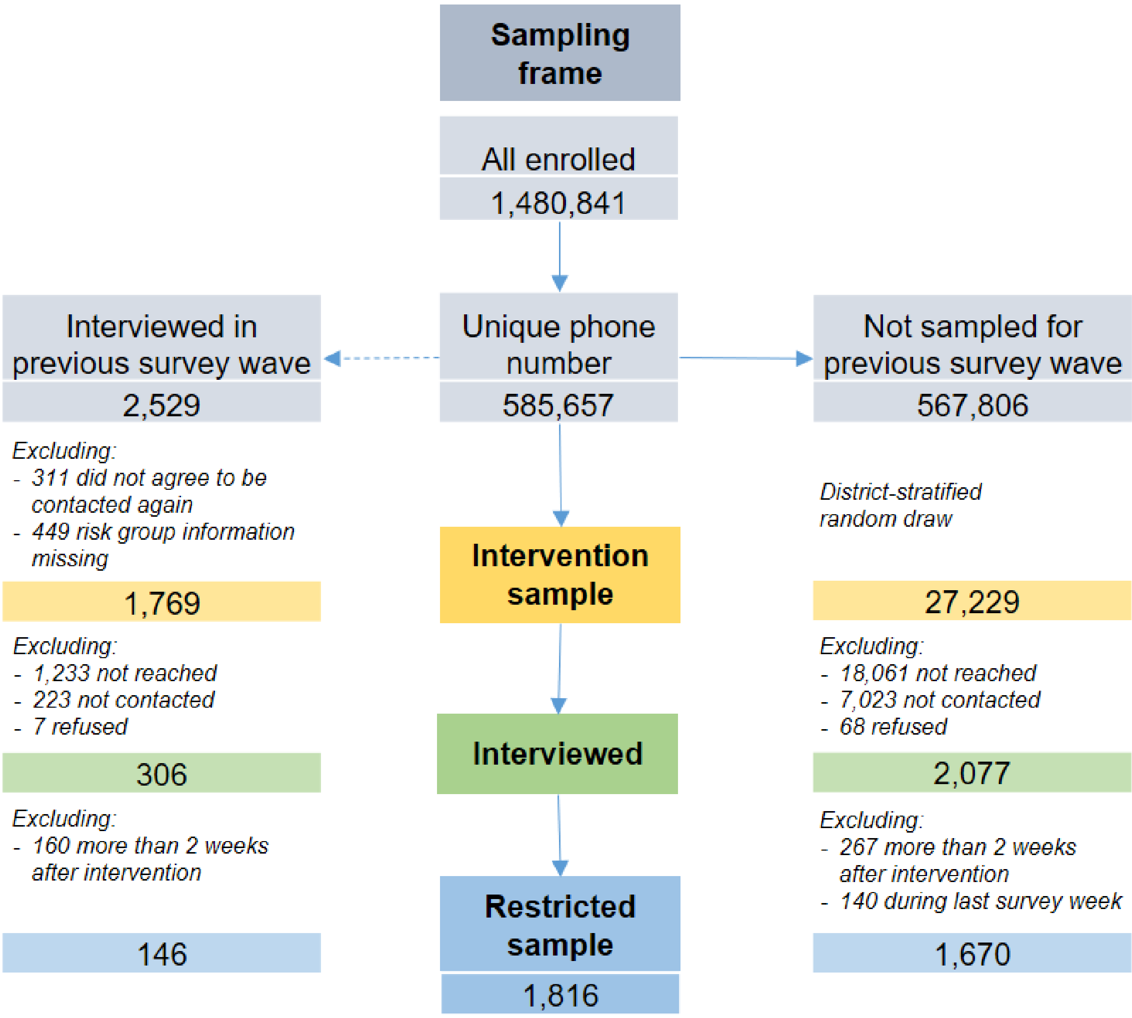


Table A 5.4 Complete sample characteristics

	Mean	SD	Min	Max	N
Intervention sample					
Cardholder age	49.59	12.57	4	111	29,182
Cardholder female	0.17	0.38	0	1	29,181
Wealth (PMT score)	16.75	6.14	0	27	29,182
Region					
- North	0.29	0.45	0	1	29,183
- Central	0.22	0.41	0	1	29,183
- Hindko	0.09	0.29	0	1	29,183
- South	0.14	0.35	0	1	29,183
Any claim	0.15	0.36	0	1	29,183
Interviewed					
Respondent age	47.57	14.87	18	86	2,408
Any member >60	0.60	0.49	0	1	2,243
Number members >60	1.58	2.15	1	60	1,065
Wealth (PMT score)	17.33	5.97	0	27	2,395
Female	0.06	0.24	0	1	2,413
Respondent literate	0.44	0.50	0	1	2,394
Household literacy	0.78	0.41	0	1	2,105
Respondent					
- Cardholder	0.77	0.42	0	1	2,414
- Household head	0.01	0.12	0	1	2,414
- Spouse	0.03	0.16	0	1	2,414
- Child	0.15	0.36	0	1	2,414
- Other family	0.04	0.19	0	1	2,414
Education					
- Up to primary	0.46	0.50	0	1	2,385
- Secondary	0.16	0.36	0	1	2,385
- Tertiary	0.38	0.49	0	1	2,385
Occupation					
- Civil servant	0.10	0.30	0	1	2,106
- Private employee	0.13	0.33	0	1	2,106
- Self-employed	0.23	0.42	0	1	2,106
- Daily wage laborer	0.33	0.47	0	1	2,106
- Unemployed	0.11	0.31	0	1	2,106
- Other	0.11	0.31	0	1	2,106

Intervention sample refers to all households who were included in the treatment randomization; Interviewed refers to all respondents of the post-intervention survey; a higher PMT score indicates more wealth.

Table A 5.5 Intervention sample balance based on administrative data characteristics

	Treatment group mean	Control group mean	p-value
Cardholder age	49.49	49.64	0.32
	(12.54)	(12.59)	
Cardholder gender	0.18	0.17	0.23
	(0.38)	(0.38)	
PMT score	16.73	16.76	0.68
	(6.15)	(6.14)	
Claim history	0.15	0.15	0.49
	(0.36)	(0.36)	
N	19,400	9,783	

Intervention sample refers to all households who were included in the treatment randomization; p-values for the test of difference between treatment and control group mean are based on t-tests. Standard deviations in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 5.6 Interviewed sample balance

	Treatment group mean	Control group mean	p-value
Cardholder age	48.43	49.19	0.12
	(10.94)	(11.49)	
Cardholder female	0.13	0.14	0.62
	(0.34)	(0.35)	
PMT score	17.40	17.29	0.66
	(5.88)	(6.02)	
Claim history	0.18	0.16	0.12
	(0.39)	(0.36)	
Respondent age	46.78	47.96*	0.07
	(14.79)	(14.89)	
Respondent female	0.06	0.06	0.52
	(0.23)	(0.25)	
Respondent education			0.551
- Primary or less	0.49	0.45	
	(0.50)	(0.50)	
- Secondary	0.14	0.16	
	(0.35)	(0.37)	
- Tertiary	0.37	0.38	
	(0.48)	(0.49)	
N	1,622	792	

Interviewed refers to all respondents of the post-intervention survey; p-values for the test of difference between treatment and control group mean are based on t-tests for all binary characteristics and on the Pearson chi-squared test for the categorical education variable. Standard deviations in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Attrition analysis

We test for differential attrition from the whole intervention sample to respondents of the post-intervention survey in the following three ways. We display all tests for the complete intervention sample using characteristics from the administrative records and display additionally more detailed characteristics for the subset that was interviewed in a previous survey wave. As displayed in Figure A 5.1, the majority (77.5%) of households are lost to follow up because they were contacted at least 3 times according to the calling schedule, but not reached or interviewed. An additional 22.5% of sampled households was not contacted before the stopping rule applied.

First, we test whether there is differential attrition between treatment and control group by regressing a binary attrition indicator on the binary treatment indicator:

$$Attrit_i = \alpha + \beta Treat_i + \varepsilon_i \qquad \textit{(A1)}$$

Secondly, we test whether there is differential attrition based on observable characteristics y_i. For the whole sample, this is restricted to the administrative health insurance data: age of main cardholder, gender of main cardholder, poverty score, region of residence, and any previous claim experience. For the interview sample, this can be extended to survey-based respondent characteristics: age, gender, education and occupation.

$$y_i = \alpha + \beta Attrit_i + \varepsilon_i \qquad \textit{(A2)}$$

Finally, we examine whether these characteristics are significantly different among attrited treatment and control households by restricting the sample to attrited households only:

$$(y_i | Attrit = 1) = \alpha + \beta Treat_i + \varepsilon_i \qquad \textit{(A3)}$$

Table A 5.7 Attrition 1: Test for differential attrition between treatment and control group

	Intervention sample	Interviewed in previous survey wave
	Attrited	Attrited
Treatment group	-0.00171	0.00455
	(0.00341)	(0.0193)
N	29150	1769

Regression of a binary attrition indicator (sampled, but not (re-)interviewed) on a binary treatment indicator following equation A1. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 5.8 Attrittion 2: Test for differential attrition based on observable characteristics in intervention sample

	Cardholder's age	Cardholder female	Wealth (PMT score)	At least one health insurance claim
Attrited	0.421	0.0363***	-0.603***	-0.0144*
	(0.260)	(0.00806)	(0.131)	(0.00765)
Observations	28965	29148	29117	29150

Separate regressions of each characteristic on the binary attrition indicator (sampled, but not interviewed) using equation A2. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 5.9 Attrition 2: Test for differential attrition based on observable characteristics in households interviewed in a previous survey wave

	Cardholder age	Cardholder female	Proxy Means Test	At least one health insurance claim	Respondent age	Respondent female
Attrited	0.373	0.00103	0.121	-0.00984	-0.519	-0.00343
	(0.701)	(0.0229)	(0.363)	(0.0229)	(0.924)	(0.0146)
N	1765	1769	1768	1769	1743	1739

Separate regressions of each characteristic on the binary attrition indicator (sampled, but not re-interviewed) using equation A2 in the sub-sample that was interviewed in a previous survey wave. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 5.10 Attrition 3: Test for difference along observable characteristics between treatment and control group among the attrited in the complete sample

	Cardholder's age	Cardholder female	Wealth (PMT score)	At least one health insurance claim
Treatment group	-0.0124	-0.00651	0.0440	0.00601
	(0.159)	(0.00492)	(0.0794)	(0.00463)
N	26579	26755	26727	26757

Separate regressions of each characteristic on the binary treatment indicator (sampled, but not interviewed) using equation A3. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

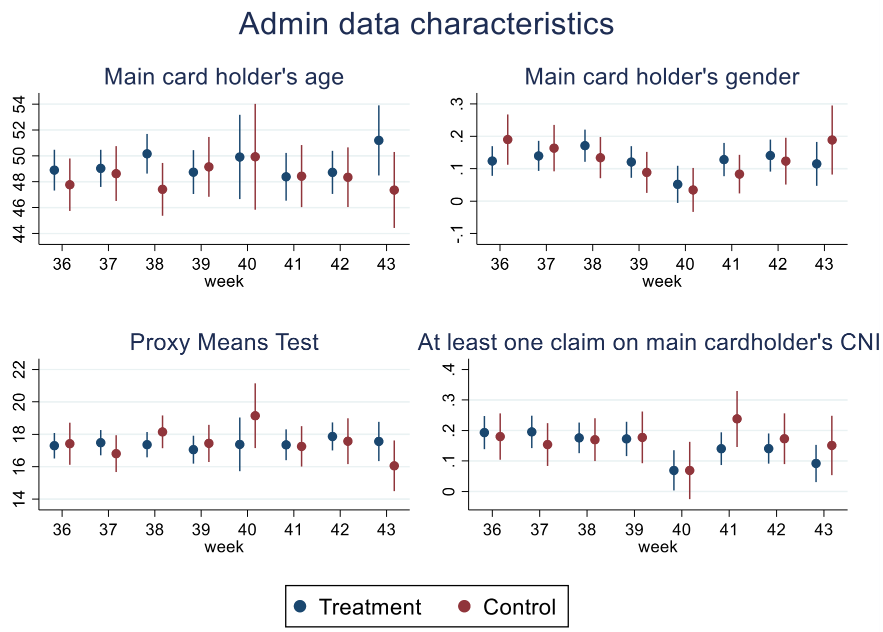
Table A 5.11 Attrition 3: Test for difference along observable characteristics between treatment and control group among the attrited in the previously interviewed sample

	Cardholder age	Cardholder female	Wealth (PMT score)	At least one health insurance claim	Respondent age	Respondent female
Treatment group	1.185*	-0.0176	-0.0317	0.0118	0.541	-0.0281**
	(0.628)	(0.0205)	(0.325)	(0.0206)	(0.841)	(0.0131)
N	1,477	1,481	1,480	1,481	1430	1427

*Separate regressions of each characteristic on the binary treatment indicator (sampled, but not re-interviewed) using equation A3 in the sub-sample that was interviewed in a previous survey wave. Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

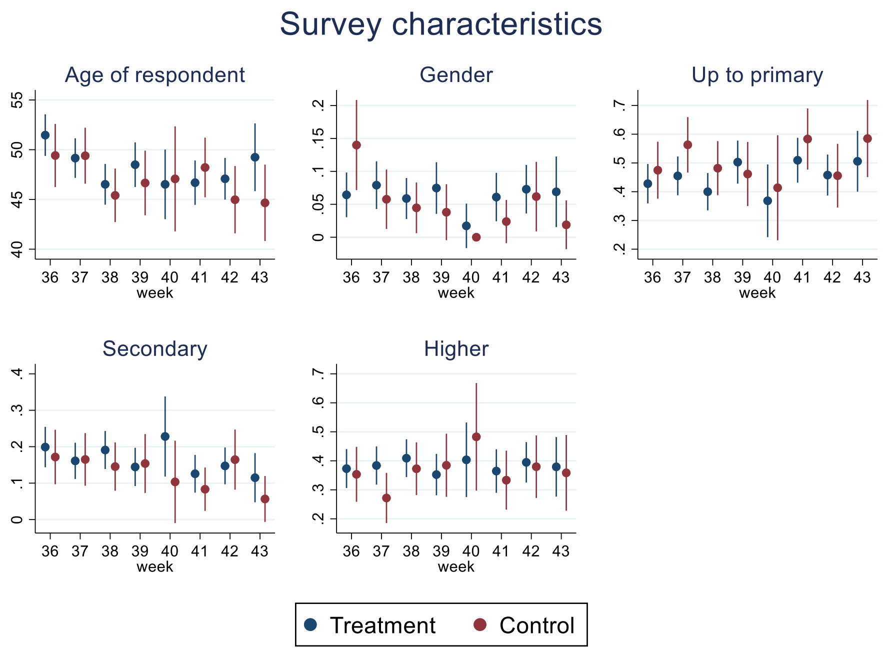
Sample restriction

Figure A 5.2 Admin data sample balance over time



Sample balance in terms of household characteristics from the administrative data across treatment and control group in each data collection week (only for those interviewed up to one week after the intended interview date).

Figure A 5.3 Survey data sample balance over time



Sample balance in terms of respondent characteristics from the administrative data across treatment and control group in each data collection week (only for those interviewed up to one week after the intended interview date).

Table A 5.12 Treatment effects on preventive practices (hypothesis 1): specification with and without control variables

	Preventive practices index		Handwashing		Wearing masks		Telemedicine if sick	
Treated	0.116**	0.101*	0.0582**	0.0525**	0.0295	0.0252	0.0457*	0.0517**
	(0.0521)	(0.0514)	(0.0266)	(0.0263)	(0.0258)	(0.0255)	(0.0251)	(0.0250)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
N	1605	1605	1605	1605	1605	1605	329	329
Control group mean	1.524	1.524	0.470	0.470	0.604	0.604	0.0182	0.0182

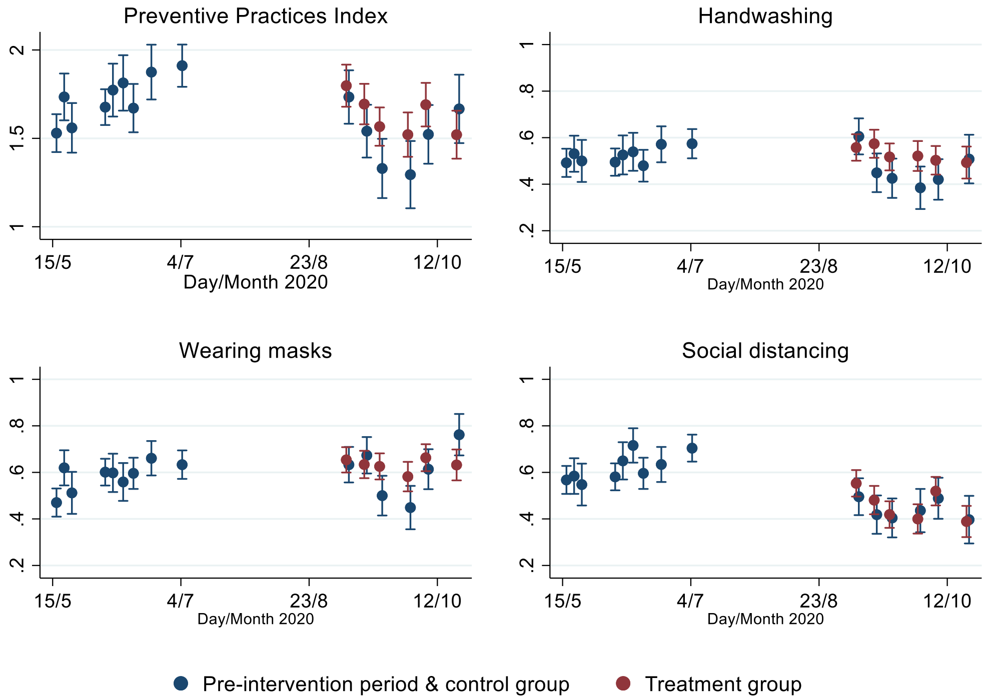
*Estimation results of equation 1 with the respective preventive practice on the binary treatment indicator. The sample is restricted to being interviewed within one week of the intended interview date and excluding the last week of data collection. The preventive practices index is a count-index ranging from 0 to 4 counting whether the respondent mentioned to practice handwashing, social distancing or mask wearing on a regular basis and/ or using telemedicine in case of a health need. The sample for telemedicine usage is restricted to households who has a health need during the previous month. Control variables: respondent age, gender, education, household wealth. Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 5.13 Treatment effects on preventive practices among risk and non-risk group (hypothesis 2)

	Preventive practices index		Handwashing		Wearing masks		Telemedicine if sick	
Treated	0.1003	0.0800	-0.0017	-0.0045	0.0080	-0.0010	0.0417	0.0439
	(0.0919)	(0.0909)	(0.0468)	(0.0466)	(0.0455)	(0.0451)	(0.0575)	(0.0575)
Risk group	0.0655	-0.0014	-0.0562	-0.0689	0.0218	-0.0019	0.0225	0.0153
	(0.0918)	(0.0917)	(0.0468)	(0.0470)	(0.0454)	(0.0455)	(0.0534)	(0.0534)
Treatment x Risk group	0.0489	0.0437	0.0947*	0.0862	0.0457	0.0492	0.0069	0.0098
	(0.1120)	(0.1107)	(0.0571)	(0.0568)	(0.0554)	(0.0550)	(0.0641)	(0.0643)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
N	1576	1568	1576	1568	1576	1568	326	324

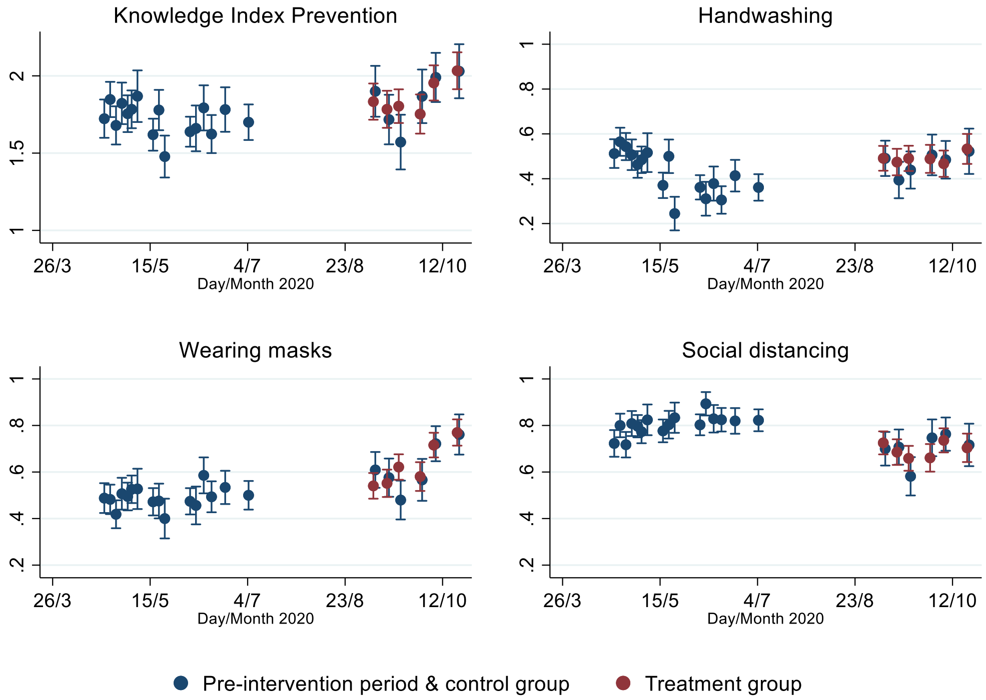
*Estimation results of equation 2 with the respective preventive practice on the binary treatment indicator. The preventive practices index is a count-index ranging from 0 to 4 counting whether the respondent mentioned to practice handwashing, social distancing or mask wearing on a regular basis and/ or using telemedicine in case of a health need. Risk group means having at least one household member above the age of 60 and/ or with a precondition that increases the risk for a severe COVID-19 infection. The sample for telemedicine usage is restricted to households who has a health need during the previous month. Control variables: respondent age, gender, education, household wealth. Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01.*

Figure A 5.4 Preventive practice outcomes over time and across treatment and control group



Plotted mean estimates over time intervals in pre-intervention period (blue), and by treatment (red) and control group (blue) in the intervention period; with 90% confidence intervals; each displayed estimate is based on 218 observations on average (min: 108, max: 358) that were collected over the course of 1-6 days (in five cases 7, 9, 10 and 17 days).

Figure A 5.5 Prevention knowledge outcomes over time and across treatment and control group



Plotted mean estimates over time intervals in pre-intervention period (blue), and by treatment (red) and control group (blue) in the intervention period; with 90% confidence intervals; each displayed estimate is based on 218 observations on average (min: 108, max: 358) that were collected over the course of 1-6 days (in five cases 7, 9, 10 and 17 days).

Table A 5.14 Treatment effects on preventive practices in risk and non-risk group separately

	Preventive practices index		Handwashing		Wearing masks		Telemedicine if sick	
Group	Risk	Non-risk	Risk	Non-risk	Risk	Non-risk	Risk	Non-risk
Treated	0.1447**	0.0887	0.0900***	-0.0018	0.0542*	0.0011	0.0480	0.0417
	(0.0642)	(0.0922)	(0.0327)	(0.0472)	(0.0315)	(0.0465)	(0.0300)	(0.0454)
Control variables	No	No	No	No	No	No	No	No
N	1054	514	1054	514	1054	514	256	68
Control group mean	1.5347	1.4790	0.4538	0.5090	0.6012	0.5868	0.0230	0.0000

*Estimation results of equation 1 with the respective preventive practice on the binary treatment indicator, separately in the sub-sample of households with a risk group member and no household member in the risk group. The preventive practices index is a count-index ranging from 0 to 4 counting whether the respondent mentioned to practice handwashing, social distancing or mask wearing on a regular basis and/ or using telemedicine in case of a health need. Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 5.15 Treatment effects on risk knowledge (hypothesis 4): specification with and without control variables

	Knowledge index risk		Old age		Precondition	
Treated	0.0460	0.0324	0.0443*	0.0372	0.0017	-0.0048
	(0.0368)	(0.0358)	(0.0256)	(0.0252)	(0.0238)	(0.0235)
Control variables	No	Yes	No	Yes	No	Yes
N	1656	1656	1656	1656	1656	1656
Control group mean	0.8699	0.8699	0.5818	0.5818	0.2881	0.2881

*Estimation results of equation 1 with the respective knowledge outcome on the binary treatment indicator. The sample is restricted to being interviewed within one week of the intended interview date and excluding the last week of data collection. The risk knowledge index is a count-index ranging from 0 to 2 counting whether the respondent mentioned age or a correct precondition as risk factors for a complicated COVID-19 disease course. Control variables: respondent age, gender, education, household wealth. Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 5.16 Treatment effects on prevention knowledge (hypothesis 4): with and without control variables

	Knowledge index prevention		Social distancing		Handwashing		Wearing masks		Telemedicine	
Treated	0.0186	0.0058	-0.0068	-0.0114	0.0193	0.0156	0.0129	0.0089	-0.0062	-0.0070
	(0.0516)	(0.0505)	(0.0239)	(0.0236)	(0.0260)	(0.0259)	(0.0252)	(0.0249)	(0.0106)	(0.0106)
Control variables	Yes	No	Yes	No	No	Yes	No	Yes	Yes	No
N	1695	1695	1695	1695	1695	1695	1695	1695	1791	1791
Control group mean	1.8358	1.8358	0.7026	0.7026	0.4690	0.4690	0.6113	0.6113	0.0500	0.0500

*Estimation results of equation 1 with the respective knowledge outcome on the binary treatment indicator. The sample is restricted to being interviewed within one week of the intended interview date and excluding the last week of data collection. The prevention knowledge index ranges from 0 to 4 counting whether the respondent mentioned handwashing, social distancing or mask wearing on a regular basis and/ or using telemedicine in case of a health need as prevention methods against a COVID-19 infection. Control variables: respondent age, gender, education, household wealth. Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 5.17 Adjustment for multiple hypothesis testing for hypothesis group 1

	Preventive practices index	Handwashing	Wearing masks	Telemedicine if sick
Treated	0.1214	0.0597	0.0310	0.0461
	(0.0197)**	(0.0242)**	(0.2285)	(0.0648)*
	[0.0969]*	[0.0969]*	[0.3656]	[0.1727]
Observations	1,614	1,614	1,614	331

*Estimation results of equation 1 with the respective preventive practice on the binary treatment indicator. The preventive practices index is a count-index ranging from 0 to 4 counting whether the respondent mentioned to practice handwashing, social distancing or mask wearing on a regular basis and/ or using telemedicine in case of a health need. Unadjusted p-values in parentheses, q-values adjusted for multiple hypothesis testing following Benjamini and Hochberg (1995); * p/q < 0.1, ** p/q < 0.05, *** p/q < 0.01.*

Table A 5.18 Adjustment for multiple hypothesis testing for hypothesis group 2

	Preventive practices index	Handwashing	Wearing masks	Telemedicine if sick
Treated x Risk group	0.0489	0.0947	0.0457	0.0069
	(0.6623)	(0.0974)*	(0.4100)	(0.9147)
	[0.7569]	[0.1948]	[0.5466]	[0.9147]
Observations	1,576	1,576	1,576	326

*Estimation results of interaction coefficient in equation 2 with the respective preventive practice on the binary treatment indicator times the binary risk group indicator. The preventive practices index is a count-index ranging from 0 to 4 counting whether the respondent mentioned to practice handwashing, social distancing or mask wearing on a regular basis and/ or using telemedicine in case of a health need. Unadjusted p-values in parentheses, q-values adjusted for multiple hypothesis testing following Benjamini and Hochberg (1995); * p/q < 0.1, ** p/q < 0.05, *** p/q < 0.01.*

A5.2 Supplementary information

Power calculation

To determine the sample size that is needed to detect an effect on the main outcomes, we first derived the expected minimal detectable effect size (MDE) using the pre-intervention interview data. Based on the theory of change, we expected the effect of reported practices to be driven by an increase in knowledge of risk groups and preventive practices. The MDE was therefore determined following formula A1 as the sum of the difference in adoption of each preventive practice *i* that might be associated with closing the gap of knowing the respective practice and at least one of the major risk factors of a complicated COVID-19 infection. We expected that around 1/3 of endline respondents in the treatment group would have received and read the messages and therefore had a chance to improve their knowledge on risk and practice information that is conveyed in the messages. This ratio is reasonable as 34% of respondents reported to have received our SMS announcing the interview. A similar share of pilot message recipients could recall receiving and reading the messages. The needed sample sizes were calculated following formula A2 for the whole sample and separately for the group of households with and without at least one member that is in the risk group *r*. As both knowledge and adoption of the aggregate measure of social distancing were already high and not as related, sample sizes of above 7000 in each sample would be required to detect a 2 percentage points (pp) increase. As this was not logistically not feasible, we focus the outcome measurement on handwashing, wearing mask and using telemedicine. To detect a difference of 6.4-7.7pp for both handwashing and wearing masks, a sample size of slightly above 1000 is needed in both the risk and the non-risk group. The effect sizes in the risk group can be expected to be slightly larger if the respondent becomes aware of the specific risk that the household is exposed to rather than any risk factor in general. Hence, to detect an effect in the total population will require a sample size of around 1000 and a sample size of 2500, where 2/3 are allocated to the treatment group should ensure being able to detect a difference of 6-7pp between risk and non-risk group and personalized versus generic messages.

$$(A1)\ mde_{ir} = \left((1 - know.prac_{ir}) * \frac{1}{3}\right) * (prac_{ir} * know.prac_{ir} - prac_{ir} * not.know.prac_{ir}) + \left((1 - know.risk_r) * \frac{1}{3}\right) * (prac_{ir} * know.risk_r - prac_{ir} * not.know.prac_{ir})$$

$$(A2)\ \ n_{ir} = \frac{prac_{ir}}{\left(\frac{2}{3} * mde_{ir}^2\right)} * \frac{-prac_{ir} + 1}{\frac{1}{3}} * (-1.28 - 0.84)^2$$

The sample size for the outcome of telemedicine usage could not be calculated in the same way ex-ante as telemedicine usage in case of a health need was only included in the survey at a later stage, so that there is not a sufficient number of observations. Out of the 200 respondents, around 18% reported a health need not related to COVID-19 in the family during the previous month, but only one reported to have called a doctor, and none reported the use of a telemedicine helpline. Around half reported self-treatment and the other half visited a doctor or hospital. One reason for this might be a low awareness of the recommended use of telemedicine before visiting a doctor – when asked about what is currently recommended to do in case someone has a health need that is not related to COVID-19, only two mentioned telemedicine and three mentioned calling a doctor. Hence, any change in knowledge and practice with respect to telemedicine should be detectable in the sample that can detect changes in the other practices.

In order to account for non-response in the post-intervention survey, it was necessary to draw a substantially larger intervention sample. Based on the experiences from a previous follow-up survey wave, it was expected that 30% of those who were previously interviewed would be reached again for follow-up and 10% of the previously uncontacted households will be reached. To reach an interview sample of 2,500, it will therefore be necessary to contact around 21,500 numbers, the intervention will have been sent to two thirds of these (around 14,300).

Data collection and processing

For this study, we used a research infrastructure that was established with the helpline firm ICU healthcare and the Social Health Protection Initiative before the onset of the COVID-19 pandemic. This infrastructure builds on a data sharing portal as well as a platform for web-based questionnaires that ensure protection of the personal data.

The pre- intervention survey was collected over the phone in three waves between April and July 2020 as a rapid response to document attitudes, knowledge and actions of the sample population over the course of the COVID-19 outbreak. As depicted in Figure 5.1 in the main text, the first survey wave started on April 19, a few weeks into the nationwide lockdown and a few days before the onset of Ramadan. Hence, most of the first wave took place during Ramadan and a follow-up wave with the same respondents was conducted within the last week of Ramadan, but after the strictest lockdown regulations were lifted. For the third wave after Ramadan, a new sample was selected following the same sampling procedure as before. The main areas covered by the survey were: Socio-economic characteristics of the respondent and the household; attitudes such as trust in different groups and organizations regarding their message on corona and the government's reaction; knowledge of coronavirus (symptoms, transmission, prevention, treatment, risk groups); prevention practices as well as actions in the case of a suspected corona case in the family / community; disease perceptions (severity and likelihood) and capacity for self-isolation. Where possible, the survey instruments were taken from previously validated and standardized questionnaires. The questionnaire was translated into Pashto, Urdu and Hindko language by the local research partners and administered in the language that the interviewee was fluent in.

In order to follow the social distancing recommendations, the trained interviewers conducted the interviews over the phone from their homes. They were using SIM cards with an official and uniform number from ICU healthcare. Informed consent was taken verbally, and the interview data was entered into a web-based form, which is part of the secure data framework. The research team is only able to download anonymized datasets, but can still link all datasets using the anonymized identifiers.

We took several measures to tackle non-response. First, we are aware that many telephone numbers are not valid anymore as the owners have changed numbers since enrollment (which might date up to five years back). For the valid numbers, in order to build trust, text messages announcing the call were sent at least one day before the first call. If the respondent was not reached at the first call, s/he was re-called 2 times according to a protocol (call 2: one hour after unsuccessful call 1 and call 3: at a different time on the next day). Interviewers would also take appointments. We aimed to interview the main cardholder, which was successful in around 77% of the interviews (see appendix Table A 5.4). If it was not possible to conduct the interview with him/ her, e.g. due high age (above 65 years), hearing or language difficulties or not being willing to be interviewed, another household member (ideally the household head or the main cardholder's spouse) was interviewed. If the listed main cardholder was not a member of the household (anymore), this household was excluded.

Post-intervention interviews were conducted following the same procedure. The survey was designed to not last longer than 10-15 minutes and only includes a subset of questions from the previous more detailed survey. The questions that remained cover all outcome measurements (as described in section 5.3.4) as well as an additional section that elicits mobile phone usage as well as whether and how our messages were received. In order to keep the time between receiving the intervention and the interview constant across respondents, the start of the intervention was staggered according to the amount of interviews that the interviewer team was expected be able to conduct in one day. As the time between receiving the last message and the interview should be one week, the first interviews began on September 2nd. The termination rule for data collection was that all sampled households have been either interviewed or contacted at least three times according to the calling schedule. As this was not reached after one month as intended, the intervention and data collection was continued for another four weeks.

The enumerators were 14 students and graduates of Khyber Medical University. Beyond thorough survey piloting and enumerator training, where possible, we programmed error-checks into the questionnaire, and closely monitored the consistency of the data during and after data collection.

In addition to the survey data, we use calls to the Sehat Insaf Card helpline as well as the Public Health Association's (PHA) telemedicine helpline, which are both administered by ICU healthcare. Call-logs as well as a short questionnaire on the demographics and reason for calling were incorporated into the data portal and matched to the study sample using anonymized identifiers based either national identification number or telephone numbers.

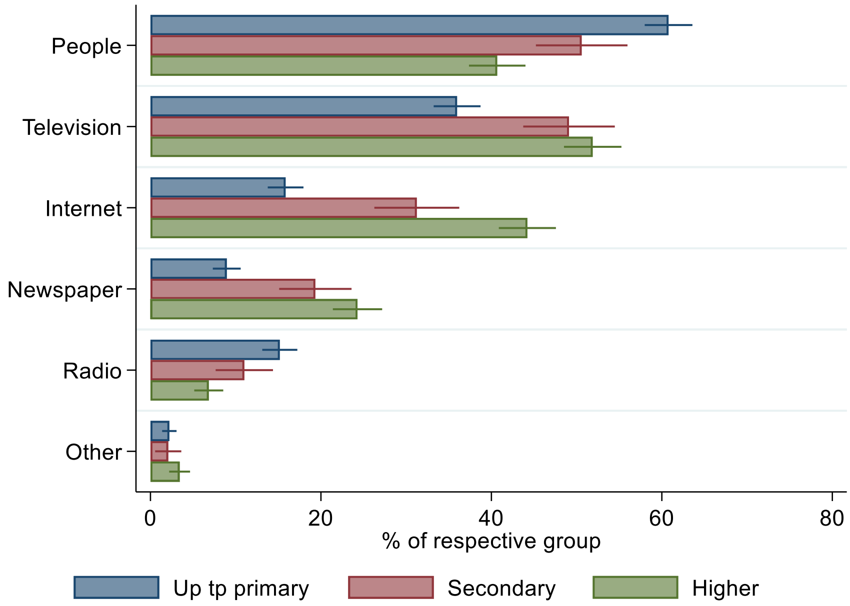
Insights from pre-intervention survey and intervention piloting

We relied on two kinds of pilot data: quantitative interview data and qualitative interviews after a pilot intervention.

The sample characteristics of the pre-intervention survey were very similar to the post-intervention survey. On average, respondents are around 50 years old, and more than half have a household member that is above 60 years old. Around half of the sample have not more than primary education, 14% have secondary and 32% tertiary. Most are either daily wage laborers or self-employed, 15% are unemployed, 11% are private employees and 9% civil servants. While only 51% of respondents say that they are literate, 75% have at least one family member who can read in Urdu, so that the majority of the sample would be able to read an SMS. Only 42% on the other hand report any access to the internet, so the majority of the sample could not be reached by a web-based information campaign.

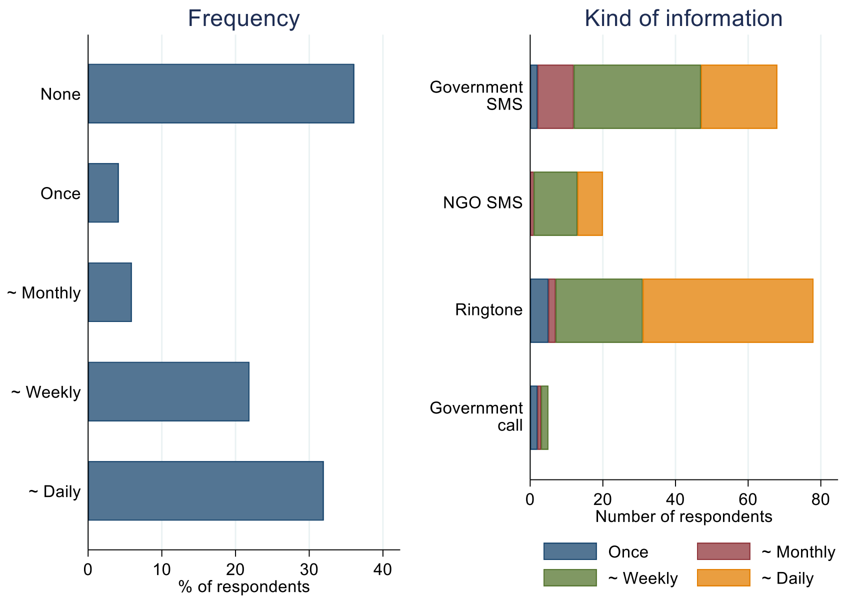
Literacy rate and internet access also reflect in the way information on COVID-19 is sought. As depicted in Figure A 5.6, the majority of respondents relied on others and television for information, while word of mouth is a much more common source of information among those with at most primary education and internet and newspaper only play a large role for those with above primary education. Though rarely mentioned freely in the open question on the information source, around 75% of the 250 interviewees in the last weeks of data collection confirmed that they had received some information on COVID-19 through their mobile phone. Out of those, around half reports to have received information on a daily basis, which is mainly driven by listening to the caller tune with every outgoing call, around the same number of respondents reports to have received government SMS, but with a lower frequency (see Figure A 5.7).

Figure A 5.6 COVID-19 information source during the previous week by education level of the respondent



Share of each education group reporting to have used the respective information source during the pre-intervention survey period; including 95% confidence interval around each group mean.

Figure A 5.7 Frequency and type of mobile-phone based COVID-19 information



For subset of 189 respondents during the last weeks of data collection that reported to have received COVID-19 information through their mobile phone.

Risk groups for a complicated COVID-19 disease course can be identified from the survey data based on age and preconditions following the definitions in chapter 5.3.4. We see that almost 50% of households have at least one household member that is over 60 years old and 38% reported to have at least one household member with the previously mentioned medical conditions that indicate increased risk based on a precondition. As depicted in Figure 5.7 in the main text, half of this age-based risk group can also be identified in the administrative data using the age of the main cardholder in the enrollment data and 28% of the households that reported a relevant precondition could be identified from the claims data. Within the risk group that can be identified in the survey data, around 2/3 are characterized by age risk. Precondition-based risk is dominated by household members with hypertension and diabetes followed by cardiovascular diseases more generally, while respiratory diseases and cancer take up a much smaller share. Similarly, a large share of households with a precondition also has a member over the age of 60 and different preconditions coincide within one household (Table A 5.19).

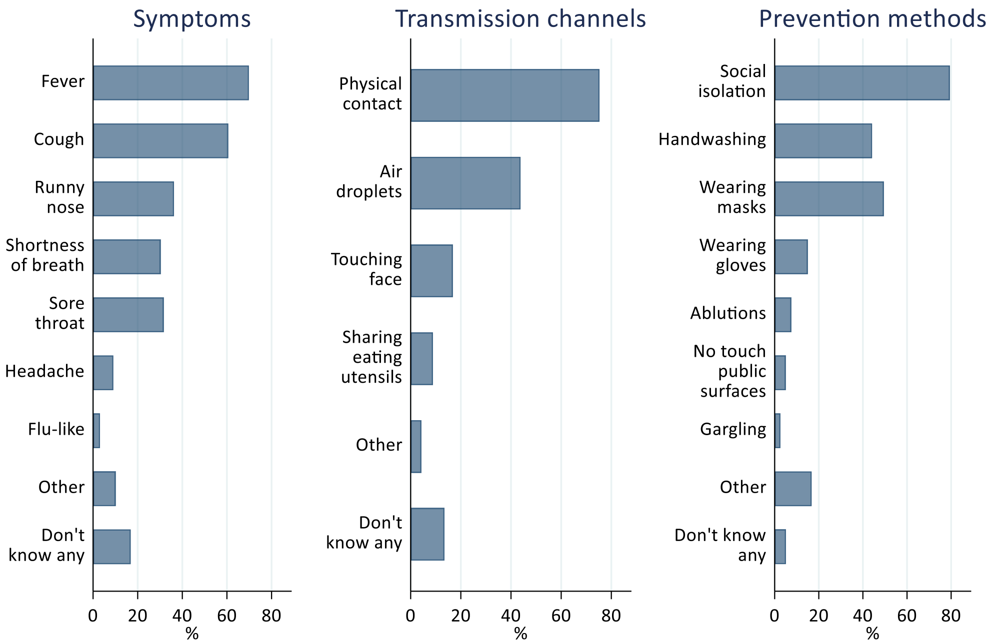
Table A 5.19 Risk factor distribution in the pre-intervention survey sample

	Any risk	Age >60	Any precondition	Hypertension	Diabetes	CVD	Respiratory	Cancer
% of households	69	60	26	14	14	10	3	1
Number of households	1,416	1,239	540	295	278	201	54	17
+ Age >60				203	189	134	40	12
+ Hypertension					86	67	12	7
+ Diabetes						64	13	7
+ CVD							11	5
+ Respiratory								3

Number of households in the pre-intervention survey sample with the respective risk factor and below the pairwise number of coinciding risk factors.

The survey sections on disease knowledge and action reveal a generally high awareness of COVID-19 and its severity, but also significant gaps. Only half of the respondents could name both fever and cough as symptoms of COVID-19, 75% knew that it can be transmitted through physical contact but only 44% that it can also be transmitted via air droplets (Figure A 5.8). Social distancing is widely known as prevention method, wearing masks by about half and increasing over time, but hygiene measures such as handwashing were named by less than half of the respondents and decreasingly over time. Risk group knowledge seems more limited, around 60% of respondents are aware of old age being a risk factor, but only 20% mention any precondition while over 30% falsely mention children.

Figure A 5.8 Listed symptoms, transmission or prevention knowledge item



Displays share of respondents who mentioned the respective item in open questions regarding symptoms, transmission channels and prevention methods respectively.

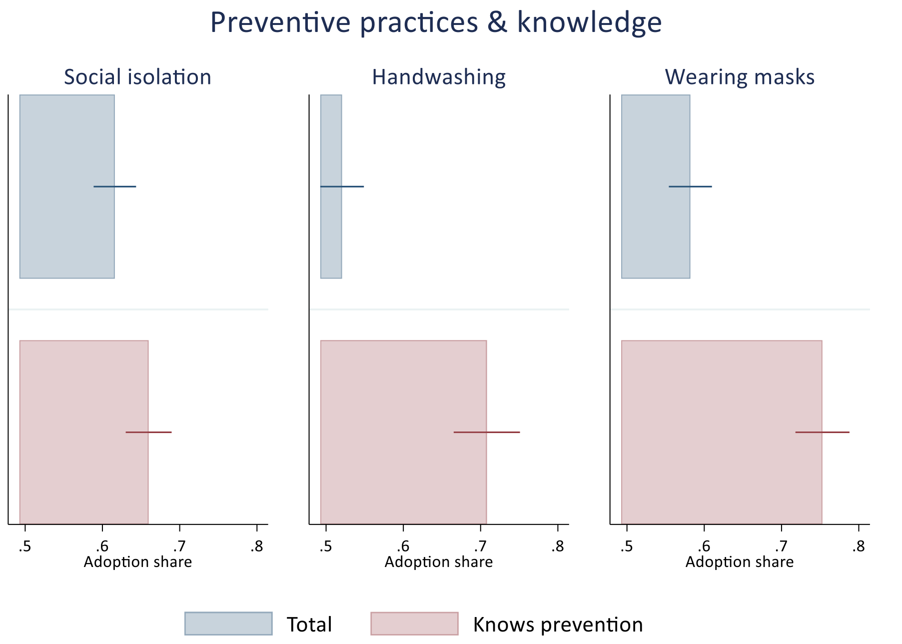
We further find evidence for the channels that are predicted by the theory of change. The overall state of knowledge and practice does not seem to differ strongly across risk and non-risk group (Table A 5.20). Only knowledge of all main symptoms (fever, cough and shortness of breath), old age being a risk factor and the use of masks are slightly higher in the risk group. One reason for the lack of a difference might be that almost half of risk group households are not aware of at least one of the own risk factors. The data further hints that the adoption of preventive practices is strongly associated with knowledge of the practice, both in the overall sample (Figure A 5.9) and the risk group in particular when knowledge of the own risk and the preventive practice are combined as it is the case in the intervention (Figure A 5.10). This gives us confidence that an intervention that raises awareness for both risk groups and effective preventive measures could contribute to closing gaps in adoption of preventive practices.

Table A 5.20 Mean knowledge and practice in full sample and comparison between risk and non-risk group

	Full sample	No risk	Any risk
Knowledge			
- main symptoms	0.1907	0.1650	0.2067**
	(0.3930)	(0.3714)	(0.4051)
- fever& cough	0.5272	0.5162	0.5341
	(0.4994)	(0.5000)	(0.4990)
- airborne	0.4380	0.4161	0.4513
	(0.4963)	(0.4932)	(0.4978)
- smear transmission	0.8004	0.7836	0.8106
	(0.3998)	(0.4120)	(0.3920)
- Social distancing	0.7941	0.8043	0.7878
	(0.4045)	(0.3970)	(0.4090)
- hygiene	0.4420	0.4220	0.4542
	(0.4967)	(0.4942)	(0.4981)
- mask	0.4949	0.4847	0.5012
	(0.5001)	(0.5001)	(0.5002)
- age risk	0.6264	0.6032	0.6401*
	(0.4839)	(0.4896)	(0.4802)
- precondition risk	0.2002	0.1824	0.2107
	(0.4002)	(0.3865)	(0.4080)
Practice			
- going out daily	0.6855	0.6640	0.6981
	(0.4644)	(0.4727)	(0.4593)
- times going out	4.1955	4.3354	4.1174
	(4.2549)	(5.2881)	(3.5501)
- for shopping	0.6234	0.6123	0.6295
	(0.4847)	(0.4876)	(0.4831)
- for work	0.4931	0.5089	0.4845
	(0.5001)	(0.5003)	(0.5000)
- for prayer	0.3829	0.3667	0.3917
	(0.4862)	(0.4823)	(0.4883)
- social distancing	0.6383	0.6747	0.6184
	(0.4808)	(0.4693)	(0.4862)
- hygiene	0.5279	0.5479	0.5169
	(0.4995)	(0.4986)	(0.5002)
- mask	0.6092	0.5685	0.6316*
	(0.4882)	(0.4961)	(0.4828)
Suspect action			
- consult health worker	0.4575	0.4798	0.4456
	(0.4983)	(0.5000)	(0.4972)
- get test	0.8129	0.8085	0.8152
	(0.3901)	(0.3938)	(0.3883)
Telemedicine			
Heard of	0.4153	0.3783	0.4340
	(0.4931)	(0.4859)	(0.4961)
Willing to use	0.8208	0.8068	0.8279
	(0.3837)	(0.3955)	(0.3778)
N	2,529	1,127	1,402

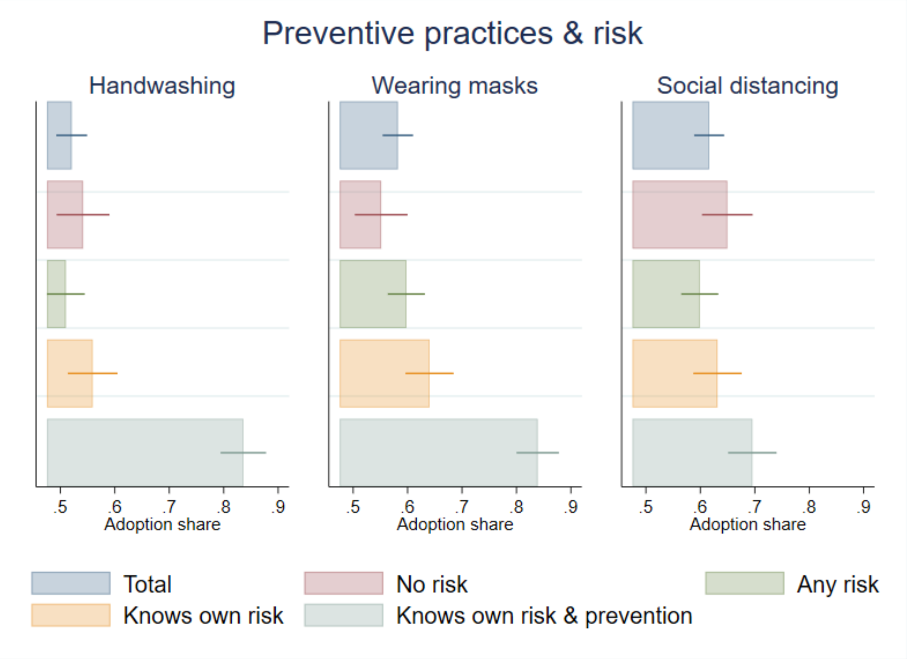
*Standard deviations below mean; stars indicate significant difference between no risk and risk group based on t-test, * 0.1 ** 0.05 *** 0.01*

Figure A 5.9 Mean preventive practice adoption in full sample compared to those who stated to know the practice



Bars depict mean estimates with 95% confidence intervals.

Figure A 5.10 Preventive practices in pre-intervention survey period



Bars depict the adoption share of the respective practice in the complete sample (blue), among those who have no at-risk household member (red), at least one at-risk household member (green), those who additionally know about the own household's risk (yellow) and those who additionally mentioned the respective practice in the prevention knowledge question (light green) with 95% confidence intervals.

Intervention piloting

We further pre-tested the intervention among 400 numbers. Shortly after receiving the messages, semi-structured in-depth interviews were conducted with 12 message recipients to understand whether and how they received the messages, and if so how they perceived them and whether they acted upon them. From the message delivery reports, we see that 15% of messages could not be delivered, so that these are likely invalid numbers. Out of the 85% for whom the messages were either delivered to phone or network, we can only find out at the time of the interview whether the number is still active and being used. Out of those who were reached and agreed to be interviewed, half report to have received and read our messages.

Respondents generally appreciated the messages even though they reported that most of the content was not new to them, but a good reminder and confirmation that this information is still valid. Many also reported that they normally have limited access to new information as they live remotely and rely on others sharing information with them. Along those lines, all but one respondent would like to keep receiving such messages with the same or even higher frequency, so that we do not expect our messages to be perceived as a burden. One respondent mentions that he doubts the existence of COVID-19 as there has not been a case in his village and therefore finds it irritating to keep receiving information on this topic.

Respondents received the messages in different ways: out of those who recalled the messages, four had read them themselves and two had either the brother or son read it to them. This shows that despite high illiteracy among respondents, they can rely on other household members to read the message and receive it nevertheless. One case also shows the limits of this strategy as one of the respondents said that his brother would have normally ready it to him, but could not as he was sick. If respondents did not recall the messages, the interviewers read the messages to them to still elicit their opinion on content and wording. After reading it, one further respondent remembered that his brother had told him about the message as it had mentioned his name. Three respondents did not even find the message on the phone anymore. For respondents who could not recall receiving the messages, interviewers read out the messages to them to still elicit their opinion on wording and content.

When asked about which content they recall, the preventive practices are mentioned most, so that this seems to be the content that is absorbed most. Two also mentioned the risk group information. Only three said that they received new information through the messages, one in general, one regarding telemedicine and one regarding diabetes. This is in line with most respondents saying that they feel in general well informed about COVID-19 as they know about basic preventive measures, but are unsure regarding more details. The focus on the practice information is also apparent in the actions that they have or plan to take after receiving the messages. Most mention following the preventive practices, but rather as a reinforcement of what they will continue to be doing instead of starting a new habit. In addition, eight respondents mention explicitly that they will tell others about the information, two of those specifically that they will share it with elderly members of the family.

Furthermore, the respondents confirmed that the messages were perceived to be trustworthy. Stated reasons are that they consider the sender (Sehat Insaf Card program) to be a trustworthy source for health information, that the helpline number was mentioned for further information and that they were addressed by their name. Most also say that the message concerns them as they are aware of the pandemic and perceive the message as a good service for them. As mentioned above, the language and literacy barrier can be lifted to some degree through other household members and some respondents also like about the messages that they are sent in Urdu rather than English like some other official campaigns. Yet, some respondents say that they would prefer the messages to be sent in Pashto rather than Urdu language or even prefer phone calls as they are more personal and accessible for illiterate people. These will remain the limits of an SMS-based intervention, which we have addressed to the degree possible by including the name, a reference to the family as well as the chance to call the helpline for more information. All in all, these results gave us confidence that the messages would be received well if read and have the potential to reflect in preventive action.