

**Health challenges of the 21st century –
Empirical essays on the health and economic burden of
non-communicable diseases and climate change in
Southeast Asia**

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*“The pleasures of life are worth nothing if one is not alive
to experience them.”*

David Cutler, Angus Deaton and Adriana Lleras-Muney
in their article “The Determinants of Mortality” (2009)

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1 Introduction

1.1 Health challenges of the 21st century

Decent health is arguably among the most invaluable assets for a satisfactory and productive life. In low- and middle-income countries (LMICs), where “work” often implies hard physical labor and endurance, and health care system capacities are limited in terms of human and financial resources, decent health can be pivotal for securing a minimum living standard. Taking a macroeconomic perspective, decent levels of public health and low inequalities in health also foster economic growth in the long run (Bloom et al., 2014, 2004; Cervellati and Sunde, 2011; Grimm, 2011; Lorentzen et al., 2008; Weil, 2007).¹

Historically, health agendas in LMICs were occupied with addressing infectious diseases, inadequate maternal conditions and malnutrition, which until the end of the 20th century continued to be the leading cause of death (Cutler et al., 2006; Global Burden of Disease Collaborative Network, 2021). In the ongoing 21st century, however, LMICs face two health challenges that are different from what these countries have experienced in the 19th and 20th century. First, they are confronted with surging rates of non-communicable diseases (NCDs), namely cardiovascular diseases, cancer, chronic respiratory diseases, diabetes and mental disorders, which are by now the leading cause of death in all world regions, except sub-Saharan Africa (Global Burden of Disease Collaborative Network, 2021). Second, climate change will take its toll and is predicted to cause catastrophic health impairments, ranging from the accelerated spread of infectious diseases due to warmer temperatures, over increased risk for certain types of cancer, to heat strokes and death (Epstein and Yanovich, 2019; Friel et al., 2011; Hiatt and Beyeler, 2020; Kjellstrom et al., 2010).

The World Health Organization (WHO) declares NCDs and climate change as the 21st century’s major health and development challenges (World Health Organization, 2018a, 2022a,b). Both will pose a disproportionate burden on LMICs,

¹While most macro-economists agree that health is intrinsically linked to economic development, the actual magnitude, the specific channels as well as differential effects on aggregate GDP and GDP per capita remain debated (Acemoglu and Johnson, 2007, 2014; Bloom et al., 2022, 2004).

which are also the countries least able to cope with them. Hence, increasing rates of NCDs, climate change and the related health consequences hinder the progress towards reaching the Sustainable Development Goals. Specifically, by threatening individual health and socioeconomic improvements and by posing an immense burden on already constrained health care systems, they impede the progress in poverty reduction and widen health inequities between the rich and the poor (Beaglehole et al., 2011; Friel et al., 2011; Frumkin and Haines, 2019; NCD Alliance, 2016; Nugent et al., 2018). Hence, LMICs that want to prevent a setback in their public health achievements and economic development in the decades to come will need to reorient their national health agendas towards addressing these two major health challenges.

Against this background, this thesis investigates the potential of NCD prevention and treatment measures in the context of Southeast Asia², with case studies in Indonesia. Specifically, it seeks to understand what kind of health interventions have the potential to be (cost-)effective considering the cultural background, lifestyle, health literacy, income levels and health system capacities in the region. Further, this thesis analyzes the interplay between NCDs and climate change and assesses the financial burden that both might pose in the decades to come. Hence, this thesis contributes to a better understanding of how the two health challenges of the 21st century, NCDs and climate change, can be addressed in the context of Southeast Asia and offers insights into what type of health policies and interventions can play a supportive role.

1.1.1 Non-communicable diseases in low- and middle-income countries

Until the second half of the 20th century, NCDs constituted only a small share of the diseases burden in LMICs. Yet, with the dawn of the 21st century, the disease patterns have shifted and LMICs have experienced an unprecedented health and epidemiological transition. Driven by rapid urbanization, globalization, economic development and unhealthy lifestyles, NCDs have become the leading cause of death and disease burden (Bollyky et al., 2017; Frenk and Gomez-Dantes, 2011; Global Burden of Disease Collaborative Network, 2021).

Figure 1.1 displays this disease transition for Southeast Asia, the geographical setting for this thesis. In the region, NCDs nowadays account for 72% of deaths in comparison to 46% in 1990, whereas the total disease burden stemming from

²Throughout this thesis I use the geopolitical classification of Southeast Asia and not the classification of the World Health Organization, unless explicitly stated otherwise. Southeast Asia is composed of eleven countries: Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste and Vietnam. The analyses presented in this thesis do not refer to the two high-income countries Singapore and Brunei.

communicable diseases, maternal, neonatal and nutritional health conditions has dropped from 43% in 1990 to now 20%. For example, in Indonesia, the three leading causes of death are NCDs (stroke, ischemic heart disease and diabetes) and together account for 41% of all deaths in the country. In Thailand, Myanmar and Vietnam, more people nowadays die from diabetes than from road injuries, HIV/Aids, dengue or tuberculosis (Global Burden of Disease Collaborative Network, 2021).

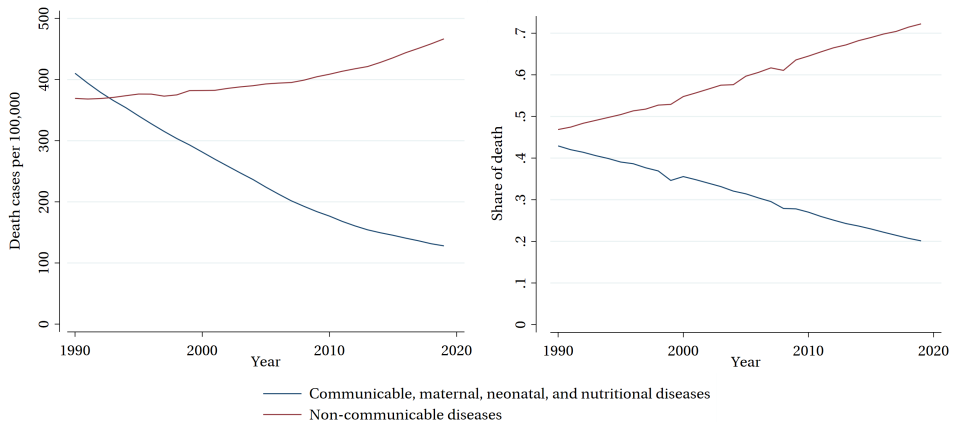


Figure 1.1: Death rates per 100,000 and share of death by cause in Southeast Asia - The figure presents the change in the cause of death between disease types for LMICs in Southeast Asia between 1990 and 2019. The left graph presents the death rate per 100,000, the right graph presents the share of death. Source: Global Burden of Disease Collaborative Network (2021).

One might argue that such a transition is the logical consequence of economic and public health development and that high-income countries similarly underwent this transition. Yet, two facts underline why the transition we observe today in LMICs is distinct from what high-income countries have experienced previously. First, the transition evolving today is accelerating much faster than the one which high-income countries have experienced (Bollyky et al., 2017; Miranda et al., 2008). Especially the increase in diabetes rates is unprecedented. For example, in Malaysia, Indonesia and Thailand, the prevalence rates of diabetes have more than doubled, almost tripled, in the last 20 years, reaching higher prevalence rates than in the US (International Diabetes Federation, 2000, 2021). Second, the transition experienced by high-income countries was linear and clear-cut in a sense that the rise in NCDs implied an almost complete eradication of the disease burden attributed to infectious diseases, undernutrition, maternal and child mortality. The current rise of NCDs in LMICs, however, has not brought a similarly strong reduction in other diseases as high-income countries have experienced it (Daniels et al., 2014; Global Burden of Disease Collaborative Network, 2021).

As a result, many LMICs nowadays suffer from a double diseases burden: surging rates of NCDs and high rates of communicable diseases. Against this, however, they have only limited health care system capacities and financial resources to fight. Moreover, LMICs also carry the largest burden in terms of premature death from NCDs. In fact, NCDs occur in general at much lower age levels compared to the average age of NCD onset in high-income countries. Further, 86% percent of all NCD-related premature deaths, defined as dying before the age of 70, occur in LMICs (Benziger et al., 2016; Daniels et al., 2014; World Health Organization, 2022a).

Once developed, NCDs are of chronic nature, i.e., they persist over a long duration and individuals often die of them only after an extended period of suffering (World Health Organization, 2022a). Moreover, symptoms of, e.g., diabetes, cancer or heart diseases are not instantaneous but often become apparent only in late stages of the disease trajectory, leaving affected individuals unaware of the disease. Late occurring symptoms together with low awareness of risk factors and limited screening activities in primary health care make a timely diagnosis of NCDs often difficult (Kruk et al., 2015). Estimates suggest that in Indonesia more than 70% of diabetes cases remain undiagnosed (International Diabetes Federation, 2021). Similarly, studies in Vietnam and the Philippines record prevalence rates of undiagnosed hypertension higher than 50% (Capuno et al., 2021; Nguyen et al., 2016).

Late occurring diagnoses then often imply that cure is either no longer possible or very costly, hence, very often long-term treatment is the only option to reduce the individual disease burden. This in turn can lead to high out-of-pocket households' health expenditures, especially in the absence of health insurance, and thereby cause or deepen poverty. At the same time, it increases treatment cost for chronic care on the health care provider side. Further, the disease driven limited productivity or the inability to work does not only have detrimental implications for households' living standards, but also causes large economic productivity losses at the aggregate level. Estimates from Bloom et al. (2011) suggest that over the period 2010-2030 NCDs will have caused costs around US\$21 trillion in terms of costs of illness and productivity losses in LMICs, which translates into yearly cost equivalent to 5% of the total GDP in 2010 of LMICs. A related study by Bloom et al. (2015) estimates that Indonesia alone faces expected economic output losses due to NCDs (without mental illnesses) of US\$3.49 trillion over the period 2012-2030.

While NCDs have detrimental health and economic consequences, premature deaths from NCDs are largely preventable. Specifically, the four main NCDs, namely cardiovascular diseases, diabetes, cancer and chronic respiratory diseases, are to a vast extent caused by four modifiable behavioral risk factors: smoking, physical inactivity, unhealthy diets and excessive alcohol consumption (World Health Organization, 2022a). As in other LMICs, rapid urbanization, globalization

and economic development of the last decades have led individuals in Southeast Asian countries to increasingly adopt unhealthy and sedentary lifestyles. For example, Indonesia ranks first in the male smoking rate worldwide, Myanmar and Timor-Leste follow on rank two and three (World Health Organization, 2022c). Likewise, consumption patterns have changed towards processed foods high in fat, salt and sugar, whereas consumption of fruits and vegetables remains comparably low (Baker and Friel, 2016; Dans et al., 2011; Murray, 2019). This has led to increasing rates of people suffering from overweight and obesity in the Southeast Asian region (Angkurawaranon et al., 2014; Chan et al., 2017; Rachmi et al., 2017).

Such behavioral risk factors trigger the appearance of metabolic risk factors, such as increased blood pressure, high blood glucose and lipids, which ultimately lead to a higher risk of contracting NCDs and to a higher risk of dying from them. Hence, efforts to promote healthier lifestyles can contribute to both, lower rates of NCDs in the first place and lower risk of mortality, once an individual is affected by NCDs. In fact, about 80% of the premature NCD burden could be prevented or postponed to older ages if individuals adopted healthier lifestyles (World Health Organization, 2022a).

To reap the gains of potential NCD prevention, however, the rapid change in the structure of the disease burden in Southeast Asia needs to be accompanied by a change in the alignment of health policies and health care system priorities. Some countries, such as Indonesia, the Philippines and Myanmar, have made a first step into this direction by starting to integrate the WHO's "Package of Essential Noncommunicable Disease (PEN) interventions for primary health care" into their national health agendas, yet with limited success so far (Aye et al., 2020; Capuno et al., 2021; Rattanavipapong et al., 2016; World Health Organization, 2020a). Low awareness of and knowledge about NCDs, as well as the historical focus on combating communicable and infectious diseases and providing acute instead of preventive care limit the effectiveness of such interventions (Dans et al., 2011; Kruk et al., 2015; Meiqari et al., 2020; Widyaningsih et al., 2022).

An adequate response to the current surge of NCDs also remains a difficult task due to the limited governmental spending on public health in many Southeast Asian countries (Daniels et al., 2014). In 2018, Indonesia, Thailand, Myanmar and Vietnam, for example, spent a smaller share of their GDP on health (2.9%, 3.8%, 4.6%, 5.2%) than all LMICs on average (5.3%) (World Bank, 2022). Considering further the minuscule share of flows of development assistance for health that goes to NCDs (less than 2% of global public health financing), it is crucial to identify cost-effective and easy-to-scale NCD interventions (Beaglehole et al., 2011; Dans et al., 2011; Institute for Health Metrics and Evaluation, 2021).

Despite their importance, economic health research has widely neglected NCDs in LMICs in the dawn of the 21st century (Behrman et al., 2009). While this has been

changing (slowly) more recently, the scientific evidence is still scarce and research on NCDs remains underfunded (Frumkin and Haines, 2019). As a result, evidence from high-income countries is often extrapolated to LMICs. This leaves substantial demand for local and context-specific research and solutions (Revill and Sculpher, 2012), towards which this thesis aims to contribute.

1.1.2 Interplay of climate change and non-communicable diseases

Climate change will affect human health in the forthcoming decades through multiple pathways, with LMICs being most severely affected (Costello et al., 2009). Increases in water-, food- and vector-borne diseases driven by warmer temperatures, deterioration of the agricultural sector and related nutritional deficiencies, destruction of health facilities through natural disasters, to name just few examples, will pose a threat to decent human health.

What has so far been understudied, however, is the interplay between climate change and NCDs (Friel et al., 2011). Yet, the surge of NCDs and climate change share certain characteristics that make them intrinsically linked (NCD Alliance, 2016). Both are (to some extent) man-made, accelerated by unhealthy human behaviors, excessive consumption patterns and globalization. Further, both could (to some extent) be prevented or attenuated by changes in human behavior and lifestyle. For example, a reduction in the excessive consumption of meat products can lower the risk for NCDs, while reducing the need for livestock production, which significantly contributes to the global greenhouse gas emissions (NCD Alliance, 2016). Riding a bicycle instead of taking the car reduces cardiovascular disease risk and air pollution at the same time. The latter, in turn, can link back to a reduction in the incidence of respiratory diseases. While these are only a few out of many examples, it shows the scope for addressing both health challenges jointly.

Yet, not only do they emerge from similar causes, but climate change will also exacerbate the NCD challenge further, and this through multiple direct and indirect channels (Friel et al., 2011; Frumkin and Haines, 2019).

The direct channel encompasses primarily the effects of excessive heat, poor air quality and ozone levels, and elevated ultra-violet (UV) radiation on the NCD burden. Excessive heat can directly worsen cardiovascular, respiratory and diabetic conditions. In particular, heat causes accelerated blood circulation and heart rate, and changes in blood pressure levels. This can lead to a cardiac output which is insufficient to fulfill the thermoregulatory needs of the human body. The latter, in turn can lead to heat exhaustion, dehydration and heat stroke (Epstein and Yanovich, 2019). Moreover, excessive temperatures affect the respiratory tract and lungs. Main pathways are increases in air pollutants, allergens and ozone levels, which exacerbate chronic respiratory conditions, such as asthma, and can cause

respiratory track irritation and lung diseases (Kjellstrom et al., 2010). Excessive temperatures can also worsen the health status of individuals suffering from diabetes. In particular, since their skin's blood flow and sweating response are lower compared to that of healthy individuals during heat-exposure, excessive heat can have detrimental consequences for an individual's glycemic control, leading to glycemic shocks (Kenny et al., 2016). Moreover, increases in UV radiation, ozone levels and poor air quality will have a direct impact on the development of certain types of cancers (Hiatt and Beyeler, 2020).

Through an indirect channel, climate change induced natural disasters, such as floods, storms or forest fires can destroy critical health infrastructure and hinder the access to life-saving medication and routine visits (Friel et al., 2011; Frumkin and Haines, 2019; Ryan et al., 2015). Forest fires additionally increase the risk of respiratory diseases and lung cancer (Hiatt and Beyeler, 2020).

In this thesis, I aim to contribute to the evidence focusing on the direct channel. Specifically, in Chapter 3 of this thesis, I assess the effects of heat on the NCD burden in the context of Indonesia.

1.2 Strands of the NCD literature

The following section provides a glimpse into different strands and current focuses in the field of NCD prevention and treatment in LMICs. Empirical evidence from Southeast Asia is embedded wherever available. Yet, the aim is not to present an exhaustive literature review, but rather to provide the broader context for the chapters presented in this thesis. The review will touch upon some of the debates and point to research gaps in the respective areas that will be addressed in the chapters that follow.

1.2.1 Cost-effectiveness and the WHO's "PEN" and "best buys"

Since 2010, the WHO has promoted its "Package of Essential NCD Interventions (PEN)", which later have been updated and renamed "best buys" (World Health Organization, 2017, 2020a). They consist of a set of NCD interventions that are deemed to be (cost-)effective and are endorsed to be implemented throughout LMICs to improve the prevention and control of NCDs. However, the major share of evidence that can inform such interventions still comes from high-income countries. Country- or region-specific evaluations in LMICs remain scarce. A literature review by Allen et al. (2018), for example, finds that interventions aligned with the best buys were underused and only studied in 11% of all LMICs. Consequently, contextual evidence is required and strongly advocated by researchers and policy

makers (Allen et al., 2018; Isaranuwachai et al., 2020).

One strand of the literature focuses in particular on cost-effectiveness of the PEN/best buy interventions in different contextual settings, i.e., specific countries or regions, making primarily use of modeling or micro-simulation exercises (e.g., Cecchini et al., 2010; Dukpa et al., 2015; Ginsberg et al., 2012; Ngalesoni et al., 2016; Ortegón et al., 2012). Cost-effectiveness studies for Southeast Asia were conducted, for example, by Rattanavipapong et al. (2016), who analyze the cost-effectiveness of diabetes and hypertension screening in the context of Indonesia. Levy et al. (2006) investigate the cost-effectiveness of several tobacco control policies in the context of Vietnam, and Ha and Chisholm (2011) assess the cost-effectiveness of prevention strategies to reduce consumption of salt and tobacco also in Vietnam. Overall, these studies conclude that the WHO's best buys promise to be cost-effective.

Other studies also evaluate the PEN/best buy interventions, but depart from the cost and modeling perspective and investigate whether the interventions are functionally implemented and effective in the first place. Such studies rely often on (quasi-)experimental evidence or on individual-level surveys, aiming to derive causal evidence. Despite such evidence being much more limited than cost-effectiveness studies, some examples for (Southeast) Asia exist. Nazar et al. (2020) rely on a quasi-experimental approach to assess the impact of India's national tobacco control program. Further, Capuno et al. (2021) use an experimental approach to investigate whether opportunistic cardiovascular disease risk screening improves individual health behaviors and reduces risk in the Philippines. And Aye et al. (2020) rely on a mixed-methods approach to evaluate the state of implementation of the PEN interventions, their effectiveness and corresponding barriers in the implementation in Myanmar. In contrast to the modeling studies, however, all of the three studies mentioned here find only small effects that can be causally related to the interventions, highlighting the need for identifying more effective approaches.

1.2.2 Contextual constraints

Another strand of the literature focuses on different contextual constraints that limit NCD prevention and treatment efforts and thereby result in the persistence of unhealthy lifestyles and risk factors. Different limiting factors have been identified in the literature, of which three will be briefly touched upon in the following.

A first barrier for the effective prevention and treatment of NCDs in LMICs is the limited access to health care, including the absence of health insurance, and the unavailability of medication and treatment, especially in rural areas. This in turn complicates a timely diagnosis of NCDs and effective treatment. A recent study by Chen et al. (2022), for example, assesses the current progress of health insurance

coverage in 56 LMICs and finds that only one in five people are in the possession of health insurance. Gakidou et al. (2008) conduct a review on access to cancer screening activities in 57 LMICs and find that the average population coverage of cancer screening lies at only 19%. In some countries, for example in Bangladesh, it is as low as 1%. Manne-Goehler et al. (2019) document for a sample of 28 LMICs a significant share of unmet needs for diabetes care and conclude that only half of the individuals with diabetes achieve adequate diabetes control. Similarly, Geldsetzer et al. (2019) present evidence from 44 LMICs about levels of appropriate hypertension medication and control and show that less than a third of individuals with hypertension receives medication and only 10% achieve adequate control of their blood pressure. Lastly, Flood et al. (2022) provide evidence for 42 LMICs that rural-urban differences in diabetes care and management are substantial and that rural patients have significantly worse glycemic and cholesterol control.

Health literacy is a key determinant of health and health care seeking behavior (World Health Organization, 2013b). Hence, even if access to care is granted, low levels of knowledge about NCDs, their risk factors, symptoms and consequences limit the effectiveness of NCD prevention and treatment interventions. As a consequence, a vast literature has emerged assessing knowledge, awareness and health practices concerning NCDs among the general population (e.g., Demaio et al., 2013; Islam et al., 2014; Legesse et al., 2022), among NCD patients (e.g., Amarasekara et al., 2016; Gautam et al., 2015), or among (community-) health care workers (e.g., Ojo et al., 2017; Onagbiye et al., 2020; Widyaningsih et al., 2022). These studies find evidence for a strong negative relation between levels of knowledge and awareness and the prevalence of NCD risk factors and unhealthy behaviors, including low health care seeking. To conclude, while a minimum level of pre-existing NCD knowledge and awareness seems to be required for interventions to be effective, it is often not met in the context of LMICs. Therefore, it exists substantial demand for knowledge- and awareness-raising interventions and campaigns.

A last contextual constraint to be briefly reviewed here are the limited capacities and resources of community health workers, which play a pivotal role in many LMICs. Primary care activities have been shifted from health care facilities towards community health workers to bring primary care activities directly into the communities (Schneider et al., 2016; World Health Organization, 2020c). This has been found to be very effective in the delivery of maternal, newborn and childhood care, or family planning (e.g., Gilmore and McAuliffe, 2013; Gogia and Sachdev, 2010; Perry et al., 2014; World Health Organization, 2020c). With the increase of NCDs, however, many countries have started to also shift NCD prevention activities, such as blood pressure or blood glucose screening, towards the communities. While this is thought to be a promising approach (Mishra et al., 2015), it can result in community health workers being responsible for different types of primary care inter-

ventions. This in turn may take too much of the time and resources which may then be lacking at other places. Widyaningsih et al. (2022) report that community health workers in Indonesia, often working on a voluntary basis, have to provide up to five different community programs, all regulated under different directorates of the Ministry of Health. A lack of financial resources and inadequate training of the health care workers were also identified as problematic. Long et al. (2020) assess the barriers for expanding community health worker services to NCD prevention and care in Vietnam and find that shortages of trained health personnel, limited training provision and imbalanced workload pose substantial challenges. Similar results have been found for community health workers programs in Bangladesh (Rawal et al., 2021), Nepal (Rawal et al., 2020) and Uganda (Musoke et al., 2021).

1.2.3 The economic burden of non-communicable diseases

Another strand of the literature focuses on the economic burden that NCDs might cause. This strand is the least extensive among those reviewed here, correspondingly the demand for more research in LMICs is high. It differentiates between a microeconomic perspective, i.e., the individual level cost of diseases (“cost-of-illness studies”) and effects on labor productivity or household income, and a macroeconomic perspective investigating the long-term effects on health expenditure, economic growth, human capital accumulation or savings on a country or even world-level (Suhrcke et al., 2006; Suhrcke and Urban, 2010).

For the micro-perspective, evidence from LMICs is somewhat more readily available, especially when it comes to cost-of-illness studies. Overall, such studies find that out-of-pocket expenditures are substantial and that spending due to NCDs can reach catastrophic dimensions. Studies for Malawi or rural Nigeria, for example, show that annual costs can reach levels of up to 40% of households’ disposable income (after subsistence needs have been met) for a significant share of NCD-affected households (Janssens et al., 2016; Wang et al., 2016). Similarly, studies for Indonesia (Finkelstein et al., 2014), Vietnam (Minh and Tran, 2012) or India (Verma et al., 2021) conclude that households affected by NCDs are prone to encounter catastrophic health expenditures and impoverishing effects. A prominent difficulty of such cost-of-illness studies, however, given that they often rely on descriptive evidence and miss a well-defined counterfactual scenario, is to derive causal evidence.

Other studies aiming to overcome this limitation use quasi-experimental approaches to estimate the causal effects of NCDs on individual labor productivity or income; yet such studies are considerably scarcer for LMICs. Two exceptions for the context of Southeast Asia, however, should be mentioned. Gertler and Gruber (2002), for the context of Indonesia, find that increases in chronic disease

symptoms reduce the probability of labor market participation. Thanh and Duong (2022), for the context of Vietnam, find that the occurrence of NCDs among adult household members leads to a substantial reduction in labor days and earnings and an increase in received remittances as well as in the depletion of assets.

Studies focusing on the macroeconomic perspective almost exclusively come from high-income countries. Systematic reviews on the economic burden of NCDs on the national level repeatedly find that only a small number of studies is conducted in LMICs (Muka et al., 2015; Seuring et al., 2015). A notable exception is a recent study by Kabajulizi and Awuku Darko (2022), who use data from 24 countries in sub-Saharan Africa and document a significant negative impact of NCDs on countries' net savings.

Given the limited evidence for LMICs, more research contributing to this strand of the literature is needed. Evidence on the adverse economic consequences of NCDs could help international donors and development agencies to restructure their funding for NCDs. Remarkably, despite the disproportionate burden that NCDs impose globally, they received only 1.7% of all development assistance for health in 2018 (Institute for Health Metrics and Evaluation, 2021).

1.3 Contribution and outline of the thesis

1.3.1 Research questions and objectives

The literature overview highlighted that there are still ample constraints that hinder (cost-)effective NCD prevention and control. Identifying innovative solutions to address such constraints, specifically within given country contexts, can therefore support LMICs in their endeavors to fight NCDs. Further, the literature overview concluded that the demand for studies assessing the economic impact of NCDs is high. Against this background, this thesis aims to contribute to the knowledge of how NCD prevention and control in LMICs, particularly in Southeast Asia, can be enhanced and their economic consequences be reduced. Specifically, this thesis aims to answer three major research questions:

1. What type of NCD prevention and treatment interventions promise to be effective in the context of Southeast Asia? (Chapter 2)
2. To what extent might climate change increase the NCD and financial burden further and thereby counteract the success of such interventions? (Chapter 3)
3. Can social media platforms function as a promising tool for cost-effective interventions to tackle NCDs? (Chapter 4)

The objective of this thesis is multi-fold. First, it aims to provide a complete picture on the available evidence of NCD interventions in Southeast Asia of the last two decades and, thereby, to establish a knowledge base that can inform local policy makers as well as future research in this region. In particular, it aims to provide policy makers with feasible strategies to improve or adjust current health interventions. Second, this thesis aims to inform about the inter-linkages of NCDs and climate change and to investigate the potential setbacks in the NCD prevention efforts that might come with climate change. Specifically, the objective is to derive concrete causal numbers for the climate-change driven increase in the NCD and economic burden. Lastly, this thesis aims to provide evidence for an actual cost-effective solution that can increase awareness and screening activities for diabetes. To this end, this thesis presents a newly designed awareness campaign and a corresponding impact evaluation to demonstrate the potential and feasibility of using social media awareness campaigns to improve health behavior.

While the two studies that address the second and third research question do so in the country context of Indonesia, I argue that the evidence derived in both studies is also relevant to other countries in the region, and potentially other LMICs. Yet, Indonesia presents an extraordinary interesting and feasible context for the studies, mainly due to the following reasons. First, it has the highest diabetes prevalence rates as well as the highest male smoking rates in the Southeast Asian region, and hence in particular requires innovative solutions to change health-related behavior. Second, Indonesia has very recently established a universal health insurance scheme and is in a phase of re-orienting their health agenda, with shifting efforts for NCD prevention to community levels. Third, in contrast to other countries in the region, the availability of health data in Indonesia is excellent, which is an important precondition for rigorous empirical research.

1.3.2 Content and methods of the chapters

This thesis consists of three self-contained articles – one presented in each chapter – which are ordered such that one proceeds from a general perspective to more narrow aspects. Each article relies on a different methodological approach. The thesis starts with a systematic review about a broad set of NCD interventions in the entire region of Southeast Asia to derive sound evidence about what types of interventions have been found to effectively address the NCD burden. The thesis then zooms into the country case of Indonesia and uses a quasi-experimental approach to investigate the interplay between climate change, surging rates of NCDs and the economic burden this might imply for health care providers. Lastly, again in the setting of Indonesia, the thesis investigates a concrete health intervention aimed at raising awareness of and screening for type 2 diabetes, using experimental evi-

dence from a randomized control trial (RCT).

In Chapter 2, which is co-authored with Hanna Frommel, we systematically synthesize the evidence of a broad set of NCD interventions in Southeast Asia from the last two decades. We focus on interventions which aim to achieve a reduction in NCD risk factors, an increase in NCD prevention efforts or an improvement in the general practices of health facilities. In the form of a systematic review, complemented with a meta-analysis, meta-regression and moderator analysis, we provide evidence about what types of interventions are most promising in the given context. Overall, we extract 204 estimates from 51 studies and sort them into six different intervention categories with respect to their targeted disease, risk factor or intervention design. In total, we look at a universe of 23 different health outcomes that such interventions can address.

We find that especially programs focusing on smoking cessation, on the take-up of preventive screening activities or educating patients on how to cope with NCDs achieve sizable impacts. Dietary and physical activity interventions fail to achieve improvements in analyzed health outcomes. In line with the latter, we also show that health outcomes related to weight loss, i.e., BMI and waist circumference, are those that seem hardest to address by the interventions under study. We also document evidence of substantial publication bias, which we address with a meta-regression approach to obtain reliable estimates. Lastly, we show that the number of contact moments study participants have with the implementing health authorities strongly relates to the intervention effectiveness. Also, the age of the targeted participants and whether the intervention is implemented in a group design moderate the effect size.

Chapter 3 focuses on the country case of Indonesia to investigate how climate change, specifically increasing temperatures, raise the NCD burden further. Moreover, it assesses the implications in terms of the financial burden posed on the health care system, specifically the new national health insurance scheme. Individuals affected by NCDs are especially at risk to suffer from rising temperatures, since their already exhausted bodies are less able to cope with further shocks and heat can exacerbate a variety of health conditions. To investigate this link, I study whether the number of health visits related to diabetes, cardiovascular diseases and chronic respiratory diseases in the Indonesian primary health care facilities (*Puskesmas*) increase on days with extremely high temperatures. To do so, I use a novel and representative data set from the Indonesian national health insurance scheme *Jaminan Kesehatan Nasional* (JKN). I link the data to several meteorological data sets to extract information on the local temperature and to control for possible confounding factors such as rainfall, humidity, air pollution or wind speed. The final daily-district panel, consisting of more than 370,000 observations, allows to estimate the causal effect of increasing temperatures empirically by relying on a

quasi-experimental approach and making use of a semi-parametric specification that includes a series of fixed-effects.

The results show that on days with extremely high temperatures, the number of visits with a diagnosis of diabetes and cardiovascular diseases increase by 25% and 14%. Yet, I find no evidence for an increase in the number of visits related to respiratory diseases. I further assess the existence of so called “harvesting effects”, i.e., whether the increase in health care visits is temporary or persistent. The analysis shows that the latter is the case. Increases in the number of health care visits related to NCDs are not offset, even after a period of four weeks. This has major implications for the burden imposed on health facilities and health care workers. Lastly, I rely on different climate change and population growth scenarios to simulate the future increase in NCD-related health care visits and related cost by the end of the current century. The results from this exercise forecast a substantial financial burden for the Indonesian health care system with additional yearly cost of up to US\$31 million to be spent on primary health care services.

In Chapter 4, which is co-authored with Michael Grimm, Ingmar Weber, Elad Yom-Tov and Benedictus Praditya, we stay in the country context of Indonesia and focus specifically on type 2 diabetes. In this study, we assess whether social media can serve as an efficient and cost-effective instrument to increase type 2 diabetes awareness and encourage individual risk screening activities. To do so, we rely on experimental evidence from a diabetes awareness campaign that we implemented on the social media platform “Facebook”. Specifically, we randomly distributed graphical ads related to the risk and consequences of diabetes to Indonesian Facebook users in the cities of Jakarta and Yogyakarta to test which type of message and graphical design is most effective in incentivizing users to visit an information website and to perform a diabetes self-screening activity.

Our results suggest that ads with an “information” or “shocking” content are most effective in terms of completed self-screening activities. With a complementary follow-up survey six weeks after the online screening, we provide evidence that approximately 28% of high-risk respondents indeed also comply with the received recommendation to contact a physician for a professional screening. Regarding the cost side of this intervention, we conclude that such an online public health campaign can be very cost-effective with a cost of approximately US\$9 per newly diagnosed person with type 2 diabetes.

1.3.3 Contribution of the thesis

Together, the three articles presented in this thesis contribute to the understanding of possible pathways towards (cost-)effective solutions for the prevention of NCDs in Southeast Asia and possibly other LMICs. Further, the thesis contributes to the

understanding of the interplay of climate change and NCDs and how the former might offset some of the efforts undertaken to reduce the NCD burden. Hence, this thesis consolidates a cautious attempt to support LMICs in their endeavors to address two major health challenges of the 21st century.

Chapter 2 contributes in particular to the identification of concrete interventions that can improve NCD prevention and treatment in the region. It also investigates the underlying mechanisms that either lead to an intervention success or failure. It thereby provides policy makers with feasible strategies to improve or adjust health programs. A major innovation of this chapter is that we address the intertwined nature of the four main NCDs and their four main risk factors and review a wide scope of NCD interventions, which has largely been ignored in the evaluation of interventions' effectiveness so far. We thereby go beyond the common approach of focusing on a single disease, single risk factor or single country, as the vast literature in the field has done. Moreover, this chapter also makes a methodological contribution by addressing several shortcomings and biases that are commonly neglected in conventional meta-analyses with econometrically more sophisticated methods. Specifically, we use weighted least squares random-effects meta-regressions, which allow for clustering the standard errors at the study level. Further, by employing a population average model, we adjust the emphasis on estimates from studies with a higher (lower) number of estimates downwards (upwards). Lastly, we rely on a measure of effect size that accounts for pre-existing differences at baseline between treatment and control populations, an issue that has received surprisingly little attention in former meta-analyses.

The major contribution of Chapter 3 is that it provides first-time evidence for the interplay between climate change and health effects on the primary health care level. Previous studies solely investigated the implications for higher level facilities, such as emergency departments or hospitals more generally. Focusing on primary health care visits instead of hospitalization rates and emergency visits provides important information about how climate change will affect the primary health care sector, which is pivotal in many LMICs. Further, the article contributes to the literature by using health visits data that represent not only one of the largest countries in the world, but also come from a middle-income country. Generally, only few studies assess the health impacts of heat in non-western and LMICs. Since these countries tend to have comparably more tropical and humid climate zones, poorer health system capacities, and a larger share of the workforce being exposed to outside temperatures and relying on physical strength, e.g., in the agricultural sector, this relationship might be thoroughly different from what has been found in other settings. Another strength of this chapter is its contribution to the understanding of the economic burden that climate change and NCDs will imply in the decades to come. This might be beneficial especially for policy makers in Indonesia dealing

with the financial sustainability of the national health insurance scheme.

Chapter 4 contributes towards the understanding of how screening rates for NCDs and their risk factors can be increased by making use of a social media campaign. The major innovation of this chapter is the actual design and implementation of a new awareness campaign on the social media platform Facebook in the form of a randomized controlled trial (RCT). Moreover, this study stands out as the very first to implement a health-related field experiment via Facebook in a middle-income country context. Overall, this chapter contributes to the better understanding of how awareness can be raised and uptake of screening for NCDs in LMICs can be enhanced, i.e., in a context where the general awareness of NCDs is low. Lastly, it contributes to a literature mainly rooted in psychology that explores what kind of framing or pictorial content drive health-related decisions and whether exposure to information improves health behavior. We thereby provide evidence about which psychological channels can effectively incentivize individuals to learn about their risk and to engage in essential health screenings. While the chapter focuses in particular on the uptake of screening rates for diabetes, the results of this study can also be transferred to other health aspects, especially to fields in which individuals postpone highly cost-effective health-related decisions, such as vaccination. Similarly, such a campaign could easily be transferred to countries other than Indonesia, where user rates of social media are equally high.

1.3.4 Limitations and outlook for future research

The different studies presented throughout this thesis come with certain limitations, hence, leaving space for further research. Likewise, some findings are worth exploring in more detail. While Chapter 2 aims to provide solid and encompassing evidence about the effectiveness of a broad set of NCD interventions, a limitation results from the fact that we only review the English literature of the field. While this could not be circumvented given language barriers, future research might include country-specific evidence in the local language. Further, we identified several evidence gaps for risk factors that future work could address. For instance, we identified only a single study that focused on smoking cessation in the context of Indonesia, which is surprising given the extraordinarily high male smoking rates in the country. Additionally, we identified only a modest effect for diet and physical activity interventions, which occasionally even resulted in adverse effects. Further investigations why such interventions can result in undesirable effects would be valuable. Moreover, this calls in particular for future research activities that explore innovative solutions for addressing the rising rates of obesity throughout the Southeast Asian region.

In Chapter 3, I present evidence that climate change might offset some of the

endeavors that countries undertake in terms of NCD prevention, since rising temperatures increase the NCD and economic burden further. A limitation of this study is that it relies on data that cover only a limited time period and therefore does not allow to account for any form of human adaptation, intensification of climate effects or general equilibrium effects, which are also vital to comprehensively model health effects in the long run. This directly translates into the demand for further research on the interplay of NCDs and climate change covering longer time spans. Studies covering a longer time period might then also allow to investigate the relationship between climate change and cancer. Also, it would have been interesting to investigate the channels through which high temperatures, according to the medical literature, drive the increase in health visits. A more detailed examination would provide valuable insights into the mechanisms at work and how to encounter the interplay between NCDs and climate change.

Lastly, in Chapter 4, we provide causal evidence that information about diabetes effectively incentivize individuals to participate in a risk-screening activity. A remaining limitation is that we cannot circumvent the self-selection of participants into our follow-up survey. This restrains our ability to provide causal evidence on activities happening after the online-screening. While we aim to address this self-selection by providing suggestive evidence that the resulting sample is not different from the overall sample, the sample size limits our efforts. For future research activities, we aim to expand the awareness campaign to other parts of Indonesia, and potentially other countries, to increase the power and external validity of our study. Moreover, we also provide descriptive evidence for why certain high-risk individuals refrain from complying with the received advice. Studies that explore how these restricting factors can be addressed would potentially make an important contribution.

2 How to dampen the surge of non-communicable diseases in Southeast Asia: Insights from a systematic review and meta-analysis [†]

With Hanna Fromell

Abstract: Non-communicable diseases (NCDs) have overtaken infectious diseases as the number one cause of death worldwide. The rise is especially grave in Southeast Asia, where existing research however falls short on offering guidance on how policy can best prevent and control NCDs in the region. Additionally, low- and middle-income countries in Southeast Asia cannot directly incorporate lessons drawn from interventions in richer countries, since health system capacities and human and financial resources are thoroughly different. Preventive interventions, thus, need to correspond to local capacities and require contextual solutions. In this article, we provide a systematic review of a wide scope of NCD interventions conducted in Southeast Asia to inform about existing intervention designs and to derive sound evidence of their effectiveness. Our literature search results in 51 studies from which we can extract 204 estimates. We sort the studies into six intervention categories and analyze them with respect to 23 different health and behavioral outcomes. While we find positive and significant average effects across all six types of interventions, we also document evidence of substantial publication bias. Using a meta-regression approach in which we correct for the publication bias, we instead fail to confirm positive average effects for some interventions. Especially dietary and physical activity interventions fail to achieve improvements in analyzed health outcomes, while programs focusing on smoking cessation, on the take-up of preventive screening activities or educating patients on how to cope with NCDs achieve sizable effects. We also present evidence that the size of the effect differs with the participants' characteristics as well as with design features of the intervention. For local policy makers, the results provide important knowledge on how to address the increasing NCD burden in the coming years.

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2.1 Introduction

Non-communicable diseases (NCDs), such as diabetes, cancer, cardiovascular diseases and chronic respiratory diseases, have overtaken infectious diseases as the number one cause of death worldwide (Bollyky et al., 2017; Niessen et al., 2018). The spread of NCDs is especially grave in the Southeast Asian region, which, compared to other regions, saw the steepest increase in NCD deaths between 2000 and 2012 (World Health Organization, 2014)¹ and which suffers a loss of more than 8.5 million deaths yearly due to NCDs (World Health Organization, 2020b). Especially vulnerable are the region's poor, who face the risk of carrying the greatest burden of NCDs and, as a result, also of facing the consequences of further widening health and economic inequalities (Mirelman et al., 2016; Niessen et al., 2018; Nugent et al., 2018). This escalation is to a large extent driven by urbanization, economic development and globalization, which rapidly have pushed the region's populations towards adopting more unhealthy lifestyles, such as consuming unhealthy diets, foregoing physical activity and smoking tobacco, and ultimately to a larger risk of contracting NCDs.

The double burden of both communicable and non-communicable diseases poses a substantial challenge for Southeast Asia's commonly fragile health care systems and limited health budgets (Bollyky et al., 2017; Dans et al., 2011). Moreover, health care systems in the region have been designed to focus on infectious diseases and acute care and are, thus, not well prepared to respond to the increasing need for chronic care (Dans et al., 2011; Meiqari et al., 2020). As a response, the World Health Organization (WHO) has started the development of multi-sectoral national action plans for the prevention and control of NCDs in Southeast Asia (World Health Organization, 2013c, 2015). Yet, the prioritization of NCDs on the global and local health agenda remains limited (Heller et al., 2019). The success of these action plans will crucially depend on the identification of regionally effective approaches. Therefore, systematic evaluations of local NCD interventions and programs to inform effective disease management strategies are urgently needed (Allen et al., 2018; Nikpour Hernandez et al., 2021).

A vast body of literature covers NCD-related policies in western and high-income countries.² Economic health research is lagging behind, however, when it comes to NCDs in the developing world (Behrman et al., 2009). The insights from western and high-income countries cannot alone constitute the decision base for designing effective implementation measures for Southeast Asian countries since

¹An equally steep increase was seen in the WHO Western Pacific region. The numbers are based on the WHO classification of the Southeast Asian and Western Pacific Region.

²See for example Adler et al. (2014); Baker et al. (2015); Cobiac et al. (2010); Dunkley et al. (2014); Gaziano et al. (2017); Graudal et al. (2014); Hartley et al. (2016); Li et al. (2010); Long et al. (2015); Pennant et al. (2010).

these face distinctly different cultural backgrounds, lifestyles, health literacy, income levels and health system capacities. For example, using letters to invite women for breast cancer screening is a currently recommended policy in richer countries (Ritchie et al., 2020). Yet, such a policy may have lower impact in poorer contexts where the ability to reach individuals in remote areas is limited, health literacy and thus take-up rates might be lower and the (opportunity-)cost to attend such screenings might be higher. Additionally, results from high-income countries might not be applicable to low- or middle-income countries if the ability to provide and finance health services is substantially lower (Revill and Sculpher, 2012). Similarly, as health insurance coverage is low in Southeast Asia and health expenses are largely financed out-of-pocket, individuals will be less willing to seek health care as long as they do not face acute health problems. This may, in comparison to western countries, reduce the effectiveness of NCD interventions, which largely rely on preventive measures.

Granted, the diversity of Southeast Asian countries might also limit the possibility for transferring evidence and lessons within this region as well. Yet, the geographic and cultural proximity and similarities, especially in the economic development and health system capacities, and the limited amount of evidence from single countries make a strong case for these countries to draw on the knowledge about effective NCD policies from this region as a whole. The objective of our review is, therefore, to provide a complete picture on the available evidence of NCD interventions in Southeast Asia and, thereby, establish a knowledge base that can inform local policy makers as well as future research in this region.

To this end, we conduct a systematic review and meta-analysis of interventions that address NCDs in low- and middle-income countries in Southeast Asia and thereby contribute to the literature in three ways. First, we review articles covering the entire region of Southeast Asia, aiming to derive policy conclusions that could be valid at the regional level and to identify countries for which evidence is vast or scarce, respectively. Second, we consider different types of NCD interventions jointly and thereby address the intertwined nature of the four major NCD risk factors (tobacco consumption, alcohol consumption, unhealthy diet and physical inactivity). Third, we address several shortcomings that are commonly neglected in conventional meta-analyses with econometrically more sophisticated methods.

We consider all evaluations implemented within the past 20 years and that are based on a method that allows for deriving causal evidence, leading to a sample of 51 studies, which we classify into six distinct intervention categories. We analyze the extracted estimates in a standard meta-analysis and in a more conservative meta-regression model in which we address problems of publication bias, cluster standard errors at the study level and account for the different number of estimates per study. We also estimate effect sizes for different health outcomes, intervention

categories and countries.

The remainder of this article is organized as follows. Section 2.2 presents the search strategy and inclusion criteria that we applied to select the studies. In Section 2.3, we outline statistical considerations on how to calculate harmonized effect sizes and the analytical approach of the meta-analysis and meta-regression. We present the results in Section 2.4, including the presentation of the included studies and extracted outcome estimates, statistical and meta-analytical results, and the results of a moderator analysis. Section 2.5 provides a discussion of the results and implications for future interventions and research. Section 2.6 concludes.

2.2 Methods

2.2.1 Literature search

The literature search was conducted using the databases *Cochrane Library*, *EconLit*, *PubMed*, *Sociological Abstracts* and *Web of Science* and complemented by a search with *Google Scholar*. We categorized our search terms under the following sections: i) major NCDs and related risk factors; ii) Southeast Asian region and countries; iii) intervention setting; iv) evaluation study; and v) effectiveness or cost-effectiveness study. A detailed description of the search terms and procedure is provided in Appendix 2.A.³ Titles and abstracts were screened independently by two researchers and studies were excluded if they missed quantitative assessments, were duplicates or irrelevant. Information from the included studies was extracted by the researchers according to a coding tool. The information extracted consisted of the general information of the publication, i.e., author(s), title, year and type of publication. Furthermore, the country or countries and target population(s) were characterized for each study, as well as the outcome(s) measured, the type of intervention(s) and intervention impacts. Included studies were also characterized according to their research methodology, sampling strategy and sample size and time period covered. Discrepancies and unclear citations were resolved through discussions. For included studies, we further made use of citation tracking (forward searching) and screened their list of references for further relevant studies (backward searching). The forward- and backward search procedures were ended whenever a further search did not lead to new results.

³We follow the Preferred Reporting Items for Systematic review and Meta-Analysis protocols (PRISMA). The study protocol was not pre-registered yet the authors declare that the study protocol has not been adjusted since the initiation of the study implementation and no further analyses have been conducted in addition to the ones mentioned in this paper.

2.2.2 Inclusion criteria

We defined our inclusion criteria following a basic PICO(S) (population, intervention, comparison, outcome, study design) framework (Haynes, 2006). We included studies that focus on any population within the Southeast Asian region with the exception of Singapore and Brunei.⁴ Studies had to evaluate the (cost-)effectiveness of health interventions that focused on the prevention or control of NCDs and/or any of their related main risk factors. Studies evaluating solely the impact of a specific drug or medical treatment alone were excluded.⁵ Given the broad scope of health interventions covered, our inclusion criteria for the outcome measure were also relatively comprehensive. We included studies that evaluated at least one relevant health outcome (such as metabolic or anthropometric measurements) or behavioral outcome (such as smoking, conducting physical activity or taking-up screening) directly related to NCDs or NCD risk factors. We did not consider outcomes that were mere measures of individuals' knowledge, beliefs, attitudes or intentions as outcomes. The study design had to be such that one could infer a causal relationship between intervention and outcome from the results. Studies were therefore included if they performed an impact evaluation that was based on either an experimental design, such as a randomized controlled trial (RCT), or a quasi-experimental design (i.e., with non-random assignment) that used a control group or alternative intervention for comparison. Finally, we only included studies that were written in English and published in an academic peer-reviewed journal after the year 2000.

2.3 Statistical considerations and analysis

2.3.1 Computation of effect sizes

Conducting a meta-analysis and meta-regression requires that extracted effect sizes are harmonized. A standard measure for continuous effect sizes is the standardized mean difference (SMD) (Higgins et al., 2019). The measure expresses the single difference in a given indicator between a treatment and control group after some intervention, standardized by the pooled standard deviation of the same indicator before the intervention (i.e., at baseline). Yet, this measure relies on the

⁴Singapore and Brunei stand out as the high-income countries in the region, while remaining countries are classified as lower and upper middle-income countries with a GNI per capita between USD 1,026 and USD 12,375 (World Bank, 2020). We use the geographical classification of Southeast Asia, which includes the ten ASEAN countries and Timor-Leste, which are all located in either of the two WHO regions of Southeast Asia and Western Pacific.

⁵We excluded studies that simply test the effectiveness of a drug on medical outcomes, e.g., the effect of anti-hypertensives, as we focus our analysis on interventions that are primarily dependent on behavioral responses and thus likely sensitive to geographic-specific factors such as customs and culture.

assumption of statistically identical groups at baseline, because only then the entire effect can be attributed to the intervention. This requirement is often not met in studies that use non-random selection strategies or small samples, which makes the risk of falsely declaring equal samples at baseline worryingly high.

To minimize the risk of estimating effects incorrectly, we calculate the effect sizes for all studies while also accounting for existing differences between control and treatment populations at baseline. We do this by calculating the effect size θ for continuous outcomes as the standardized mean difference-in-difference (SMDD):

$$\theta_{SMDD} = \frac{((\mu_{T2} - \mu_{T1}) - (\mu_{C2} - \mu_{C1}))}{SD_{pooled}} \quad (2.1)$$

where μ is the mean value of the respective outcome, with $T1$ and $T2$ representing the treatment group at baseline and follow-up respectively and $C1$ and $C2$ the control group at baseline and follow-up respectively, and SD_{pooled} is the standard deviation of the outcome at baseline pooled over both groups. Note that the numerator corresponds to the single difference in means if the means at baseline are identical ($\mu_{T1} = \mu_{C1}$). Additionally, since many included studies work with very small sample sizes, we adjust for possible upward biases due to small samples, using Hedges' correction factor (Hedges, 1981; Hedges and Olkin, 1985):

$$\theta_{SMDD_{hedges}} = \left(1 - \frac{3}{4 * (n_T + n_C - 2) - 1}\right) * \theta_{SMDD} \quad (2.2)$$

where n_T and n_C represent the number of individuals in the treatment and control group, respectively.

For binary outcome variables, one standard measure for reviews and meta-analyses is the odds ratio (OR), which is the ratio of odds of an outcome in the treatment group over the odds of the same outcome in the control group. Just as the regular standardized mean difference for continuous outcomes, odds ratios at follow-up do not correct for differences at baseline. We calculate ORs while correcting for such baseline differences by computing the difference in odds between follow-up and baseline:⁶

$$OR_{corr} = e^{(\ln(OR_2) - \ln(OR_1))} \quad (2.3)$$

where OR_{corr} is the OR corrected for between-group differences at baseline, and OR_1 and OR_2 correspond to the OR at baseline and follow-up respectively. For

⁶The difference in odd ratios (e.g., used in Parekh et al. (2012)) corresponds to the double difference for continuous outcomes. Note that by computing the exponent of the difference in log odds ratios, the resulting odds ratio, OR_{corr} , takes the same value as the follow-up odds ratio whenever there is precisely no difference between treatment and control at baseline.

studies that do not present outcome measures at baseline, we compute OR_{corr} by assuming an OR_1 equal to one (equivalent to there being no difference in the outcome variable between treatment and control at baseline). To be able to compare estimates across outcomes and studies, we transform the corrected odds ratios to standardized effect sizes, θ_{OR} , using the standard procedure of multiplying the log odds ratio with a factor of $\sqrt{3}/\pi$ (Borenstein et al., 2011; Ringquist, 2013).

In a last step, we code all measures such that desirable changes in health outcomes (e.g., a decrease in weight or an increase in physical activity) produce positive effect sizes and undesirable changes (e.g., an increase in weight or a decrease in physical activity) result in negative effect sizes. In the remaining part of the article, we will use the term “effect size” (simply denoted as θ), irrespective of whether it has been retrieved from continuous outcomes or odds ratios.

2.3.2 Meta-analysis

The broad specification of the inclusion criteria is likely to result in studies that vary substantially with respect to specific design features, approaches and outcomes. Therefore, a random-effects meta-analysis, which assumes that the true effect size is a normally distributed random variable that varies across studies, is preferred over a fixed-effect meta-analysis (Borenstein et al., 2011; Ringquist, 2013). Individual study- and outcome-specific effect sizes can therefore differ from the average effect size due to two components: the individual within-study variance, v , and the random-effects variance component, τ^2 , with the latter being an indicator of the between-study heterogeneity (Gallet and Doucouliagos, 2017; Ringquist, 2013). The estimated effect size $\hat{\theta}_{it}$ of an outcome estimate i in study t can therefore be described as

$$\hat{\theta}_{it} = \theta_i + \varepsilon_{it}, \text{ with } \varepsilon_{it} \sim N(0, v_{it} + \tau_i^2) \quad (2.4)$$

where θ_i is the true effect size for outcome i , and ε_{it} is an error with zero mean and a variance of $v_{it} + \tau_i^2$. The weights used in the random-effects meta-analysis are the inverse of the total variance (DerSimonian and Laird, 1986).

2.3.3 Meta-regression

The meta-analytical approach described in the previous sub-section comes with three distinct drawbacks. First, estimates from the same study are likely to be strongly correlated, violating the assumption of independent errors when we pool the estimates. Because it is not possible to cluster the standard errors on a study level in the meta-analysis, the estimated average effect is likely to be biased. Sec-

ond, the number of estimates can vary greatly across studies. If studies that contribute with more estimates find systematically larger or smaller effects, the estimated average effects will be biased towards this direction.⁷ Third, the average effect might be influenced through publication bias, commonly driven by under-powered studies.

To be able to analyze the overall effect sizes while accounting for such potential sources of bias, we use generalized estimation equations and conduct weighted least squares random-effects meta-regressions. This type of regression allows us not only to cluster the standard errors at the study level, but also for adjusting the emphasis on estimates from studies with a higher (lower) number of estimates downwards (upwards) by using a population average model (see Ringquist, 2013, for a technical summary of this approach). We furthermore control for publication bias and small-study effects by including the squared standard error SE^2 as an independent variable, known as PEESE⁸ (Stanley and Doucouliagos, 2012, 2014), which indicates the extent of publication bias and accordingly corrects the effect size. It has been shown that including the squared standard error, instead of the linear term, reduces the likelihood of underestimation when a true effect is present (Moreno et al., 2011; Stanley and Doucouliagos, 2012, 2014). Meta-regressions also allow for analyzing the influence of moderators, which we include in a subset of regressions. The model for the meta-regression hence reads

$$\hat{\theta}_{it} = \theta_i + \beta SE_{it}^2 + \gamma \mathbf{X}'_{it} + \varepsilon_{it}, \text{ with } \varepsilon_{it} \sim N(0, v_{it} + \tau_i^2) \quad (2.5)$$

where SE^2 is the squared standard error of outcome i in study t , \mathbf{X}'_{it} is a vector of moderators and γ is the corresponding vector of coefficients. The regression is again weighted by the inverse of the total variance.

⁷This bias is only present in the subgroup analyses by intervention category, as we here include more than one outcome per study per subgroup. In the analyses by outcome type, we include never more than one outcome estimate per study within one subgroup.

⁸PEESE stands for precision-effect estimate with standard error. Including the squared term instead of the linear term has been shown to be appropriate whenever the funnel asymmetry and precision estimate test (FAT-PET) suggests that a genuine effect is present, indicated as a significant intercept in the Egger's regression test. As this is true for our data (see Section 2.4.3), we estimate effect sizes with the inclusion of the squared term. However, we re-run all of the regressions with the linear term for comparison. As expected, the effect sizes are on average smaller and occasionally lose significance. Results are available on request.

2.4 Results

2.4.1 Study identification and characterization

Our literature search resulted in 3947 studies, of which 111 studies were fully reviewed by a team of researchers and assessed according to our inclusion criteria. One additional study was identified through further literature snowballing. The complete search procedure resulted in a final sample of 51 studies and is depicted in Figure 2.1.

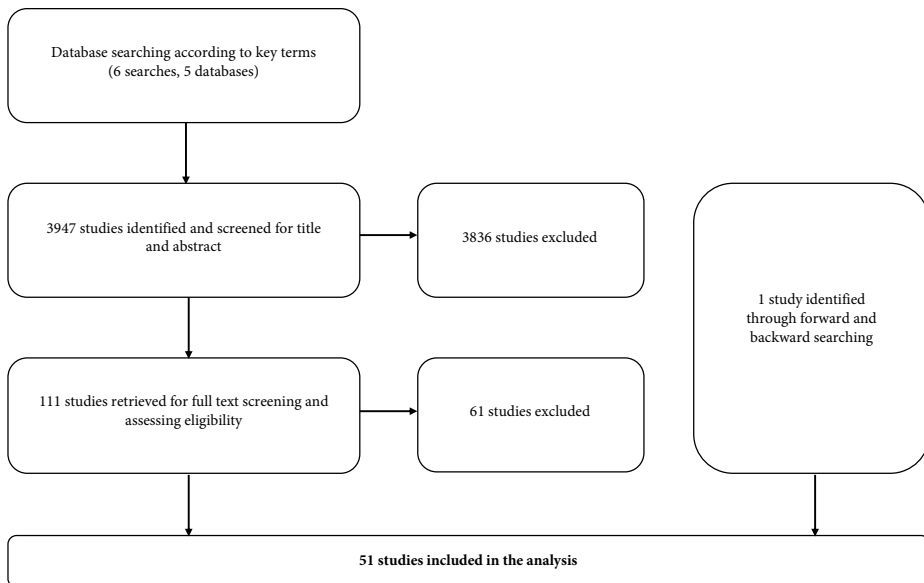


Figure 2.1: Search procedure and results

The 51 studies are described in detail in Table 2.B1 in Appendix 2.B. They cover five Southeast Asian countries. The large majority evaluate interventions conducted in the region's two upper middle-income countries Thailand (25 studies) and Malaysia (17 studies). A smaller number of studies was conducted in Vietnam (4), the Philippines (4) and Indonesia (1). Other Southeast Asian low- and middle-income countries, such as Myanmar or Lao PDR, are not covered by any of these studies. This limitation in country coverage implies that the results and implications we draw from analyses where we aggregate data across countries are foremost applicable for Thailand and Malaysia while lessons for other countries in this region should be drawn while carefully considering relevant cultural, economic and geographical differences. To further address potential heterogeneity issues across countries and present country specific lessons where possible, we

present our meta-analytical results for Thailand and Malaysia separately whenever the data allows. Despite our inclusion criteria being also designed to extract studies that focus on cost-effectiveness, none of the studies included an economic analysis of its costs.

We sort the 51 studies into six intervention categories⁹(see Table 2.1). The first three categories, which aim at preventing NCDs by directly addressing the most common NCD risk factors, focus on smoking cessation (“smoking”, 8 studies), reducing the consumption of alcohol (“alcohol”, 4 studies), and improving diets and physical activity (“diet and physical activity”, 20 studies). We assign studies concerning diet and physical activity to the same category as both risk factors are almost exclusively addressed jointly in the respective studies. The remaining studies are categorized as “screening” (4 studies), “patient education” (11 studies, e.g., studies that teach patients how to cope with their disease), or “system approach” (5 studies, e.g., studies that change NCD-related processes within health facilities).

Within the categories of screening, patient education and system approach, the interventions can also be differentiated with respect to the targeted NCD. The four screening studies focus exclusively on screening uptake for breast or cervical cancer among female patients; the last two intervention categories – patient education and system approach – focus on patients with either diabetes (13 studies) or cardiovascular diseases, such as stroke (3 studies).

For each study, we also collected information on the intervention format, i.e., whether the intervention took place in a group setting (including community settings or schools) or whether it was individually conducted (e.g., individual counseling sessions or home-based interventions). Twenty-four studies included some form of group intervention, while 22 studies were solely individually targeted. The five system approach studies focused on processes within facilities instead of directly at participants and were consequently not sorted into any of the two intervention format categories.

Study populations in our sample are consequently quite diverse and encompass elderly, adults and students as well as urban and rural populations. Individuals are of high and low risk of NCDs, or are patients that already suffer from a disease, where the respective interventions aim to prevent further adverse health consequences through education or more efficient health facility processes. In what follows, we briefly present the type of interventions that constitute each of the six intervention categories.

⁹One study, Pengpid et al. (2015), is sorted into two intervention categories, because it focusses on both smoking cessation and alcohol consumption. Therefore the sum of studies within categories adds up to 52.

Smoking

Studies within this category evaluate interventions aiming to motivate and incentivize individuals to quit smoking or reduce their tobacco consumption. They encompass different strategies, such as individual counseling sessions, financial incentives or motivational interviews. Two studies focus particularly on adolescent smoking.

Alcohol

The four studies in this category examine interventions seeking to direct study participants towards a reduction in their alcohol consumption. Studies exclusively evaluate counseling interventions and focus on risky or harmful drinking, but differ with respect to the counseling design, i.e., length, frequency and setting of the implementation.

Diet and physical activity

The large majority of included studies falls under this category and focuses on participants' behavioral changes with respect to their diet and physical activity. Interventions often consist of education sessions, joint physical activities and general health promotion, but also media-based assistance or self-monitoring tools. Also studies that evaluate school and workplace interventions and focus on obesity prevention through changing food policies are included in this category.

Screening

The four screening studies focus solely on uptake for cervical and breast cancer screening. They provide education to the target groups about self-examination and/or how to seek professional examination. They further analyze invitations and reminders for screening events.

Patient education

The studies included in this category investigate how education for NCD patients can improve their disease management. The interventions aim to improve health outcomes by increasing patients' awareness about disease complications and consequently their self-care behavior. Some studies include patients' family members or peers in part of the training to further increase the patients' understanding and adoption of the taught material.

System approach

The last intervention category includes studies that investigate how changes in the general practices of health facilities can affect patients' health outcomes. These

practices include improved coordination between staff members and an increased usage of clinical practice guidelines. Also studies that investigate how involvements of pharmacists or nurses within the facilities' processes can improve a patient's disease management are sorted into this category.

2.4.2 Description of outcome estimates

In total, we extract 204 outcome estimates from the total of 51 studies, receiving four estimates per study on average, with a minimum of one and maximum of 14 estimates per study. Overall, the studies examine 23 different NCD-related outcomes. As the list of different outcome types in Table 2.1 shows, the spectrum of study outcomes is broad, especially within the intervention categories diet and physical activity, patient education and system approach. This is unsurprising since, among these types of studies, it is common that a single intervention is expected to influence a series of NCD-related outcomes and/or their associated risk factors such as metabolic indicators (blood sugar, blood pressure and blood lipids), anthropometric measurements and physical activity. The other three intervention categories provide only specific outcome estimates since, for smoking and alcohol, the evaluated interventions are not focused on any specific NCD, but on a specific high-risk behavior. As for screening, the interventions regard not the impact of screening on a specific NCD, but on the rate at which individuals are de facto screened.

Including several outcomes for one intervention category provides the opportunity to give a more nuanced understanding of the relative impact of a given intervention and is a common approach for meta-analyses of health outcomes (e.g., Hamad et al. (2018) assess the impact of education on 25 different health outcomes). Yet, at the same time the multitude of outcomes impedes a single analysis. We consequently provide detailed subgroup heterogeneity and moderator analyses that allow for investigating differences in impact across intervention categories and countries, as well as across outcomes within intervention categories.

Table 2.1 shows that the majority of outcome estimates are metabolic indicators and anthropometric measurements. Blood sugar outcomes together with blood pressure and blood lipid outcomes account for more than half of all outcome estimates. BMI, weight and waist circumference make up for almost another quarter. The intervention category diet and physical activity does not only account for the majority of studies but also contributes with the highest number of estimates per study.

Table 2.1: Distribution of outcomes and studies

	Intervention category						Total no. of estimates	Total no. of studies
	Smoking	Alcohol	Diet & Physical Activity	Screening	Patient Education	System Approach		
Outcome								
Smoking Abstinence	9	0	0	0	1	0	10	
Alcohol Abstinence	0	1	0	0	1	0	2	
Alcohol Quantity*	0	2	0	0	0	0	2	
Alcohol Drinking Frequency*	0	3	0	0	0	0	3	
Alcohol Score*	0	2	0	0	0	0	2	
Fasting Blood Glucose	0	0	7	0	5	2	14	
HbA1c	0	0	2	0	7	3	12	
Systolic Blood Pressure	0	0	12	0	2	2	16	
Diastolic Blood Pressure	0	0	12	0	2	2	16	
Body Mass Index	0	0	16	0	3	2	21	
Weight	0	0	9	0	3	0	12	
Waist Circumference	0	0	11	0	2	1	14	
HDL-Cholesterol	0	0	8	0	2	2	12	
LDL-Cholesterol	0	0	8	0	2	2	12	
Total Cholesterol	0	0	9	0	1	2	12	
Triglycerides	0	0	9	0	2	1	12	
Salt Consumption	0	0	3	0	0	0	3	
Physical Activity	0	0	12	0	2	0	14	
Quality of Life	0	0	0	0	3	0	3	
Screening Uptake - Cervical Cancer	0	0	0	4	0	1	5	
Screening Uptake - Breast Cancer	0	0	0	3	0	1	4	
Activities of Daily Living*	0	0	0	0	2	0	2	
Illness Severity*	0	0	0	0	0	1	1	
Country								
Thailand	5	8	35	2	19	5	74	17
Malaysia	1	0	48	5	6	17	77	25
Vietnam	0	0	30	0	4	0	34	4
The Philippines	1	0	5	0	11	0	17	4
Indonesia	2	0	0	0	0	0	2	1
Total no. of estimates	9	8	118	7	40	22	204	
Total no. of studies	8	4	20	4	11	5	(52)	51

Notes: The total number of studies adds up to 52 instead of 51 because one study is included in two categories: Smoking and Alcohol. *The explanation of the outcomes denoted with an asterisk are as follows: Alcohol Quantity: number of alcoholic drinks per day or grams of consumed alcohol per week. Alcohol Drinking Frequency: times per week alcohol was consumed. Alcohol Score: a numerical score that indicates whether a person is at risk of alcohol dependence. Activities of Daily Living (ADL): score of ability to perform different self-care activities such as feeding oneself, bathing and dressing. Illness Severity: medical classification of how severe a disease or illness is.

2.4.3 Publication bias and statistical power

Before presenting the meta-analysis and meta-regression results, we examine two common meta-analytical issues that, if ignored, risk to lead to large errors in the inference of the results: publication bias and, closely related, low statistical power of the underlying studies.

Publication bias regards the phenomenon that researchers or editors favor articles that show desirable and significant results and that these consequently are more likely to be published than articles with less desirable or interesting results (Stanley, 2008). This can cause the published literature to be systematically unrepresentative of the respective population (Rothstein et al., 2005). Publication bias will, in expected terms, produce a positive correlation between positive effects and their standard error. This is because studies with larger standard errors, which are also typically smaller in sample size, are, a priori, more likely to both underestimate and overestimate the effect compared to the underlying true effect. Plotting several studies that are estimating the same underlying effect on a graph with the standardized effect size on the horizontal axis and precision (the inverse of the standard error) on the vertical axis should thus, in expected terms, result in a symmetric and inverted funnel with its center at the true underlying effect. Publication bias would however cut out some of the less favorable studies appearing on the left side, resulting in an asymmetric funnel with the scatter points for small studies at the bottom in a long right tail (Egger et al., 1997).

Figure 2.2 displays the funnel plot for all 204 effect sizes. The red vertical line presents the estimated average effect from the meta-analysis. The funnel is clearly asymmetric and with a long right tail for small studies. This suggests that a publication bias is present, in which results that show positive impacts of health interventions are favored. The distance between the vertical green line – which is the estimated overall effect from the meta-regression, which controls for publication bias – and the red line – which is the overall effect absent any controls – supports this suggestion.

To assess the presence of publication bias more formally, we follow the recommendation of Higgins et al. (2019) and use Egger's regression test to test for funnel asymmetry. The test regresses the standardized effect size on its standard error weighted by the inverse of the standard error. A statistically significant value of the slope coefficient in this weighted regression indicates the presence of publication bias. The result of the test confirms the visual findings from the funnel plot. The coefficient is positive and statistically significant. Moreover, also the intercept is statistically significant, indicating that a genuine effect is present. This supports our decision to opt for the PEESE method and to routinely include the squared standard error as independent variable in all meta-regressions.

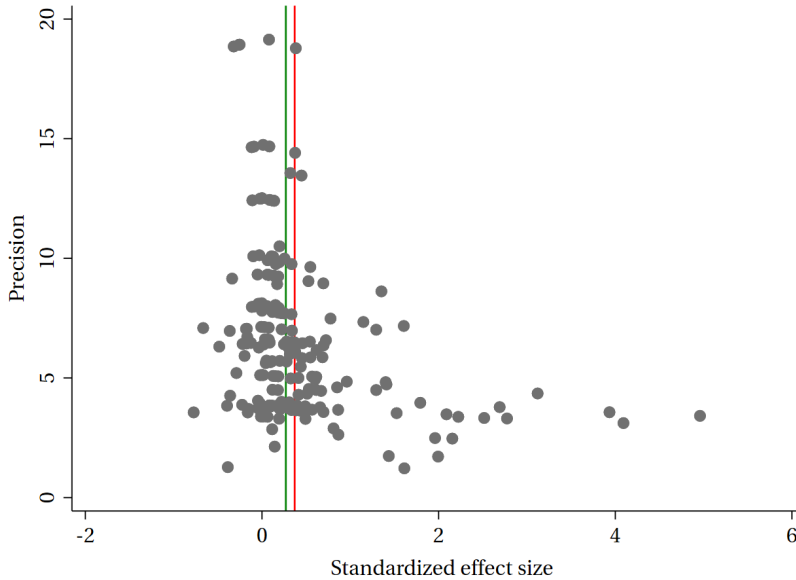


Figure 2.2: Funnel Plot (n=204) - Precision is the inverse of the standard error of the effect size. The red vertical line represents the average effect from the meta-analysis. The green vertical line represents the average effect from the meta-regression corrected for publication bias.

Closely related to publication bias is the issue of statistical power. Underpowered studies typically have lower levels of precision and will, in expected terms, together form the greatest variance around the true underlying effect. While they have a higher probability of committing a Type II error, they also have a higher probability of producing false positives, i.e., they detect falsely a significant effect and reject the true null effect (Christley, 2010; Gelman and Carlin, 2014; Ioannidis, 2005; Wacholder et al., 2004). A process of publication bias whereby studies with undesirable results (such as negative and null effects) are systematically removed (or reduced in number) may overestimate the average effect at any level of standard error. Yet, in expected terms, this overestimation will be larger the higher the standard error, since the average effect is larger among low-power compared to high-power studies for the subset of studies that produce desirable results. Consequently, publication bias paired with the inclusion of several low-power studies is particularly prone to generate overestimated effects, also known as small-study effect. Since the majority of included studies in our analysis work with comparatively small sample sizes, we next assess their statistical power.

We follow the approach proposed by Ioannidis et al. (2017). Assuming a statistical significance level of 5% and a power level of 80%, we divide the estimated average effect per intervention category from the weighted random-effects meta-

analysis by 2.8 (being the sum of 1.96, representing a 5% significance level, and 0.84, representing the 20/80% split in the cumulative standard normal distribution). This gives a threshold to compare the standard errors of the individual underlying estimates. If the standard error is smaller than this threshold, the estimate is said to have sufficient power to reveal the true average effect. We find that only 46 (or 22.5%) of the 204 estimates in our sample, stemming from 13 of the included studies, have sufficient power.¹⁰ This finding once more supports our choice to complement our simple meta-analyses with a more elaborated meta-regression using the PEESE method to reduce the biases stemming from publication bias and underpowered studies.

2.4.4 Meta-analysis

Figure 2.3 shows the results of the random-effects meta-analysis with the subgroup analysis by intervention category and by country. When pooling all 204 estimates of all intervention categories, we find a positive and significant overall effect of 0.37 (p-value: 0.000).

However, the between-subgroup I-squared statistic indicates large heterogeneity across estimates ($I^2 = 96.42$), which is unsurprising, given that these stem from different intervention categories and health outcomes. The subgroup-analysis also yields significant positive effects for each intervention category: 0.38 (p-value: 0.015) for interventions aimed at smoking reduction, 0.74 (p-value: 0.004) for interventions aimed at reducing alcohol consumption, 0.28 (p-value: 0.000) for those aimed at improving diets and physical activity, 0.27 (p-value: 0.025) for those promoting uptake of cancer screening, 0.31 (p-value: 0.007) for interventions providing education to NCD patients, and 0.87 (p-value: 0.009) for interventions making general adjustments in the health care system.

The analysis by country reveals large effects for studies conducted in Thailand (0.63, p-value: 0.000) and Malaysia (0.32, p-value: 0.001), whereas studies conducted in the Philippines and Vietnam result in an equally small effect (0.10, p-value: 0.196 and 0.10, p-value: 0.120). The overall effect for Indonesia is large, yet insignificant (0.72, p-value: 0.450). Yet, since this coefficient is based on only two estimates from a single study, we cannot draw much conclusion from this result.

Figure 2.4 presents the subgroup-analysis by outcome type. The effect size is only significant for four of the 23 health outcomes: smoking abstinence (0.37, p-value: 0.011), HbA1c (0.83, p-value: 0.019), diastolic blood pressure (0.56, p-value: 0.006) and illness severity (0.53, p-value: 0.016).

¹⁰A separate meta-analysis with only the sufficiently powered estimates can be found in Figure 2.C1 in Appendix 2.C. The results of this sub-meta-analysis are close to the results from the meta-regression, indicating that the PEESE method used in the meta-regression performed well in correcting the effect sizes. We thank an anonymous reviewer for proposing to include this additional sub-analysis.

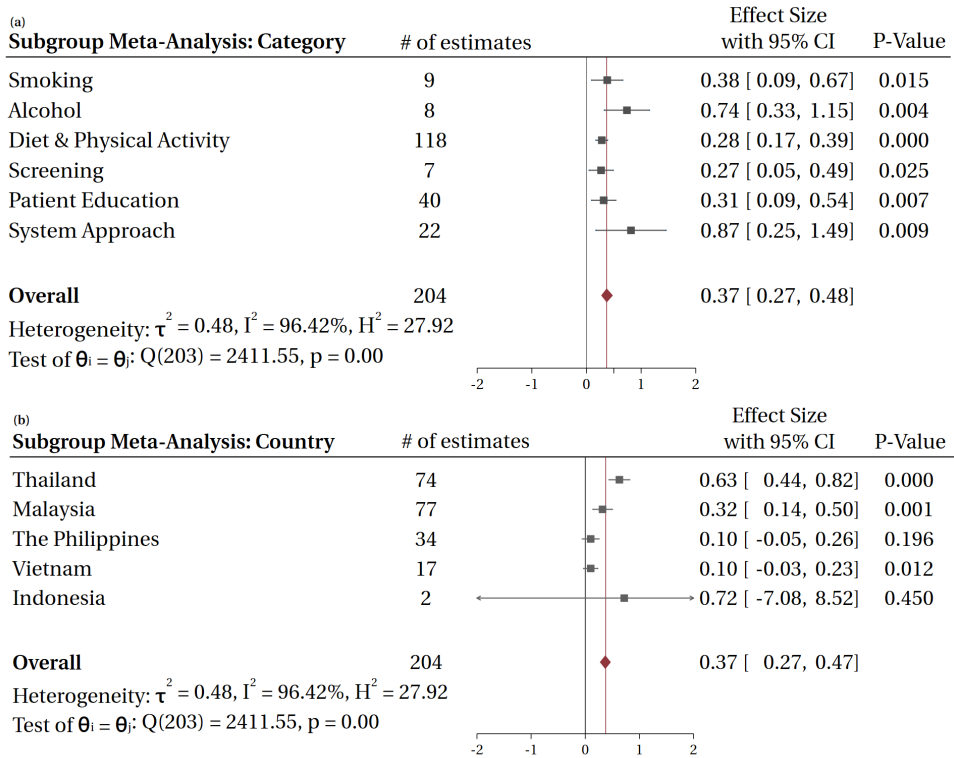


Figure 2.3: Results of the random-effects meta-analysis by (a) intervention category and (b) country - The meta-analysis pools all 204 estimates. Estimates are grouped by intervention category and country.

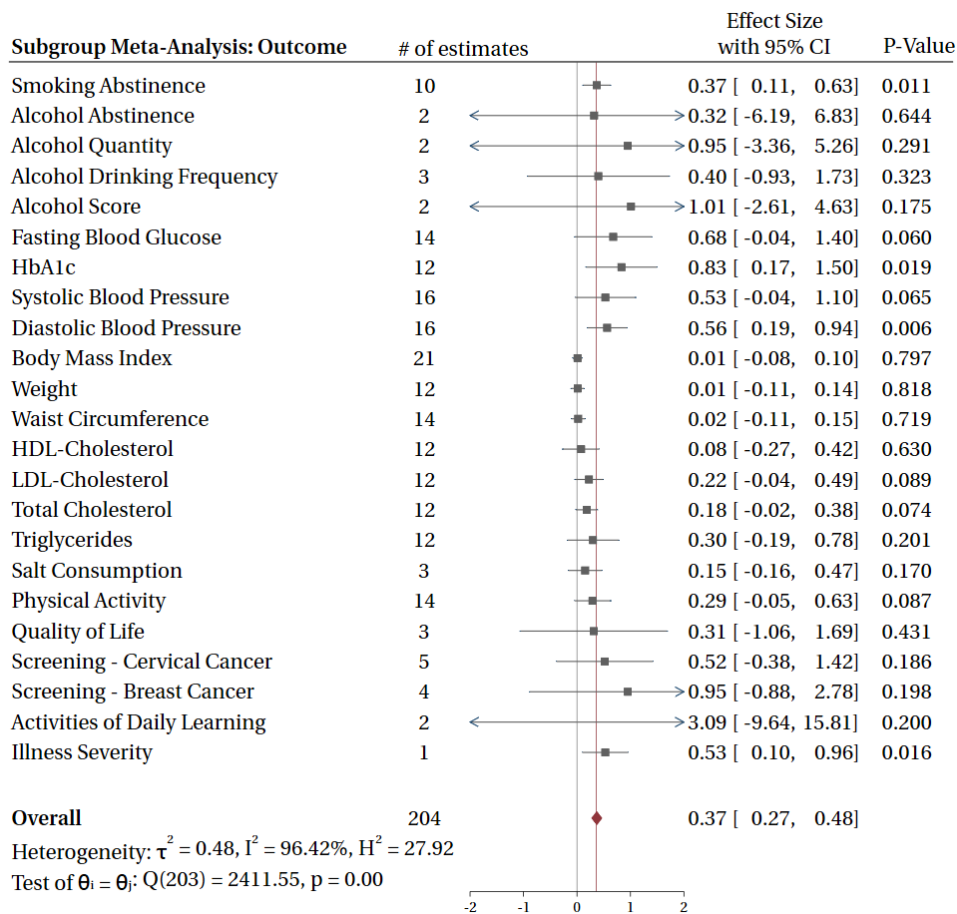


Figure 2.4: Results of the random-effects meta-analysis by outcome type - The meta-analysis pools all 204 estimates. Estimates are grouped by outcome type.

Two additional metabolic indicators also result in sizable effects: fasting blood glucose (0.68, p-value: 0.060) and systolic blood pressure (0.53, p-value 0.065); although neither of them is significant at conventional levels. All of the anthropometric outcomes as well as all measures of alcohol reduction are insignificant. The reason why these effects are insignificant may be because these outcomes were truly not affected by the interventions but could also be explained by the fact that several of them stem from only a small number of studies, resulting in wide confidence intervals. Meta-analyses by outcome type for each intervention category separately are presented in Figures 2.C2-2.C7 in Appendix 2.C.

2.4.5 Meta-regression

In this section, we present the meta-regression results in which we routinely control for publication bias and small-study effects (proxied by the squared standard error), cluster standard errors at study levels and use a population average model to account for different numbers of estimates per study. The model in Column (1) of Table 2.2 estimates the average effect size for the pooled sample of 204 estimates. Compared to the overall effect size of the simple meta-analysis (0.37), the average effect in our more conservative model is noticeably reduced (0.27, p-value: 0.002). The statistical significance of the coefficient for the squared standard error formally confirms the existence of publication bias and hence underlines the importance of controlling for it. Columns (2)-(7) show the effect for each intervention category separately, which are, in comparison to the meta-analytical results, smaller in size. The effects for screening and patient education show a small reduction but remain strongly significant (0.180, p-value 0.000 and 0.228, p-value: 0.025). The effects for smoking and alcohol are also somewhat reduced in size and significance (0.226, p-value: 0.079 and 0.617, p-value: 0.061), while the effect sizes for diet and physical activity and system approach are markedly reduced and insignificant, with the former being close to zero (0.039, p-value: 0.225).

Table 2.2: Meta-regression results

	(1) Full Sample	(2) Smoking	(3) Alcohol	(4) Diet & Physical activity	(5) Patient Education	(6) Screening	(7) System Approach	(8) Thailand	(9) Malaysia
Effect size	0.273*** (0.089)	0.226* (0.129)	0.617* (0.329)	0.039 (0.067)	0.228** (0.102)	0.180*** (0.001)	0.225 (0.272)	0.483*** (0.127)	-0.082 (0.140)
SE ²	3.779** (1.888)	3.006*** (0.634)	2.884 (3.472)	6.625*** (2.012)	5.454 (5.104)	0.652*** (0.017)	16.837** (7.889)	2.585 (2.005)	12.474*** (3.513)
Number of estimates	204	9	8	118	40	7	22	74	77
Number of studies	51	8	4	20	11	4	5	25	17

Notes: All models are random-effects meta-regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. Column (1) includes the full sample of 204 estimates. In Columns (2) to (7) we show the results separately for each intervention category, in Column (8) and (9) we show the results separately for Thailand and Malaysia. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In Column (8) and (9) we present the average effect separately for the two countries that contribute with the major share of included studies, Thailand and Malaysia. While the average effect for Thailand is – as in the simple meta-analysis – larger than the overall effect and significant, the Malaysian effect is now close to zero, suggesting that the results from Malaysia suffer from the biases outlined above. A disaggregated analysis by intervention category shows that this overall insignificant effect for Malaysia results from a lack of positive effects in three intervention categories, namely diet and physical activity, screening and system approach, while a large positive effect is detected among the patient education studies (see Table 2.C1 in Appendix 2.C).

We next present meta-regressions by outcome type in Table 2.3; for the full sample in Column (1), for each intervention category separately in Columns (2)-(7), and again separately for Thailand and Malaysia in Column (8) and (9).

We are able to confirm the positive and significant effects on HbA1c, diastolic blood pressure and illness severity for the full sample, which were also identified in the standard meta-analysis above. Furthermore, the coefficients for alcohol quantity, alcohol score, LDL-cholesterol and activities of daily living become positive and significant. Instead, the effect on smoking abstinence, which was positive and significant in the meta-analysis turns insignificant in our more conservative estimation.

As we instead investigate whether the effect on any single outcome is different compared to the other outcomes, we find this only to be the case for seven outcomes (see Table 2.D1 in Appendix 2.D). Alcohol quantity, alcohol score and activities of daily living stand out as significantly larger than the average effect, while three anthropometric measures (BMI, weight and waist circumference) and alcohol abstinence are significantly smaller than the average effect. When we re-do the regressions by intervention category, we find that generally the metabolic indicators, such as blood pressure, blood sugar and cholesterol levels, show changes that are significantly larger than the average effect, while the effects for weight, BMI and waist circumference are significantly smaller in all intervention categories (Tables 2.D2-2.D6, Appendix 2.D).

When we observe the results for specific outcome types for each intervention category separately in Columns (2)-(7) in Table 2.3, we can confirm that studies that only focus on smoking do increase the rate of smoking abstinence (0.26, p-value 0.079). When we only include the studies related to alcohol, we find that they have negative significant effects for three of the four alcohol-related outcomes. This change in sign occurs since the correlation between the effect size and the SE^2 term within the intervention category is dramatically larger than for the pooled sample (43.255 vs. 4.010). This causes large reductions in the estimated outcome coefficients since, when SE^2 is controlled for, these represent the effect if standard

errors are assumed to be zero. For the studies that focus on diet and physical activity, there is a marginally larger SE^2 coefficient of 6.811 which also contributes to further reduction in the estimated coefficients. Still, these interventions show significant improvements on participants' level of HbA1c and diastolic blood pressure. Yet, the coefficients for weight and BMI turn negative. Studies that focus on patient education instead display lower levels of publication bias and we can confirm significant improvements on patients' level of fasting blood glucose, HbA1c, cholesterol, physical activity and activities of daily living. The effects on the two screening uptake measures are positive and statistically significant for the screening studies. Instead, in the model for the system approach studies, the correction for the very large correlation between the SE^2 term and the effect size (39.573) results in insignificant or even negative effects for all outcomes.

These negative effect sizes occur not because the underlying estimates (i.e., the extracted raw estimates) are negative, but because the estimated publication bias in some models, specifically for alcohol studies and system approach studies, is large enough for the effect size coefficient (representing the estimated effect for when the SE^2 term is set to zero) to turn negative. While for the given specification, the results are consistent with that the true effect is negative, we deem this implausible in our case. The regression including the full sample (Column (1), Table 2.3) estimates that an increase in the SE^2 of 1 inflates the estimated effect size by 4. Granted, the coefficient of the squared standard error is merely an approximation of what remains an unknown relationship between the standard error and the effect size, which, in probabilistic terms, arises in the presence of a potential publication bias. Yet, the same specifications for the alcohol and system approach studies alone estimate that a one-unit increase in the SE^2 increases the effect size by a staggering 43 and 39 units, respectively. It seems unlikely that the problem of small studies or publication bias should be ten times as large as that of other studies included in this review and more likely that the relationship between SE^2 and the degree of inflated effect sizes is simply overestimated in these two specifications. Comparing SE^2 estimates presented in other meta-regression studies further confirms that the specifications in Columns (3) and (7) likely overestimate the extent of small-study effects (e.g., Neves and Sequeira (2018) and de Linde Leonard and Stanley (2020) present SE^2 estimates of 5.25 and 4.18, respectively). To further illustrate that the strongly negative estimates in Columns (3) and (7) are due to the high SE^2 coefficients in these specifications, we run the same regression as in Column (1) of Table 2.3 while including interaction terms between each outcome and a dummy that equals 1 if the estimate is from an intervention in the alcohol category and interaction terms between each outcome and a dummy for system approach studies. None of the estimates of the two categories remains significantly negative; instead all but one estimate (BMI estimated for system approach stud-

ies) switch to a positive sign (results available upon request). For these reasons, we deem the results insufficient to interpret the sign of single outcomes in the one or other direction whenever the coefficient of the SE^2 term is extremely high (i.e., in the categories alcohol and system approach).

Column (8) confirms the overall large and positive effect for studies conducted in Thailand, with large and positive effects for alcohol outcomes, several metabolic indicators, quality of life, cervical cancer screening and illness severity. The result for the Malaysian studies, shown in Column (9), reveal that also the disaggregation by outcomes does not alter the overall insignificant effect, yet again, it is the metabolic indicators that outperform other health outcomes.

Table 2.3: Heterogeneity by outcome

	(1) Full Sample	(2) Smoking	(3) Alcohol	(4) Diet & Physical Activity	(5) Patient Education	(6) Screening	(7) System Approach	(8) Thailand	(9) Malaysia
Smoking Abstinence	0.138 (0.165)	0.226* (0.129)			0.060 (0.435)			0.291 (0.198)	0.244 (0.732)
Alcohol Abstinence	-0.050 (0.203)		-5.369*** (0.469)		-0.147 (0.171)			0.578* (0.327)	
Alcohol Quantity	0.693*** (0.221)		-0.970*** (0.192)					0.862*** (0.257)	
Alcohol Drinking Frequency	0.302 (0.192)		-1.158*** (0.110)					0.340 (0.257)	
Alcohol Score	1.032*** (0.149)		0.0742 (0.269)					0.972*** (0.212)	
Fasting Blood Glucose	0.463* (0.237)			0.169 (0.199)	0.320*** (0.090)		0.707 (0.600)	0.306** (0.124)	0.525 (0.334)
HbA1c	0.618*** (0.239)			1.980*** (0.477)	0.262** (0.121)		0.049 (0.076)	0.745* (0.401)	0.610* (0.345)
Systolic Blood Pressure	0.317* (0.175)			0.123 (0.093)	-0.048 (0.340)		0.396 (0.397)	0.770* (0.394)	0.240 (0.324)
Diastolic Blood Pressure	0.375*** (0.122)			0.306*** (0.099)	0.187* (0.107)		-0.315 (0.233)	1.043** (0.436)	0.051 (0.321)
Body Mass Index	-0.124 (0.078)			-0.180* (0.096)	-0.115 (0.100)		-0.865 (0.560)	0.010 (0.133)	-0.323 (0.278)
Weight	-0.045 (0.077)			-0.161** (0.075)	0.039 (0.103)			0.058 (0.116)	-0.348 (0.383)
Waist Circumference	-0.021 (0.073)			-0.126 (0.080)	-0.055 (0.096)		-0.171 (0.217)	-0.032 (0.136)	-0.322 (0.324)
HDL-Cholesterol	0.052 (0.160)			-0.056 (0.256)	-0.084 (0.093)		-0.306*** (0.094)	-0.102 (0.096)	-0.349 (0.311)

Table continues next page

	(1) Full Sample	(2) Smoking	(3) Alcohol	(4) Diet & Physical Activity	(5) Patient Education	(6) Screening	(7) System Approach	(8) Thailand	(9) Malaysia
LDL-Cholesterol	0.219** (0.111)			0.102 (0.142)	0.258*** (0.053)		-0.398** (0.161)	0.495* (0.278)	-0.215 (0.309)
Total Cholesterol	0.135 (0.100)			0.027 (0.121)	0.157** (0.069)		-0.377*** (0.145)	0.313* (0.167)	-0.144 (0.310)
Triglycerides	0.228 (0.188)			0.091 (0.184)	0.158 (0.142)		0.026 (0.217)	0.380 (0.467)	-0.153 (0.339)
Salt Consumption	0.155 (0.147)			-0.001 (0.153)					
Physical Activity	0.082 (0.167)			-0.084 (0.220)	0.254*** (0.078)			0.574* (0.331)	-0.407 (0.370)
Quality of Life	0.288 (0.312)				0.327 (0.228)			0.580*** (0.058)	-1.061 (0.776)
Screening - Cervical Cancer	0.366 (0.260)					0.186*** (0.001)	-4.507*** (0.249)	1.639*** (0.371)	-0.137 (0.382)
Screening - Breast Cancer	0.073 (0.539)					0.305*** (0.007)	-4.423*** (0.254)	0.521 (1.350)	-0.186 (0.754)
Activities of Daily Living	2.696*** (0.705)				2.950*** (0.748)			2.892*** (0.739)	
Illness Severity	0.337*** (0.085)						-1.388*** (0.093)	0.437*** (0.110)	
SE ²	4.010** (1.773)	3.006*** (0.634)	43.255*** (3.206)	6.811*** (2.033)	0.914 (1.833)	0.450*** (0.025)	39.573*** (1.918)	1.944 (2.268)	12.696*** (3.628)
Number of estimates	204	9	8	118	40	7	22	74	77
Number of studies	51	8	4	20	11	4	5	25	17

Notes: All models are random-effects meta-regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. Column (1) includes the full sample of 204 estimates. In Columns (2) to (7) we show the results separately for each intervention category. No constant is included, the coefficients represent the mean for the respective outcome. *** p<0.01, ** p<0.05, * p<0.1.

2.4.6 Moderator analysis

In a final step, we perform a moderator analysis to gauge the potential influence of a series of different factors: *Contact moments* measures the number of contacts between study participants and study officials (excluding measurement take-up); *share of males* measures the share of study participants that were male; *mean age* measures the average age of all study participants; the dummy *group* indicates whether participants were treated as a group as opposed to individually; and *length* measures the time period from the start of the intervention until the follow-up in months.¹¹ Table 2.4 presents this analysis for the pooled sample and by intervention category and country.

In the full sample, the number of contact moments has a small positive influence (0.027, p-value: 0.056) on the average effect size. The number of contacts also turns out to play a major role in three of the intervention categories. In diet and physical activity, screening and system approach studies, one more contact moment between the study officials and participants increases the effect by 0.04 (p-value: 0.000), 0.15 (p-value: 0.004) and 1.3 (p-value: 0.000), respectively. The number of contacts also moderates the effect size when assessing it separately for Thai and Malaysian studies. This suggests that increased interaction with patients or individuals at risk and repeated stimulation can help to maximize an intervention effect. This seems plausible, assuming that with each contact moment, the participants are again encouraged or reminded to take actions to improve their health. The finding is also in line with the results from earlier meta-analyses and studies assessing the impact of interventions intended to address nutrition and physical activity (Anderson et al., 2009; Greaves et al., 2011).

Neither for the pooled sample nor for any intervention category, we find an effect associated with the share of males among the participants, which also aligns well with the broader literature (see for example Murray et al. (2017) on interventions focusing on physical activity or Gallet and Doucouliagos (2017) on health care spending).

¹¹Additional summary statistics and details on the definition of the moderators can be found in Appendix 2.E. It would have been interesting to investigate the *length of the intervention* as another possible moderator but this information was not available in enough studies to allow for a meaningful analysis.

Table 2.4: Moderator analysis

	(1) Full Sample	(2) Smoking	(3) Alcohol	(4) Diet & Physical Activity	(5) Patient Education	(6) Screening	(7) System Approach	(8) Thailand	(9) Malaysia
Moderator									
<i>Study design</i>									
Contact moments	0.027* (0.014)	0.012 (0.018)	-0.179 (0.184)	0.040*** (0.011)	-0.002 (0.048)	0.153*** (0.053)	1.310*** (0.004)	0.036** (0.026)	0.055** (0.018)
Length	0.001 (0.008)	0.003 (0.885)	-0.295*** (0.000)	-0.008** (0.011)	0.100* (0.058)	0.018** (0.022)	-0.008 (0.580)	0.016* (0.063)	0.035** (0.036)
Group	-0.171 (0.113)	0.023 (0.189)		0.013 (0.150)	-0.622* (0.336)	0.171** (0.078)		-0.125 (0.546)	0.007 (0.959)
<i>Participants' characteristics</i>									
Share of males	0.121 (0.164)	0.163 (0.605)	-2.650 (3.945)	-0.040 (0.132)	-0.483 (0.815)		-1.197 (2.034)	0.159 (0.558)	0.080 (0.785)
Mean age	0.005 (0.004)	0.011* (0.006)	-0.027 (0.041)	0.003 (0.003)	0.000 (0.045)	-0.009*** (0.003)	-0.007 (0.048)	0.006 (0.297)	0.023*** (0.000)

Notes: All models are random-effects meta-regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. Each coefficient is derived from a single regression in which only the respective moderator is included. Missing coefficients occur when the moderator could not be defined for a given intervention category. *** p<0.01, ** p<0.05, * p<0.1

The coefficients for the mean age moderator reveal that smoking studies with on average older participants achieve larger effect sizes (0.011, p-value: 0.054) all else equal, while screening studies with on average older participants find smaller effect sizes (-0.009, p-value: 0.007). The Malaysian studies support the results from the smoking studies. These age differences highlight the need for interventions to clearly specify the targeted age group and adjust the intervention design accordingly.

We also find evidence for an increase in the effect size for screening interventions targeted at groups (0.17, p-value: 0.028). This suggests that community- or group-based approaches can effectively increase screening rates, which is favorable, given that several Southeast Asian countries focus on community-based approaches for NCD prevention.

Finally, the evidence for whether the effect size depends on the time length between start and follow-up is mixed. The moderator seems to negatively affect the outcomes in alcohol and diet and physical activity studies, while it increases the effect size in patient education and system approach studies as well as when the effect is assessed by country. The former is well in line with the observation that behavioral changes that come with a trade-off between short-term cost (e.g. cutting back in alcohol and unhealthy food consumption) but only long-term health benefits, are often not long sustained (Hunter et al., 2018; Murray et al., 2017). On the other hand, interventions focusing on patients that are already diagnosed with an NCD, seem to be more sustainable over time, and screening interventions with a longer time horizon might allow for more individuals taking the opportunity to get screened.

2.5 Discussion and implications

2.5.1 Discussion

The objective of this review and the meta-analysis is to give an all-encompassing picture of the effectiveness of NCD prevention and control interventions in the Southeast Asian context. We identify an overall effect and also give a nuanced picture of differences in the effectiveness across various intervention categories and across many different health outcomes that these interventions target. We found 51 studies that assess credibly the effect of NCD-related interventions, ranging from studies that focus on the four common risk factors (smoking, alcohol, physical inactivity, unhealthy diet) to studies evaluating the impact of interventions on health and behavioral outcomes for patients with diabetes, cardiovascular diseases, or cancer. The 51 included studies cover only five Southeast Asian countries,

with the major share of studies being conducted in Thailand and Malaysia. This geographical restriction is a critical limitation in our aim to derive policy recommendations for the entire region and we therefore consider the results presented in this review as a base on which future research on this region can build.

With a meta-analysis using the entire sample of 204 estimates stemming from 51 studies, we find that the overall effect size is positive and significant, i.e., the interventions do on average improve the prevention and treatment of NCDs. Yet, as expected the effectiveness varies substantially across different intervention categories, but the effect remains positive and significant for each of them.

As discussed, the results from the meta-analysis are subject to several potential biases, which we address with statistically more sophisticated meta-regressions. These regressions account for problems related to publication bias and small-sample effects, correlations among estimates pertaining to the same study and differences in the number of estimates included from each single study. For the pooled regression, the overall effect size drops markedly (from 0.37 to 0.27). Additionally, the results differ substantially as we compare the meta-regression results performed for each intervention category separately. Only interventions pertaining to the screening and patient education categories remain positive and significant. The effect sizes in the smoking and alcohol studies are somewhat reduced in size and significance, and the effect for the studies in the diet and physical activity and system approach categories are close to zero.

Our relatively large sample of estimates also allows to investigate the impact on single outcomes. We find significant positive effect sizes among a few outcomes in the full sample as well as within categories. Outstanding in this aspect are metabolic indicators, including fasting blood glucose, HbA1c and blood pressure, which result in consistently positive effects across interventions. For the majority of the outcomes, however, the estimates are insignificant. Yet, it does not allow us to conclude that all other outcomes have been left unaffected by the interventions since many of the coefficients are based on only a handful of estimates (ten of the 23 outcome coefficients are represented by five or fewer estimates) which substantially limits the power to detect even moderate effect sizes.

Yet, we identify three outcomes that appear especially hard to improve: BMI, weight and waist circumference. The effects on these three outcomes are close to zero or negative in several cases. While we mentioned above that we are careful to interpret negative effects from the meta-regressions as clear evidence that these interventions have adverse effects if the SE^2 coefficient is extraordinarily large, we want to highlight here a different, actual adverse interpretation, as the SE^2 coefficient for this intervention type remains small in Column (4) of Table 2.3. Moreover, several of the underlying estimates in the diet and physical activity studies (i.e., the raw estimates extracted from the studies) are in fact negative, indicating that study

participants rather gained than lost weight. Also, the investigation of the relative effects (i.e., the effect of one outcome in comparison to the mean of all other outcomes shown in Appendix 2.D) consistently shows that these three outcomes are significantly smaller and result in an absolute effect that is close to zero. This is quite alarming given the increasing rates of people suffering from overweight and obesity in the Southeast Asian region (Angkurawaranon et al., 2014; Chan et al., 2017; Rachmi et al., 2017).

In the moderator analysis, we identified specific design features of interventions that play a significant role in explaining why some of the interventions seem to be more effective than others. Especially the number of contact moments the study participants have with the implementing authorities strongly relates to the intervention effectiveness. Also, the age of the targeted participants, whether the intervention is implemented in a group-design and the length of the follow-up moderate the effect size. These findings should be considered by policy makers aiming to design a highly effective NCD intervention.

2.5.2 Implications for interventions and future research

While our results show that some of the considered interventions are effective and may successively be integrated the region's national action plans against NCDs, other interventions lead to no effects or ambiguous effects, leaving substantial gaps that require further research.

The results for smoking interventions are mainly positive and suggest that counseling and financial interventions are a promising measure to decrease the extraordinarily high smoking rates in Southeast Asia. Yet, controlling for potential biases reduces the size and significance of the effect which questions its robustness and calls for further in-depth studies. It is also of concern that only one single study on smoking was conducted in Indonesia, given that the country has the highest smoking prevalence rate among men in the entire Southeast Asian region and that the country has not yet ratified the WHO Framework Convention on Tobacco Control (World Health Organization, 2019). More studies on how to reduce tobacco consumption in Indonesia are needed.

The average effect size for interventions that address alcohol consumption is the largest among our six intervention categories. Also, in our more conservative meta-regression the effect remains sizable. Yet, the total number of studies is small and this restriction in data availability limits an in-depth analysis for specific outcomes and prevents us from declaring this evidence as sound. Furthermore, all included studies in this category have been implemented in a single country (Thailand) which, similar to the evidence on tobacco consumption, also speaks for a need for further research in other countries in the Southeast Asian region.

Moreover, we identify only a modest average effect size for diet and physical activity interventions, which even turns insignificant in our more conservative analysis. Investigating separate outcomes shows positive effects only for HbA1c and diastolic blood pressure, while no positive effect can be confirmed for any of the remaining eleven outcomes, including measures of dietary intake and physical activity. Especially hard to improve are weight-related outcomes, such as weight, BMI and waist circumference. The gloomy results from these studies do not look much brighter as we consider the findings outside the Southeast Asian region: in a literature survey of studies promoting physical activity, Murray et al. (2017) conclude that such interventions often result in no more than short term changes in behavioral outcomes that quickly abate over time.

We can confirm a significant impact on the aggregated level for patient education interventions that typically provide education to NCD patients. Also, the outcome-specific analysis shows results of patients making lifestyle changes towards more physical activity and also shows progression in patients' activities of daily living score as well as improvements in a range of metabolic indicators such as blood lipids and blood cholesterol levels. Hence, it is safe to conclude that the patient education interventions do have a meaningful positive impact on the health of NCD patients and that this type of interventions should be considered by policy makers in Southeast Asia.

For the studies aimed at increasing rates of cancer screening uptake among women, we detect a significant positive effect size of around 0.18 in all models. The effect size is somewhat larger for breast cancer screening compared to cervical cancer screening, which could be an indication of women being generally unwilling to undergo the intimate process of performing a pap smear (Knops-Dullens et al., 2007) and feel more confident to individually perform breast cancer screening via self-examination at home.

System approach studies, focusing on internal processes in health facilities, report a large set of outcomes, which in the standard meta-analysis if taken all together give rise to a sizable effect size of 0.87. Yet, when we address the potential publication bias, this effect fully vanishes. While we can only speculate about the concrete explanations, one possible obstacle in achieving results with a structural approach could be the insufficiency of financial and human resources in health facilities and in sectors concerned with NCDs more specifically that must accompany such reforms. The urgent need for a mobilization of NCD-specific health services is also stressed by Dans et al. (2011) who review the rise of NCDs in Southeast Asia.

Our meta-analysis not only highlights the need for more rigorous evaluation designs and larger samples to determine the effectiveness of the various types of interventions considered in our review, but also a general lack of studies that ade-

quately represent all countries, dimensions and contexts relevant to the prevention and control of NCDs in Southeast Asia. First, Thailand and Malaysia serve as the implementing countries for 42 of the in total 51 studies while relatively few studies have been conducted in the remaining countries in the region. While we aimed to provide a comprehensive analysis and to derive reliable policy recommendations for the entire Southeast Asian region, this geographical restriction is a great limitation. Second, we identified no study targeting patients with chronic respiratory diseases. This is reason for concern, given that the number of life years lost due to chronic respiratory disease is the highest worldwide in the Southeast Asian region, driven by extraordinarily high smoking rates (Soriano et al., 2020). Thirdly, and related to the former, the number of studies concerned with smoking cessation and alcohol consumption were surprisingly low and such studies should be conducted more frequently in the near future.

2.6 Conclusion

Non-communicable diseases are rapidly gaining importance throughout Southeast Asia, calling for an effective policy response to adequately address and manage the problem. To provide policy makers with the relevant evidence, we reviewed the literature on NCD-related health interventions considering in total more than 20 different health outcomes. To conclude, our findings show that these interventions are on average effective, but result generally only in small improvements. Additionally, we highlight a large heterogeneity with respect to effects for different outcomes and intervention categories. We also show that this literature suffers from substantial publication bias and is based to a large extent on underpowered studies. To address the challenge of NCDs in Southeast Asia in the decades to come much more large-scale and rigorous evidence on what works is needed in this context.

Appendices

Appendix 2.A: Search terms and search procedure

Search procedure

The search was conducted using the databases *Cochrane Library*, *EconLit*, *PubMed*, *Sociological Abstracts* and *Web of Science* and complemented by a search with *Google Scholar*. For each database, we performed six searches in total. The first search was performed to identify articles that explicitly focused on a NCD or related risk factor. For this first search, we categorized our search terms under the following sections: i) major NCDs and related risk factors; ii) regions; iii) intervention setting; iv) evaluation study; and v) effectiveness and cost-effectiveness study. In each database, we thereafter performed a search that picked up any article that included at least one of the search terms from each of the five sections. This search strategy was not able to capture articles that do not explicitly address NCDs or related risk factors but nevertheless evaluate interventions of behavioral change and lifestyle modification relevant to such health conditions. Therefore, in an additional five searches, we changed the search terms in the first section that directly address behaviors such as smoking, alcohol consumption, unhealthy diets and physical inactivity. For included studies, we further made use of citation tracking (forward searching) and screened their list of references for further relevant studies (backward searching). The forward- and backward search procedures were ended whenever a further search did not lead to new results.

Information from the included studies was extracted by the researchers according to a coding tool. The information extracted consisted of the general information of the publication, i.e. author(s), title, year and type of publication. Furthermore, the country or countries and target population(s) were characterized for each study, as well as the outcome(s) measured, the type of intervention(s) and intervention impacts. Included studies were also characterized according to their methodology, sampling strategy and sample size and time period covered.

Search term sections

1 Search terms major NCDs and major risk factors

AND

2 Search terms Southeast Asia

AND

3 Search terms community or primary healthcare

AND

4 Search terms intervention, evaluation

AND

5 Search terms effectiveness, cost-effectiveness

Search Terms

(Non-communicable diseases[MeSH Terms] OR NCD[Title/Abstract] OR Diabetes Mellitus [Mesh] OR Hypertension [Mesh] OR Hypertension[Title/Abstract] OR Diabetes[Title/Abstract] OR Diabetes Mellitus[Title/Abstract] OR Pre-diabetes[Title/Abstract] OR diabetes type 2[Title/Abstract] OR Hyperglycemia[Title/Abstract] OR Metabolic Syndrome[Title/Abstract] OR Blood Pressure[Title/Abstract] OR Blood Sugar[Title/Abstract] OR raised blood pressure[Title/Abstract] OR high blood pressure[Title/Abstract] OR healthy lifestyle[Title/Abstract] OR lifestyle change[Title/Abstract] OR dietary behaviour[Title/Abstract] OR dietary change [Title/Abstract] OR physical activity[Title/Abstract] OR physical exercise[Title/Abstract] OR diet[Title/Abstract] OR smoking[Title/Abstract] OR tobacco [Title/Abstract] OR alcohol [Title/Abstract] OR CVD[Title/Abstract] OR cardiovascular disease [Title/Abstract] OR heart attack [Title/Abstract] OR stroke [Title/Abstract] OR obesity[Title/Abstract] OR cancer [Title/Abstract] OR COPD [Title/Abstract] OR Chronic Obstructive Pulmonary Disease [Title/Abstract]) AND (Southeast Asia[MeSH Terms] OR Southeast Asia[Title/Abstract] OR Vietnam[Title/Abstract] OR Myanmar[Title/Abstract] OR Indonesia[Title/Abstract]) AND (Community[Title/Abstract] OR Community-based[Title/Abstract] OR Community level[Title/Abstract] OR Community program[Title/Abstract] OR Community programme[Title/Abstract] OR community participation[Title/Abstract] OR community empowerment[Title/Abstract] OR community engagement[Title/Abstract] OR bottom up[Title/Abstract] OR communities[Title/Abstract] OR community empowerment[Title/Abstract] OR population[Title/Abstract] OR elderly[Title/Abstract] OR Primary Healthcare facility[MeSH Terms] Or Primary Healthcare facility[Title/Abstract] OR Primary Health care facility[Title/Abstract] OR Primary Healthcare facilities[Title/Abstract] OR healthcare facility[Title/Abstract] OR health clinic[Title/Abstract] OR Healthcare

clinic[Title/Abstract] OR Healthcare clinics[Title/Abstract] OR health facility[Title/Abstract] OR Healthcare programme[Title/Abstract] OR healthcare programmes[Title/Abstract] OR healthcare[Title/Abstract] OR Healthcare Program[Title/Abstract] OR Healthcare Programs[Title/Abstract] OR Facility based intervention[Title/Abstract] OR Dispensary[Title/Abstract] OR health center [Title/Abstract] Or Programs[Title/Abstract]) AND (Intervention[Title/Abstract] OR treatment[Title/Abstract] OR Prevention[Title/Abstract] OR preventing[Title/Abstract] OR Evaluation [Title/Abstract]) AND (Impact [Title/Abstract] OR Cost-effectiveness[Title/Abstract] OR cost-effective[Title/Abstract] OR effectiveness[Title/Abstract] OR cost[Title/Abstract])

433 Hits

((smoking cessation[MeSH Terms] OR (smoking[All Fields] AND cessation[All Fields]) OR smoking cessation[All Fields]) OR (smoking[MeSH Terms] AND intervention[All Fields]) OR (quit[All Fields] AND (smoking[MeSH Terms] OR smoking[All Fields]))) AND ((asia, southeastern[MeSH Terms] OR (asia[All Fields] AND southeastern[All Fields]) OR southeastern asia[All Fields] OR (southeast[All Fields] AND asia[All Fields]) OR southeast asia[All Fields]) OR (asia, southeastern[MeSH Terms] OR (asia[All Fields] AND southeastern[All Fields]) OR southeastern asia[All Fields]) OR (southeast[All Fields] AND asia[All Fields]) OR southeast asia[All Fields]) OR (indonesia[MeSH Terms] OR indonesia[All Fields]) OR (myanmar[MeSH Terms] OR myanmar[All Fields]) OR (vietnam[MeSH Terms] OR vietnam[All Fields]))

399 Hits

((Alcohol consumption OR Abstinence OR Alcohol abuse OR Smoking cessation OR Smoking abstinence) AND (Southeast Asia OR Southeast Asia OR Vietnam OR Myanmar OR Indonesia) AND (Community OR Community-based OR Community level OR Community program OR Community programme OR community participation OR community empowerment OR community engagement OR bottom up OR communities OR community empowerment OR population OR elderly OR Primary Healthcare facility Or Primary Healthcare facility OR Primary Health care facility OR Primary Healthcare facilities OR healthcare facility OR health clinic OR Healthcare clinic OR Healthcare clinics OR health facility OR Healthcare programme OR healthcare programmes OR healthcare OR Healthcare Program OR Healthcare Programs OR Facility based intervention OR Dispensary OR health center OR Programs) AND (Intervention OR treatment OR Prevention OR preventing OR Evaluation) AND (Impact OR Cost-effectiveness OR cost-effective OR effectiveness OR cost))

178 Hits

((Healthy lifestyle interventions OR behavioral change OR behavior modification OR Obesity prevention) AND (Southeast Asia OR Southeast Asia OR Vietnam OR Myanmar OR Indonesia) AND (Community OR Community-based OR Community level OR Community program OR Community programme OR community participation OR community empowerment OR community engagement OR bottom up OR communities OR community empowerment OR population OR elderly

Chapter 2

OR Primary Healthcare facility Or Primary Healthcare facility OR Primary Health care facility OR Primary Healthcare facilities OR healthcare facility OR health clinic OR Healthcare clinic OR Healthcare clinics OR health facility OR Healthcare programme OR healthcare programmes OR healthcare OR Healthcare Program OR Healthcare Programs OR Facility based intervention OR Dispensary OR health center OR Programs) AND (Intervention OR treatment OR Prevention OR preventing OR Evaluation) AND (Impact OR Cost-effectiveness OR cost-effective OR effectiveness OR cost))

330 Hits

((Diabetes self-management OR diabetes self-care OR Health promotion OR health education OR health knowledge OR Metabolic syndrome OR Healthy eating OR weight management) AND (Southeast Asia OR Southeast Asia OR Vietnam OR Myanmar OR Indonesia) AND (Community OR Community-based OR Community level OR Community program OR Community programme OR community participation OR community empowerment OR community engagement OR bottom up OR communities OR community empowerment OR population OR elderly OR Primary Healthcare facility Or Primary Healthcare facility OR Primary Health care facility OR Primary Healthcare facilities OR healthcare facility OR health clinic OR Healthcare clinic OR Healthcare clinics OR health facility OR Healthcare programme OR healthcare programmes OR healthcare OR Healthcare Program OR Healthcare Programs OR Facility based intervention OR Dispensary OR health center OR Programs) AND (Intervention OR treatment OR Prevention OR preventing OR Evaluation) AND (Impact OR Cost-effectiveness OR cost-effective OR effectiveness OR cost))

1932 Hits

((Dietary interventions OR dietary advice OR Workplace intervention OR School interventions OR Physical activity) AND (Southeast Asia OR Southeast Asia OR Vietnam OR Myanmar OR Indonesia) AND (Community OR Community-based OR Community level OR Community program OR Community programme OR community participation OR community empowerment OR community engagement OR bottom up OR communities OR community empowerment OR population OR elderly OR Primary Healthcare facility Or Primary Healthcare facility OR Primary Health care facility OR Primary Healthcare facilities OR healthcare facility OR health clinic OR Healthcare clinic OR Healthcare clinics OR health facility OR Healthcare programme OR healthcare programmes OR healthcare OR Healthcare Program OR Healthcare Programs OR Facility based intervention OR Dispensary OR health center OR Programs) AND (Intervention OR treatment OR Prevention OR preventing OR Evaluation) AND (Impact OR Cost-effectiveness OR cost-effective OR effectiveness OR cost))

675 Hits

Appendix 2.B: Included studies

Table 2.B1: Characteristics of included studies

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Smoking							
Aung et al. (2019)	Individual level counseling at district level hospital and continuous patient motivation over 3 months. Smoking cessation intervention with a focus on the first months after quitting attempt.	Thailand	RCT	319	12 months	Smoking Abstinence	0.55 (0.001)
Blebil et al. (2014)	Smoking cessation intervention with a focus on the first months after quitting attempt.	Malaysia	RCT	231	6 months	Smoking Abstinence	0.54 (<0.001)
Chansatitporn et al. (2016)	School-based smoking prevention program consisting of eight group sessions.	Thailand	Quasi-experimental	185	3 months	Smoking Abstinence	0.51 (0.027)
Giné et al. (2010)	Voluntary commitment to abstinence. Saving account as financial incentive for smoking cessation.	The Philippines	RCT	2000	12 months	Smoking Abstinence	0.20 (0.037)
Junnual et al. (2015)	Individual level counseling at smoking cessation clinics/hospitals and a stop-smoking pocket calendar that encouraged people to quit smoking.	Thailand	Quasi-experimental	80	2 months	Smoking Abstinence	0.81 (0.019)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Pengpid et al. (2015)	Screening and brief intervention (3-15 minutes counseling/simple advice) that focuses on conjoint hazardous or harmful alcohol and tobacco use.	Thailand	Quasi-experimental	620	6 months	Smoking Abstinence	-0.29 (0.132)
Tahlil et al. (2015)	School-based smoking prevention program to provide students with information and skills surrounding smoking prevention.	Indonesia	Quasi-experimental	427	6 months	<i>Health-based:</i> Smoking Abstinence	0.19 (0.523)
White et al. (2013)	Commitment contract and financial team incentives.	Thailand	RCT	215	6 months	<i>Islamic-based:</i> Smoking Abstinence	1.44 (0.013)
						Smoking Abstinence	0.44 (0.016)
Alcohol							
Areesantichai et al. (2013)	Tailored goal oriented community brief intervention consisting of four individual counseling sessions à 15-60 minutes.	Thailand	Quasi-experimental	97	6 months	Alcohol Abstinence Drinking Frequency Alcohol Quantity	0.87 (0.023) 0.85 (<0.001) 1.29 (<0.001)
Noknoy et al. (2010)	Motivational enhancement therapy counseling in primary care units conducted by nurses.	Thailand	RCT	117	6 months	Drinking Frequency Alcohol Quantity	0.57 (0.005) 0.61 (0.002)
Pengpid et al. (2015)	Screening and brief intervention (3-15 minutes counseling/simple advice) that focuses on conjoint hazardous or harmful alcohol and tobacco use.	Thailand	Quasi-experimental	620	6 months	Drinking Frequency Alcohol Score	-0.17 (0.263) 0.72 (<0.001)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Pensuksan et al. (2010)	University-based alcohol drinking prevention program using group motivational counseling.	Thailand	Quasi-experimental	225	3 months	Alcohol Score	1.29 (<0.001)
Diet & Physical Activity							
Ahmad et al. (2018)	Childhood obesity prevention program. 4 weeks parents' training to promote healthy eating behavior and physical activity for their children.	Malaysia	RCT	134	6 months	BMI WC	0.20 (0.252) 0.28 (0.115)
Angeles-Agdeppa et al. (2010)	Supplementary nutrients intake intervention.	The Philippines	RCT	60	4 months	BMI Weight WC	0.09 (0.737) 0.08 (0.753) 0.17 (0.514))
Banchonhattakit et al. (2009)	Childhood obesity prevention program.	Thailand	Quasi-experimental	375	8 months	Physical Activity	1.99 (0.001)
Calano et al. (2019)	Community-based health program including group health education sessions, motivational interviews, and individualized lifestyle modification plan.	The Philippines	Quasi-Experimental	50	2 months	DBP SBP	0.61 (0.007) 0.67 (0.004)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Chaiyasoot et al. (2018)	Lifestyle and behavior change intervention.	Thailand	RCT	110	8 months	FBG	0.60 (0.004)
						HbA1c	3.12 (<0.001)
						Triglyceride	0.01 (0.940)
						Total Cholesterol	0.96 (<0.001)
						HDL-C	0.00 (1.00)
						LDL-C	1.41 (<0.001)
						BMI	0.15 (0.449)
						Weight	-0.02 (0.914)
						WC	0.18 (0.353)
						DBP	0.41 (0.041)
Chawla et al. (2017)	Childhood obesity prevention program. Multicomponent intervention.	Thailand	Quasi-experimental	452	6 months	SBP	0.13 (0.525)
						Triglyceride	0.11 (0.284)
						Total Cholesterol	0.13 (0.199)
						HDL-C	-0.03 (0.764)
						LDL-C	-0.10 (0.319)
Fazliana et al. (2018)	Individual weight loss intervention consisting of individual diet and physical activity counseling, and provision of self-monitoring tools.	Malaysia	Quasi-experimental	328	12 months	Physical Activity	0.25 (0.011)
						FBG	0.15 (0.237)
						Triglyceride	0.06 (0.632)
						Total Cholesterol	0.19 (0.135)
						HDL-C	-0.09 (0.490)
						LDL-C	-0.12 (0.360)
						BMI	-0.02 (0.847)
						Weight	-0.01 (0.944)
						WC	0.01 (0.935)
						DBP	0.03 (0.836)
SBP	0.00 (0.980)						

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Ibrahim et al. (2016)	Community-based health lifestyle intervention in partnership with community volunteers.	Malaysia	Quasi-experimental	268	12 months	FBG	1.15 (<0.001)
						HbA1c	1.61 (<0.001)
						Triglyceride	0.24 (0.064)
						Total Cholesterol	0.00 (1.00)
						HDL-L	0.78 (<0.001)
						LDL-L	0.12 (0.362)
						DBP	0.25 (0.052)
						SBP	0.23 (0.081)
						BMI	0.21 (0.101)
						Weight	0.19 (0.152)
						WC	0.22 (0.087)
Koo et al. (2018)	Childhood obesity prevention program.	Malaysia	Quasi-experimental	63	9 months	BMI	0.26 (0.311)
						WC	0.40 (0.132)
						Physical Activity	-0.02 (0.929)
McCaffrey et al. (2005)	Implementation of group yoga sessions to reduce blood pressure and stress levels.	Thailand	Quasi-experimental	54	2 months	BMI	0.09 (0.721)
						DBP	2.52 (<0.001)
						SBP	2.22 (<0.001)
Moy et al. (2006)	Worksite health promotion program consisting of intensive individual and group counseling.	Malaysia	Quasi-experimental	150	24 months	FBG	-0.17 (0.228)
						Triglyceride	0.09 (0.590)
						Total Cholesterol	0.34 (0.019)
						HDL-C	-0.37 (0.012)
						LDL-C	0.22 (0.120)
						BMI	0.02 (0.859)
						DBP	-0.01 (0.950)
SBP	-0.18 (0.203)						

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Nguyen et al. (2012)	Community-based health promotion and hypertension management program. Information campaigns within the community to improve knowledge of NCD risk factors.	Vietnam	Quasi-experimental	4650	36 months	<i>Male</i>	
						BMI	-0.12 (0.086)
						Weight	-0.09 (0.184)
						WC	0.01 (0.849)
						DBP	0.37 (< 0.001)
						SBP	0.08 (0.221)
						Physical Activity	-0.20 (0.243)
						Salt Consumption	0.17 (0.126)
						<i>Female</i>	
						BMI	-0.26 (<0.001)
						Weight	-0.25 (<0.001)
						WC	-0.32 (<0.001)
						DBP	0.38 (<0.001)
						SBP	0.08 (0.129)
Physical Activity	-0.67 (<0.001)						
Salt Consumption	0.16 (0.127)						
Nguyen et al. (2018)	Individual storytelling intervention to improve hypertension control.	Vietnam	Quasi-experimental	160	12 months	BMI	-0.04 (0.821)
						DBP	0.33 (0.043)
						SBP	0.37 (0.023)
						Physical Activity	0.12 (0.742)
						Salt Consumption	0.03 (0.918)
Phimarn et al. (2013)	Weight management through individual counseling provided by community pharmacists.	Thailand	RCT	66	4 months	BMI	0.31 (0.223)
						Weight	0.22 (0.380)
						WC	-0.05 (0.855)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Soon et al. (2013)	Physical activity and dietary intervention consisting of group lectures and discussion sessions once a month, and a phone call reminder.	Malaysia	Quasi-experimental	56	3 months	FBG	0.33 (0.227)
						Triglyceride	0.43 (0.122)
						Total Cholesterol	0.48 (0.086)
						HDL-C	-0.77 (0.008)
						LDL-C	0.39 (0.164)
						BMI	-0.04 (0.871)
						Weight	-0.01 (0.959)
						WC	-0.15 (0.579)
						DBP	0.70 (0.016)
						SBP	0.20 (0.456)
Sriramatr et al. (2014)	Internet-based intervention to promote physical activity.	Thailand	RCT	220	6 months	Physical Activity	1.4 (<0.001)
						Physical Activity	1.4 (<0.001)
Suntayakorn and Rojjanasrirat (2013)	Community-based intervention focusing on empowerment processes for people at risk of strokes.	Thailand	Quasi-experimental	60	3 months	FBG	0.10 (0.703)
						Triglyceride	2.77 (<0.001)
						Total Cholesterol	0.12 (0.656)
						BMI	-0.02 (0.929)
						DBP	1.52 (<0.001)
						SBP	0.86 (0.002)
						Physical Activity	0.16 (0.549)
Thiengwiboonwong et al. (2013)	Worksite counseling and healthy diet intervention.	Thailand	Quasi-experimental	32	6 months	Triglyceride	-0.40 (0.134)
						Total Cholesterol	0.49 (0.067)
						HDL-C	-0.22 (0.386)
						LDL-C	0.66 (0.016)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Tran et al. (2017)	Health promotion program implemented within the communities.	Vietnam	RCT	337	6 months	FBG Triglyceride Total Cholesterol HDL-C LDL-C BMI Weight WC DBP SBP Physical Activity	0.53 (<0.001) 0.06 (0.575) -0.34 (0.002) 1.35 (<0.001) -0.05 (0.639) 0.07 (0.537) 0.14 (0.211) 0.18 (0.090) 0.07 (0.511) 0.08 (0.465) 0.69 (<0.001)
Wafa et al. (2011)	Behavior change intervention that aimed to prevent childhood obesity by counseling for parents.	Malaysia	RCT	107	6 months	BMI Physical Activity	0.18 (0.419) 0.12 (0.59)
Screening							
Abdullah et al. (2013)	A screening intervention for teachers identified at schools; letter and information pamphlets.	Malaysia	Quasi-experimental	398	6 months	Screening Uptake (CC)	0.28 (0.023)
Akhtari-Zavare et al. (2016)	Screening intervention; educational program on health awareness.	Malaysia	RCT	370	12 months	Screening Uptake (BC)	0.33 (0.105)
Crombie et al. (2005)	Screening intervention; written educational intervention or written educational intervention plus group educational sessions on breast cancer detection.	Thailand	Quasi-experimental	156	3 months	<i>Pamphlet Group</i> Screening Uptake (BC) <i>Education Group</i> Screening Uptake (BC)	-0.39 (0.623) 1.61 (0.049)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Rashid et al. (2013)	1: invitation by postal letter; 2: invitation by registered letter; 3 invitation by SMS; 4: invitation by phone call.	Malaysia	RCT	1000	2 months	<i>Phone call vs postal letter</i>	
						Screening Uptake (CC)	0.45 (0.008)
						<i>Registered letter vs postal letter</i>	
						Screening Uptake (CC)	0.04 (0.812)
						<i>SMS vs postal letter</i>	
						Screening Uptake (CC)	0.10 (0.586)
Patient Education - Diabetes							
Jaipakdee et al. (2015)	Diabetes self-management program implemented in public health centers.	Thailand	RCT	403	6 months	FBG	0.34 (0.001)
						HbA1c	0.06 (0.523)
						QoL	0.55 (<0.001)
						Weight	0.20 (0.055)
Nguyen et al. (2019)	Nutrition education about dietary guidelines for DM patients and instructions on Okara menu cooking methods to increase fiber intake.	Vietnam	RCT	49	2 weeks	FBG	0.49 (0.112)
						BMI	-0.01 (0.968)
						WC	0.06 (0.833)
						Weight	0.01 (0.961)
Uunnapiruk et al. (2014)	Behavior modification program for older individuals with diabetes type 2. Counseling and education.	Thailand	Quasi-experimental	60	3 months	FBG	0.57 (0.042)
						HbA1c	0.30 (0.267)
						Physical Activity	0.37 (0.178)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Paz-Pacheco et al. (2017)	Peer-education program.	Philippines	RCT	155	6 months	FBG	0.28 (0.072)
						Alcohol Abstinence	-0.16 (0.567)
						BMI	-0.22 (0.161)
						DBP	0.08 (0.617)
						SBP	-0.48 (0.003)
						HbA1c	0.09 (0.572)
						HDL-C	-0.17 (0.266)
						LDL-C	0.25 (0.112)
						Smoking Abstinence	0.14 (0.759)
						Triglyceride	0.36 (0.024)
Ramadas et al. (2018)	Stage-tailored recommendations delivered via a study website which aimed to address the barriers and to motivate the participants.	Malaysia	RCT	128	12 months	WC	-0.12 (0.421)
						FBG	0.12 (0.513)
HbA1c	0.05 (0.771)						
	Sharoni et al. (2018)	Health education program on foot self-care.	Malaysia	RCT	71	4 months	QoL
Tan et al. (2011)	Education program consisting of three monthly sessions: two face-to-face individual education sessions and one telephone follow-up.	Malaysia	RCT	164	12 months	HbA1c	0.62 (<0.001)
						Physical Activity	0.30 (0.064)
						Weight	0.02 (0.910)
Wattana et al. (2007)	Small group diabetes education class, four small group discussions, two individual home visit sessions.	Thailand	RCT	147	24 weeks	HbA1c	0.32 (0.060)
						QoL	0.68 (<0.001)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Withidpanyawong et al. (2019)	Education package for participants and their relatives.	Thailand	RCT	170	9 months	BMI DBP HbA1c HDL-C HDL-C SBP Total Cholesterol Triglyceride	0.05 (0.748) 0.37 (0.017) 0.70 (<0.001) 0.08 (0.614) 0.34 (0.028) 0.46 (0.004) 0.28 (0.071) 0.03 (0.822)
Patient Education - CVD							
Chaiyawat and Kulkantrakorn (2012)	Exercise program provided monthly by a physical therapist for home-based individuals once a day.	Thailand	RCT	60	24 months	Activities of Daily Living	4.09 (<0.001)
Pitthayapong et al. (2017)	Intervention program for family caregivers focused information, motivation and skills.	Thailand	Quasi-experimental	62	2 months	Activities of Daily Living	2.09 (<0.001)
System Approach - Diabetes							
Chalerm Sri et al. (2014)	Continuity of care clinic that had already been established, and up and running since several years at the time of the evaluation.	Thailand	Quasi-experimental	757	48 months	FBG HbA1c Screening Uptake (BC) Screening Uptake (CC)	0.32 (<0.001) 0.45 (<0.001) 2.16 (<0.001) 1.96 (<0.001)
Lim et al. (2016)	Additional counseling from the pharmacists, on top of the usual physician's consultation.	Malaysia	RCT	76	12 months	FBG BMI DBP HbA1c SBP	4.96 (<0.001) 0.41 (0.080) 1.79 (<0.001) 2.69 (<0.001) 3.93 (<0.001)

Table continues next page

Reference	Intervention description	Country	Study design	Sample size	Length of follow-up	Outcome	Effect size (p-value)
Ramli et al. (2016)	Multifaceted interventions based on a chronic care model in the care of patients with diabetes 2.	Malaysia	RCT	626	12 months	BMI DBP HbA1c HDL-C HDL-C SBP Total Cholesterol Triglyceride WC	-0.02 (0.788) 0.13 (0.104) 0.13 (0.120) 0.00 (1.000) 0.00 (1.000) 0.14 (0.088) 0.00 (1.000) 0.09 (0.282) -0.11 (0.175)
Sindhu et al. (2010)	Development and usage of a trans-disciplinary team that facilitates communication and coordination across health providers.	Thailand	Quasi-experimental	91	2 months	Illness Severity	0.53 (0.018)
System Approach - CVD							
Selvaraj et al. (2012)	Chronic disease management program with assistance from nurse educators and bi-weekly telephone follow-up by trained nurse educators for 24 weeks.	Malaysia	RCT	263	9 months	HDL-C LDL-C Total Cholesterol	0.15 (0.221) -0.04 (0.734) 0.00 (0.989)

Notes: The table presents the characteristics of all 51 studies included in the review. There are 52 studies listed, because Pengpid et al. (2015) is listed in two categories. BMI: Body Mass Index; DBP: Diastolic Blood Pressure; SBP: Systolic Blood Pressure; HbA1c: Hemoglobin A1c; H(L)DL-C: High (Low) Density Lipoprotein Cholesterol; WC: Waist Circumference; RCT: Randomized Control Trial; ES: Effect Size; OR: Odds Ratio; FBG: Fasting Blood Glucose; QoL: Quality of Life; BC: Breast Cancer; BSE: Breast Self-Examination; CVD: Cardiovascular Diseases.

Appendix 2.C: Additional meta-analyses and meta-regressions

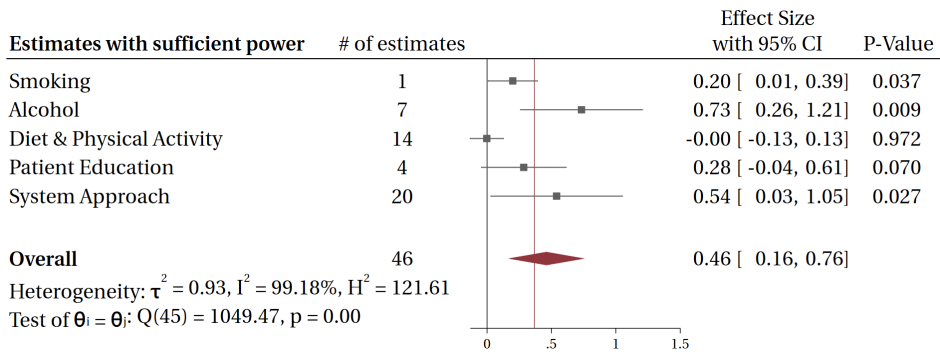


Figure 2.C1: Results of the random-effects meta-analysis: Power - The meta-analysis pools only those estimates that were found to have sufficient power to detect the category-specific effect size.

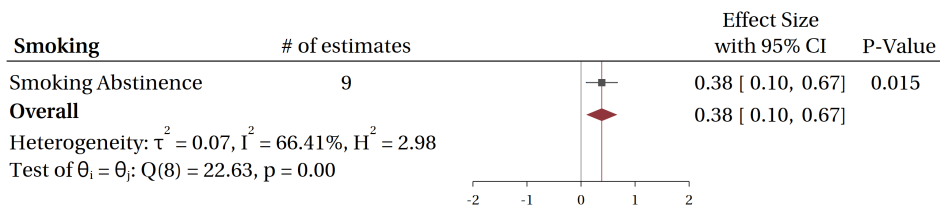


Figure 2.C2: Results of the random-effects meta-analysis: Smoking - The meta-analysis pools all 9 estimates for the smoking studies.

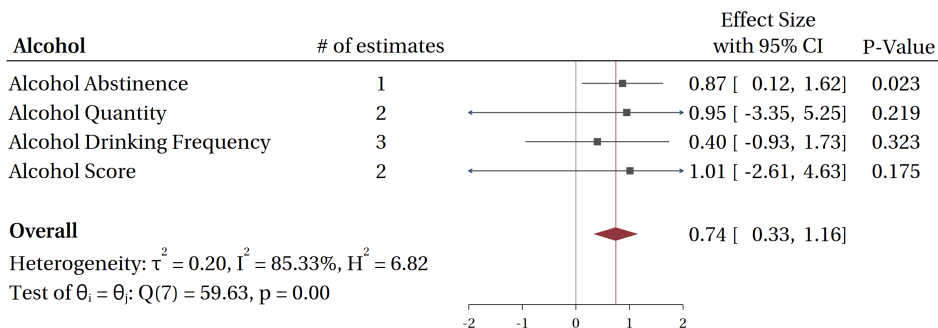


Figure 2.C3: Results of the random-effects meta-analysis: Alcohol - The meta-analysis pools all 8 estimates for the alcohol studies.

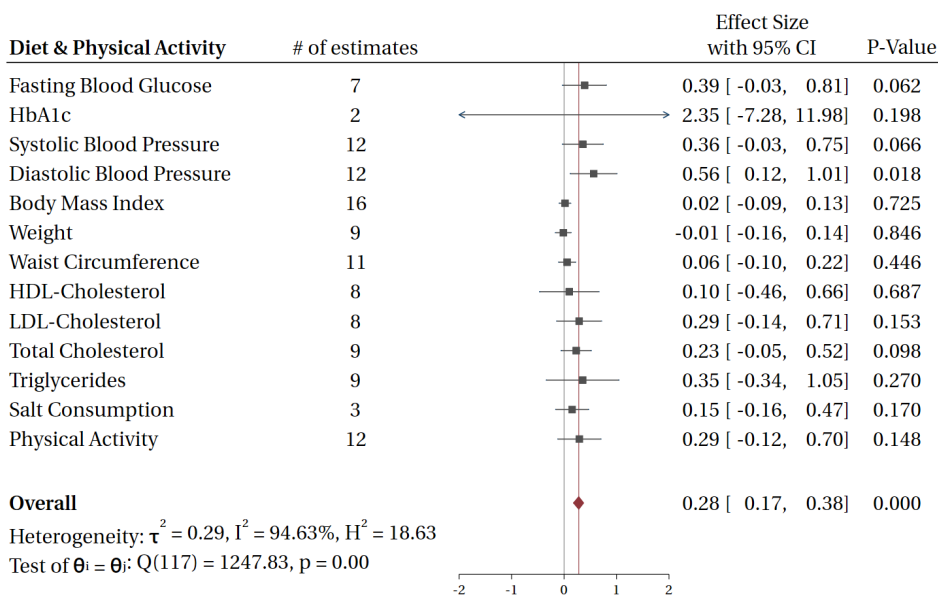


Figure 2.C4: Results of the random-effects meta-analysis: Diet and physical activity - The meta-analysis pools all 118 estimates for the diet and physical activity studies.

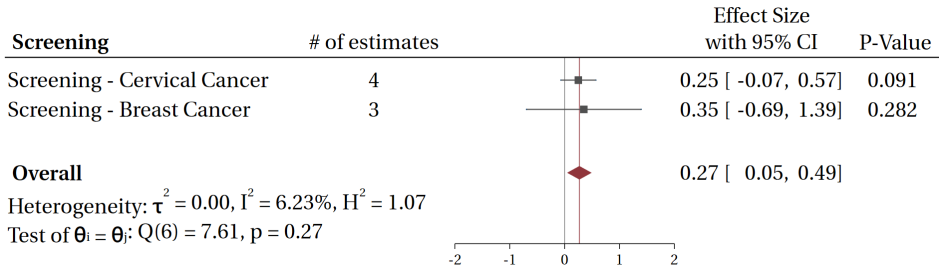


Figure 2.C5: Results of the random-effects meta-analysis: Screening - The meta-analysis pools all 7 estimates for screening studies.

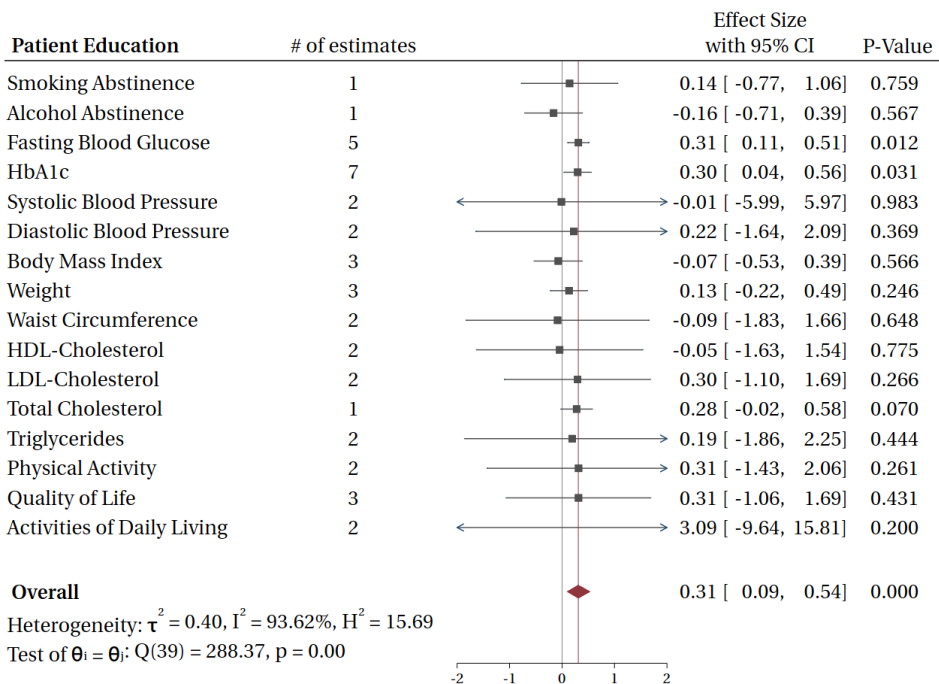


Figure 2.C6: Results of the random-effects meta-analysis: Patient education - The meta-analysis pools all 40 estimates for the patient education studies.

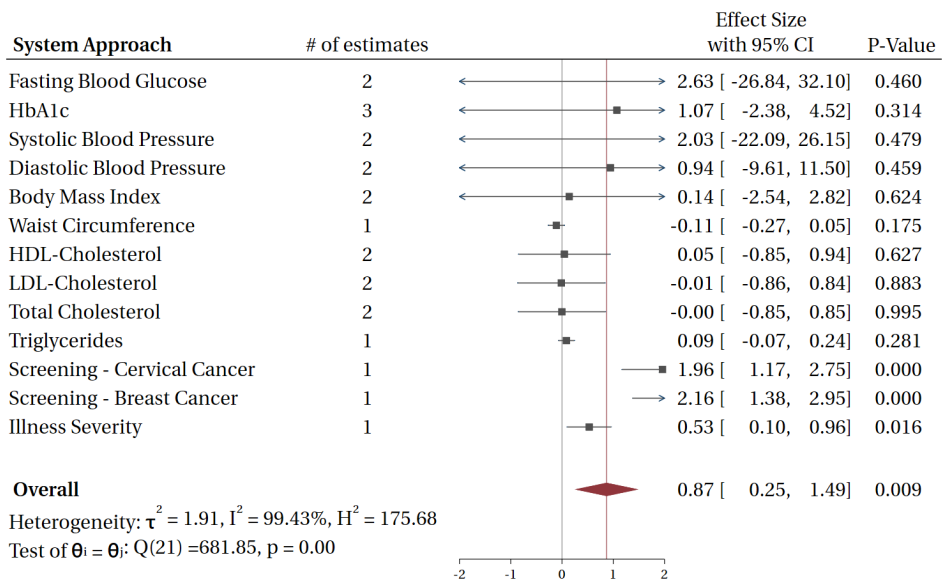


Figure 2.C7: Results of the random-effects meta-analysis: System approach - The meta-analysis pools all 22 estimates for the system approach studies.

Table 2.C1: Meta-regression results by intervention category for Thailand and Malaysia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Thailand				Malaysia				
	Smoking	Alcohol	Diet & Physical Activity	Patient Education	System Approach	Diet & Physical Activity	Screening	Patient Education	System Approach
Effect size	0.084 (0.358)	0.617* (0.329)	0.197 (0.143)	-0.338 (0.317)	0.320*** (0.010)	0.136 (0.14)	0.212 (0.529)	0.938*** (0.102)	-0.241*** (0.005)
SE ²	5.878 (6.206)	2.884 (3.472)	7.540*** (2.635)	27.98** (12.11)	10.10*** (0.949)	0.928 (1.963)	-0.381 (17.21)	-24.84*** (4.067)	43.17*** (0.651)
Number of estimates	5	8	35	19	5	48	5	6	17
Number of studies	5	4	8	6	2	7	3	3	3

Notes: Table 2.C1 shows the meta-regression results by intervention category separately for Thailand and Malaysia. All models are random-effects meta-regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 2.D: Relative effects of outcomes

Table 2.D1 displays the results for 23 different regression, in which we test whether a single outcome is significantly different from the average effect for the full sample of 204 estimates. We repeat the regression separately for each intervention category (Tables 2.D2-2.D6) and thereby test whether certain outcomes within an intervention category are significantly different from the category's average effect. Note that there is no table for the smoking category as it includes only one outcome type (Smoking Abstinence).

Table 2.D1: Relative effect of outcomes - Full sample

	(1) Smoking Abst.	(2) Alcohol Abst.	(3) Alcohol Quant.	(4) Drinking Freq.	(5) Alcohol Score	(6) FBG	(7) HbA1c	(8) SBP	(9) DBP	(10) BMI	(11) Weight	(12) Waist Circ.
Panel A												
Relative effect	-0.152 (0.157)	-0.333** (0.144)	0.457** (0.213)	-0.058 (0.176)	0.785*** (0.126)	0.255 (0.216)	0.409* (0.246)	0.128 (0.142)	0.193* (0.113)	-0.361*** (0.108)	-0.257*** (0.055)	-0.211*** (0.045)
SE ²	3.869* (1.988)	3.863** (1.958)	3.802** (1.893)	3.769** (1.885)	3.863** (1.914)	3.843** (1.917)	3.941** (1.959)	3.806** (1.897)	3.827** (1.895)	3.706** (1.866)	3.749** (1.882)	3.752** (1.886)
Average effect	0.282*** (0.091)	0.271*** (0.091)	0.264*** (0.089)	0.275*** (0.090)	0.254*** (0.090)	0.253*** (0.086)	0.236*** (0.092)	0.264*** (0.087)	0.259*** (0.091)	0.313*** (0.096)	0.287*** (0.090)	0.286*** (0.090)
# of estimates	204	204	204	204	204	204	204	204	204	204	204	204
# of studies	51	51	51	51	51	51	51	51	51	51	51	51
	(13) HDL-C	(14) LDL-C	(15) Total Chol.	(16) Trigly.	(17) Salt Cons.	(18) Physical Activity	(19) Quality of Life	(20) Screening (CC)	(21) Screening (BC)	(22) ADL	(23) Illness Severity	
Panel B												
Relative effect	-0.174 (0.160)	0.020 (0.104)	-0.077 (0.106)	0.029 (0.190)	0.003 (0.157)	-0.126 (0.138)	-0.031 (0.298)	0.096 (0.235)	-0.293 (0.584)	2.507*** (0.701)	0.076 (0.083)	
SE ²	3.737** (1.878)	3.780** (1.888)	3.762** (1.883)	3.779** (1.888)	3.775** (1.887)	3.842** (1.952)	3.773** (1.886)	3.765** (1.878)	4.072** (1.630)	3.476** (1.694)	3.774** (1.886)	
Average effect	0.283*** (0.090)	0.272*** (0.091)	0.277*** (0.091)	0.272*** (0.091)	0.273*** (0.090)	0.279*** (0.090)	0.274*** (0.090)	0.270*** (0.090)	0.265*** (0.078)	0.240*** (0.078)	0.272*** (0.090)	
# of estimates	204	204	204	204	204	204	204	204	204	204	204	
# of studies	51	51	51	51	51	51	51	51	51	51	51	

Notes: All models are random-effects meta regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. Abbreviations: Abst.: Abstinence; BMI: Body Mass Index; DBP: Diastolic Blood Pressure; SBP: Systolic Blood Pressure; HbA1c: Hemoglobin A1c; H(L)DL-C: High (Low) Density Lipoprotein Cholesterol; Chol.: Cholesterol; Circ: Circumference; Cons.: Consumption; FBG: Fasting Blood Glucose; CC: Cervical cancer; BC: Breast Cancer; ADL: Activities of Daily Living; Trigly.: Triglycerides. ***p<0.01, **p<0.05, *p<0.1.

Table 2.D2: Relative effect of outcomes - Alcohol

	(1) Alcohol Abstinence	(2) Alcohol Quantity	(3) Drinking Frequency	(4) Alcohol Score
Relative effect	-1.329 (1.809)	0.272 (0.316)	-0.493** (0.234)	0.527 (0.422)
SE ²	13.78 (17.01)	2.587 (3.097)	-4.414*** (0.956)	5.285 (5.688)
Average effect	0.252 (0.710)	0.562* (0.340)	1.121*** (0.193)	0.369 (0.358)
# of estimates	8	8	8	8
# of studies	4	4	4	4

Notes: All models are random-effects meta-regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 2.D3: Relative effect of outcomes - Screening

	(1) Screening (BC)
Relative effect	0.120*** (0.006)
SE ²	0.450*** (0.025)
Average effect	0.186*** (0.001)
# of estimates	7
# of studies	4

Notes: All models are random-effects meta-regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. There are only two outcomes in the Screening Category: Breast Cancer (BC) and Cervical Cancer (CC) Screening Uptake. The average effect thus represents the effect of CC. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.D4: Relative effect of outcomes - Diet and physical activity

	(1) FBG	(2) HbA1c	(3) SBP	(4) DBP	(5) BMI	(6) Weight	(7) Waist Circ.	(8) HDL-C.	(9) LDL-C.	(10) Total Chol.	(11) Triglyc.	(12) Salt Cons.	(13) Physical Activity
Relative effect	0.109 (0.153)	1.972*** (0.493)	0.092 (0.119)	0.303** (0.145)	-0.252*** (0.082)	-0.219*** (0.0611)	-0.177*** (0.056)	-0.138 (0.242)	0.058 (0.143)	-0.030 (0.139)	0.051 (0.238)	-0.016 (0.177)	-0.141 (0.188)
SE ²	6.643*** (1.996)	6.485*** (2.019)	6.662*** (2.000)	6.730*** (1.936)	6.588*** (2.043)	6.549*** (1.983)	6.588*** (1.990)	6.576*** (1.988)	6.644*** (2.021)	6.617*** (2.005)	6.627*** (2.012)	6.623*** (2.006)	6.979*** (2.202)
Average effect	0.032 (0.060)	0.017 (0.059)	0.028 (0.073)	0.004 (0.077)	0.078 (0.067)	0.058 (0.068)	0.058 (0.068)	0.050 (0.061)	0.034 (0.071)	0.041 (0.072)	0.035 (0.076)	0.039 (0.068)	0.040 (0.066)
# of estimates	118	118	118	118	118	118	118	118	118	118	118	118	118
# of studies	20	20	20	20	20	20	20	20	20	20	20	20	20

Notes: All models are random-effects meta regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. Abbreviations: BMI: Body Mass Index; DBP: Diastolic Blood Pressure; SBP: Systolic Blood Pressure; HbA1c: Hemoglobin A1c; H(L)DL-C: High (Low) Density Lipoprotein Cholesterol; Chol.: Cholesterol; Circ: Circumference; Cons.: Consumption; FBG: Fasting Blood Glucose; Triglyc.: Triglycerides. ***p<0.01, **p<0.05, *p<0.1.

Table 2.D5: Relative effect of outcomes - Patient education

	(1) Smoking Abst.	(2) Alcohol Abst.	(3) FBG	(4) HbA1c	(5) SBP	(6) DBP	(7) BMI	(8) Weight
Panel A								
Relative effect	-2.332 (1.879)	-0.498** (0.238)	0.088 (0.131)	0.006 (0.142)	-0.184 (0.282)	0.085*** (0.028)	-0.316*** (0.066)	-0.301*** (0.111)
SE ²	12.90 (9.835)	5.978 (5.296)	5.454 (5.074)	5.441 (5.022)	5.360 (5.232)	5.461 (5.076)	5.421 (5.172)	5.225 (4.863)
Average effect	-0.101 (0.257)	0.193** (0.097)	0.215** (0.095)	0.227** (0.111)	0.232** (0.114)	0.228** (0.104)	0.240** (0.103)	0.282*** (0.109)
# of estimates	40	40	40	40	40	40	40	40
# of studies	11	11	11	11	11	11	11	11
	(9) Waist Circ.	(10) HDL-C.	(11) LDL-C.	(12) Total Chol.	(13) Triglyc.	(14) Physical Activity	(15) Quality of Life	(16) ADL
Panel B								
Relative effect	-0.238** (0.103)	-0.219*** (0.026)	0.164** (0.072)	-0.029 (0.032)	0.053 (0.237)	-0.111 (0.131)	-0.039 (0.339)	2.787*** (0.739)
SE ²	5.486 (5.198)	5.332 (5.154)	5.484 (5.019)	5.424 (5.084)	5.450 (5.008)	5.406 (5.066)	5.393 (5.028)	5.537 (0.810)
Average effect	0.227** (0.102)	0.234** (0.102)	0.229** (0.102)	0.230** (0.102)	0.229** (0.094)	0.242** (0.104)	0.239** (0.100)	0.190*** (0.064)
# of estimates	40	40	40	40	40	40	40	40
# of studies	11	11	11	11	11	11	11	11

Notes: All models are random-effects meta-regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. Abbreviations: Abst.: Abstinence; BMI: Body Mass Index; DBP: Diastolic Blood Pressure; SBP: Systolic Blood Pressure; HbA1c: Hemoglobin A1c; H(L)DL-C: High (Low) Density Lipoprotein Cholesterol; Chol.: Cholesterol; Circ.: Circumference; FBG: Fasting Blood Glucose; ADL: Activities of Daily Living; Trigly.: Triglycerides. ***p<0.01, **p<0.05, *p<0.1.

Table 2.D6: Relative effect of outcomes - System approach

	(1) FBG	(2) HbA1c	(3) SBP	(4) DBP	(5) BMI	(6) Waist Circ.	(7) HDL-C.	(8) LDL-C.	(9) Total Chol.	(10) Triglyc.	(11) Screening (CC)	(12) Screening (BC)	(13) Illness Severity
Relative effect	1.586* (0.941)	0.327*** (0.107)	0.826 (0.575)	-0.235 (0.310)	-1.076 (0.854)	-0.229*** (0.057)	-0.103 (0.098)	-0.220 (0.138)	-0.194 (0.123)	-0.011 (0.057)	-1.531 (1.524)	-1.273 (1.601)	-0.569 (0.455)
SE ²	19.07*** (6.861)	17.63** (7.879)	16.57** (7.343)	16.67** (7.740)	15.49** (6.396)	16.82** (7.875)	16.78** (7.840)	16.73** (7.813)	16.74** (7.819)	16.81** (7.865)	22.06* (11.86)	21.31* (12.25)	16.84** (7.970)
Average effect	-0.0267 (0.137)	0.151 (0.239)	0.174 (0.246)	0.248 (0.292)	0.346 (0.361)	0.233 (0.271)	0.237 (0.278)	0.251 (0.273)	0.248 (0.274)	0.226 (0.274)	0.097 (0.286)	0.113 (0.293)	0.283 (0.296)
# of estimates	22	22	22	22	22	22	22	22	22	22	22	22	22
# of studies	5	5	5	5	5	5	5	5	5	5	5	5	5

Notes: All models are random-effects meta regressions, which apply weighted least squares, use a population average model and cluster standard errors at the study level, displayed in parentheses. Abbreviations: BMI: Body Mass Index; DBP: Diastolic Blood Pressure; SBP: Systolic Blood Pressure; HbA1c: Hemoglobin A1c; H(L)DL-C: High (Low) Density Lipoprotein Cholesterol; Chol.: Cholesterol; Circ.: Circumference; FBG: Fasting Blood Glucose; CC: Cervical cancer; BC: Breast Cancer; Triglyc.: Triglycerides. ***p<0.01, **p<0.05, *p<0.1.

Appendix 2.E: Moderator analysis

In this appendix, we present additional details of the moderator analysis. Table 2.E1 presents descriptive statistics of the variables included.

Table 2.E1: Descriptive statistics of moderators

Variable	Smoking		Alcohol		Diet & PA.		Screening		Patient Educ.		System Approach		All	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N
Contact moments	10	9	3.38	8	6.95	100	1	7	6.03	40	9.5	8	6.6	172
Share of males	0.8	9	0.93	8	0.34	118	0	7	0.33	40	0.44	21	0.39	203
Mean age	34.33	9	36.38	8	45.22	118	36.7	7	59.14	40	57.4	22	48.1	204
Implement. format														182
1 if Group		4		0		85		2		23		n.a.		114
1 if Individual		5		8		33		5		17		n.a.		68
Length	6.55	9	5.63	8	11.70	118	4.28	7	6.85	40	17.68	22	10.71	204
Total (estimates)		9		8		118		7		40		22		204
Total (studies)		8		4		20		4		11		5		(52) 51

Notes: N refers to the number of estimates for which data is available. Mean is the mean calculated at the estimate level. The total number of studies adds up to 52 instead of 51 because one study is included in two categories. Abbreviations: PA.: Physical Activity; Educ.: Education.

We include the following moderators in our analysis: *Contact moments* measures the number of contacts between study participants and study officials (excluding measurement take-up). Contacts were only counted when study officials or health personnel were in direct contact with the subject (face-to-face or via telephone) with the purpose to support participants in pursuing the study goal. We did not count contact via E-mail or text message since no study that uses such means of communication does the trace whether these were indeed read by the participants. *Share of males* measures the share of study participants that were male. We use this moderator approach instead of assessing the effect separately for men and women because almost no study presents the outcomes by gender. *Mean age* measures the average age of all study participants. The dummy *group* indicates whether participants were treated as a group as opposed to individually. Group interventions include for example community-based interventions in which village members participated in group counseling sessions or interventions focusing on peers and family support for patients or individuals at risk. Individually targeted interventions were for example home based dietary interventions or individual counseling sessions. The moderator *length* measures the time period between the baseline and follow-up data collection. Note that this is not similar to the duration of the intervention, since an intervention could also last only a few days or weeks but the follow-up data collection could take place later in time. When more than one follow-up was conducted, we always used the latest one. Some moderators could not be specified or had no variation within each intervention category. Al-

cohol studies were exclusively group interventions, the group moderator is consequently not included. Screening studies included exclusively female participants; the share of males moderator is consequently not included. For the last intervention category, system approach, we also did not define the group moderator, as interventions focused on changes within the health care system and not specifically on individuals. The information for the moderator contact moments could only be extracted from two system approach studies, in all other studies there was no direct contact between study officials and participants apart from the measurement take-up.

3 Temperature and non-communicable diseases: Evidence from Indonesia's primary health care system [‡]

Abstract: Climate change induced rising temperatures will pose a detrimental threat to decent health in the coming decades. Especially at risk are individuals with chronic diseases, since heat can exacerbate a variety of health conditions. In this article, I examine the heat-morbidity relationship in the context of Indonesia, focusing on chronic, non-communicable diseases, namely diabetes, cardiovascular and respiratory diseases. Using a novel dataset from the Indonesian national health insurance scheme JKN/BPJS and linking it with meteorological data on the daily-district level, I estimate the causal effect of high temperatures on the daily number of primary health care visits. The results show that on a hot day all-cause visits and visits with a diagnosis of diabetes and cardiovascular diseases increase by 8%, 25% and 14%, respectively. These increases are permanent and not offset by visit displacement or “harvesting”. Visits related to respiratory diseases seem not to be affected by high temperatures. I use several climate change scenarios to predict the increase in visits and costs by the end of the century, which all forecast a substantial financial burden for the health care system. These results might have relevance for other middle-income countries with similar climatic conditions.

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3.1 Introduction

Climate change will pose a detrimental threat to decent health in the coming decades, with low- and middle-income countries being the most severely affected (Costello et al., 2009). Scientific consensus affirms that, without substantial efforts to constrain greenhouse gas emissions, global average temperatures will rise between 2.1°C and 5.7°C by 2100 (Intergovernmental Panel on Climate Change, 2022). Moreover, heat waves are predicted to occur about twice as often in the coming decades compared to the number at the end of the 20th century (Lhotka et al., 2018). The rise in average and extreme temperatures can deteriorate people's livelihoods, nutrition, physical and even mental health (Ahern et al., 2005; Kovats et al., 2003; McMichael et al., 2006; Mullins and White, 2019; Stanke et al., 2013; White, 2017). Additionally, it can accelerate the spread of infectious diseases, as warmer temperatures enhance the transmission of water-, food- and vector-borne diseases (Bowen and Ebi, 2017; Pandey and Costello, 2019; Wang et al., 2009). More directly, climate change and hot temperatures can worsen all-cause and disease-specific morbidity through deteriorations in physical conditions. Extreme temperatures trigger heat stress and heat strokes; in the most severe cases, they even lead to death (Epstein and Yanovich, 2019).

Individuals with chronic, non-communicable diseases (NCDs), namely cardiovascular diseases, chronic respiratory diseases and diabetes, are especially susceptible to suffering through this channel. Extreme temperatures exacerbate a variety of chronic health symptoms, and hence pose a disproportional health risk to people suffering from or at risk of NCDs (Friel et al., 2011). While NCDs were for a long time uniquely a rich-country problem, nowadays 80% of all NCD-related deaths occur in low- and middle-income countries (Grosskurth, 2019; Islam et al., 2014; World Health Organization, 2018b). However, economic research on NCDs in these countries has received only little attention (Behrman et al., 2009). Additionally, health care systems in low- and middle-income countries are not well positioned to address NCDs and still focus to a large extent on combating transmittable, maternal and neonatal diseases (Dans et al., 2011; Kostova et al., 2017). This triple burden of surging NCDs, limited health care system capacities and impending climate change make low- and middle-income countries especially vulnerable. Yet until now, there has only been limited scientific evidence of how these factors interplay in this context.

In this article, I assess the effects of temperature on NCD-related morbidity, proxied by primary health care visits, in the middle-income country Indonesia. Specifically, I study how the daily mean temperature affects the number of daily all-cause and NCD-specific health visits, focusing on diabetes, cardiovascular diseases and chronic respiratory diseases. The data consists of a representative sam-

ple of 1.7 million individuals covered by the Indonesian national health insurance scheme *Jaminan Kesehatan Nasional* (JKN) and contains information on all primary health care visits during the two-year observation window of 2015-2016. I relate the daily number of visits within a given district to the local daily mean temperature and include a series of fixed-effects to identify the causal effect of local variations in temperature on health care visits. Finally, I use several climate change scenarios to predict the increase in health visits and related costs by the end of the century.

Whereas the link between temperature and mortality has already been extensively explored in the literature,¹ the effects on morbidity have received comparably little attention, with almost no studies being conducted for low- and middle-income countries (Campbell et al., 2018). Hence, this study makes three contributions. First, I add to the small but growing economic literature that assesses the effect of temperature on morbidity (Agarwal et al., 2021; Karlsson and Ziebarth, 2018; Lee and Li, 2021; Mullins and White, 2019; White, 2017).² These studies primarily investigate how temperature relates to emergency department visits and hospitalization rates. The main argument is that emergency visits are not scheduled (as opposed to, for example, surgeries) and are consequently representative of acute health issues resulting from excessive temperatures (Mullins and White, 2019; White, 2017). Yet this approach most likely only captures visits due to very severe health problems and misses less acute cases, with the latter forming a much higher proportion of all visits. These less acute cases are the focus of this study. I use an alternative approach of focusing on health visits below the hospital level. More specifically, I use data of health visits to Indonesian primary health care facilities, i.e., community health clinics (*Puskesmas*), where visits are also mostly unscheduled. Typically, patients appear unannounced, draw a number and wait to be examined. This feature allows for a plausible link between daily temperature and visits occurring on the same day. Focusing on primary health care visits instead of hospitalization rates and emergency visits can provide important information about how global warming will affect the primary health care sector, which is pivotal in many low- and middle-income countries.

Second, I use health visit data that represents not only of the largest countries in the world, but also comes from a middle-income country. Generally, only few studies assess the health impacts of heat in non-western and low- and middle-income countries (Campbell et al., 2018; Green et al., 2019), of which the major share looks again on mortality (e.g., Burgess et al., 2017, for India). Hence, the relationship

¹See Basu (2009) and Benmarhnia et al. (2015) for reviews of the heat-mortality literature.

²Studies that also assess the heat-morbidity nexus but take an epidemiological/public health perspective are for example Bassil and Cole (2010); Bobb et al. (2014); Johnson et al. (2005); Kovats et al. (2004); Larrieu et al. (2008); Lin et al. (2009, 2019); Nitschke et al. (2011); Schaffer et al. (2012); Song et al. (2018); Wichmann et al. (2011); Williams et al. (2012); Ye et al. (2012).

between temperature and health consequences in countries of the Global South, which tend to have comparably more tropical and humid climate zones as well as poorer health system capacities, has not yet been investigated in detail.

Third, I explore the cost of temperature increases for the newly established Indonesian national health insurance scheme, thereby contributing to the literature on the financial burden of climate change (e.g., Auffhammer, 2018; Carleton et al., 2020; Diaz and Moore, 2017). This information is especially relevant for policy makers who are concerned with the financial sustainability of this immense insurance program, which, since its implementation, has suffered from annual deficits from Rp3.3 trillion in 2015 (US\$0.24 billion) up to Rp17 trillion in 2019 (US\$1.3 billion) (Aidha and Chrisnahutama, 2020; BPJS Kesehatan, 2015, 2016, 2021; Prabhakaran et al., 2019).

The remainder of this article is organized as follows. Section 3.2 briefly summarizes the physiological mechanisms of how heat impacts human health and reviews the relevant epidemiological and economic literature. Section 3.3 presents the health and weather data. Section 3.4 outlines the empirical strategy. Section 3.5 presents the results, including a detailed robustness and heterogeneity analysis. Section 3.6 provides predictions of future increases in health visits and related costs using various climate change scenarios and Section 3.7 concludes.

3.2 The heat-morbidity relationship

The thermoregulatory function allows the human body to maintain its core temperature despite greatly varying external temperatures. Through sweating, decreasing heat production and vasodilation of the skin's blood vessels, the body cools down when the outside temperature is high. Vice versa, if the outside temperature is low, the body increases its temperature through heat production by the metabolic system, piloerection (erection of body hair) and vasoconstriction (narrowing) of the skin's blood vessels (Hall and Hall, 2020). Yet despite these physiological adjustments, the body has only limited ability to cope with too high (or too low) temperatures. While normal body temperature fluctuates around 36°C, the human comfort zone of ambient temperature typically ranges from 22°C to 27°C, depending on humidity levels. Adverse health effects of heat can be observed at ambient temperature levels that surpass this range in either direction, though few studies identify an absolute threshold (Kovats et al., 2004; Lin et al., 2009).

Elevated temperatures severely affect the cardiovascular system by causing accelerated blood circulation and heart rate, and decreased blood pressure levels. The resulting cardiac output is insufficient to fulfill the thermoregulatory needs of the human body and this in turn can lead to heat exhaustion, dehydration and heat

stroke (Epstein and Yanovich, 2019). Green et al. (2010), for example, investigated cardiovascular disease hospital admissions in California over a six-year time span (1999-2005) and found that per 10°F (5.5°C) increase in mean apparent temperature the risk of dehydration increased by 10.8%, the risk for heat stroke by as much as 404%. White (2017) also assessed the heat-morbidity relationship in California using hospitalization rates from 2005-2014 and found a relative increase in the risk of being hospitalized on a day with a temperature above 80°F (26.6°C) compared to a reference temperature of 60°F-65°F (15.5°C-18.3°C). He found the largest relative risk for what he labeled “fluid and electrolyte imbalances” which are driven by dehydration. Schwartz et al. (2004) found similar increases for several cities throughout the US. The study by Karlsson and Ziebarth (2018) supports these US findings in the German context; using data covering the years 1999-2006 and information on 170 million hospital admissions, they found that the risk of being hospitalized with a cardiovascular disease-related diagnosis on a hot day (>30°C) was between 2% and 10% higher compared to a non-hot day. In contrast, several other studies found no or even a negative effect of heat on cardiovascular disease hospital admissions in London (Kovats et al., 2003), Madrid (Linares and Diaz, 2008) and twelve other European cities (Michelozzi et al., 2009) and argue that heat deteriorates the cardiovascular function so tremendously that patients die as opposed to being hospitalized.

Heat exposure also affects the respiratory tract and lungs. The literature has documented the link between high ambient temperature and increases in respiratory hospital admissions, yet the underlying physiological mechanism is less clear. Potential pathways are increases in air pollutants and allergens through heat (Åström et al., 2013) as well as breathing hot air which exacerbates chronic respiratory conditions (Anderson et al., 2013; Michelozzi et al., 2009). While the effect on mortality has been largely covered in the economic literature (Barreca, 2012; Barreca et al., 2016; Deschênes and Greenstone, 2011; Deschênes and Moretti, 2009), evidence for the effect on morbidity is scarcer and relies largely on epidemiological studies (Green et al., 2010; Kovats et al., 2004; Lin et al., 2009; Linares and Diaz, 2008; Michelozzi et al., 2009; Ye et al., 2001). The study results are again quite context-specific and range from no effect of heat on respiratory hospital admissions in Tokyo (Ye et al., 2001) to an increased risk of 10.4% for the elderly in London (Kovats et al., 2004). However, all these studies are in line with the conclusion that the impact is most severe for the elderly population above the age of 75.

Evidence for the link between heat and diabetes morbidity relies largely on descriptive case studies (Knowlton et al., 2009; Semenza et al., 1999). A notable exception is the study by Green et al. (2010) who found that the risk of being hospitalized with a diagnosis of diabetes in California increases by 3.1% for each 10°F (5.5°C) increase in temperature. Given the rising prevalence rates of diabetes worldwide

and the fact that 80% of the affected individuals live in low- and middle-income countries, this aspect will require more attention (International Diabetes Federation, 2021). Individuals suffering from diabetes face a greater risk of heat-related illnesses as their capacity to dissipate heat is compromised. Specifically, the skin's blood flow and the sweating response of individuals with diabetes are lower compared to that of healthy individuals during heat-exposure, which can have detrimental consequences for an individual's glycemic control (Kenny et al., 2016). Paired with the fact that more than 50% of individuals with diabetes remain undiagnosed in low- and middle-income countries (Manne-Goehler et al., 2019), the relationship between temperature and diabetes needs to be carefully assessed in this context so that health care systems can adequately respond. For Indonesia, the country with the fifth highest estimated number of individuals with diabetes (both diagnosed and undiagnosed) and the third highest number of individuals with undiagnosed diabetes, investigating this link is of special importance (International Diabetes Federation, 2021).

3.3 Data

3.3.1 BPJS insurance and health visit data

The outcomes of interest in this study are the number of visits related to diabetes, cardiovascular and chronic respiratory diseases per day per 100,000 insurance members. For the sake of completeness and comparison, I also investigate the number of total ("all-cause") visits. The data comes from a representative administrative dataset on health insurance status and health visits published in 2019 by the Indonesian Social Health Security Agency (*Badan Penyelenggara Jaminan Sosial Kesehatan – BPJS Kesehatan*).

The dataset contains information on a representative 1% sample of all families and their respective family members who were enrolled in the Indonesian national health insurance scheme *Jaminan Kesehatan Nasional* by the end of 2016 (172 million individuals, representing 66% of the Indonesian population). This insurance scheme was launched in 2014 and all other prior insurance schemes (e.g., *Jamkesmas, Askes, Jamsostek*) were incorporated into it to form a single scheme for the entire country. By October 2021, it had become one of the world's largest and most ambitious single-payer health insurance programs, with around 225 million members and is expected to achieve universal cover in the next few years (BPJS Kesehatan, 2021; Prabhakaran et al., 2019).

For primary health care services, the insurance scheme works largely through a capitation-based payment structure. Each insurance member is registered with

a single primary health care facility, which works as the “gatekeeper” to the insurance system. Services at higher-level facilities and specialists are only granted if a primary health care facility that is registered with BPJS was approached first. A gatekeeper is either a *Puskemas* (the Indonesian community health clinics), a *Klinik Pertama* (clinics that provide primary health care) or a general practitioner. Every facility receives a monthly capitation payment from BPJS which is calculated on the basis of the number of insurance members registered with the respective facility and performance-based indicators (such as contact rate, referral rate and services offered). For each registered insurance member, the facilities receive between Rp6,000 and Rp10,000 per month (about US\$0.50-0.80).³ Hence, for a primary facility that caters to an average 10,000 to 20,000 members, the capitation payments from BPJS are about US\$5,000 to US\$10,000 per month, which equals approximately 70% to 90% of primary facilities’ total funds (KOMPAK, 2017; Prabhakaran et al., 2019). Certain health services are not covered by this capitation scheme (primarily services related to delivery, postpartum care and contraceptive management). For these services, the facility needs to claim reimbursement payments directly from BPJS based on the provided services. In all circumstances, the service is supposed to be free for the insured patient and entirely covered by the insurance.

The families included in the sample were selected based on a stratified sampling procedure, leading to 1,697,452 individuals from 586,969 sampled families. Additional details on the sampling procedure and a more detailed description of the data are provided in Appendix 3.A. There, I also present details on how the sample population compared to the general Indonesian population in 2015-2016; with the main fact that a certain social group – the non-poor informal working class – was largely not covered by the insurance in its early years.

In total 1,733,759 visits were documented for the sampled individuals over the two-year observation window. The following information was recorded for each visit: the respective insurance member and visit ID, the date, the location of the facility, the ICD-10-code (International Classification of Diseases) of the primary diagnosis, whether it was an outpatient service or inpatient admission, as well as information about whether a patient received a referral to a higher-level facility. Furthermore, for the non-capitation health services, the amount requested as re-

³The capitation payment per registered insurance member is set by the Indonesian Ministry of Health (see Ministry of Health decrees No. 69, year 2013 (<https://peraturan.bpk.go.id/Home/Details/153871/permenkes-no-69-tahun-2013>) and No. 52, year 2016 ([http://hukor.kemkes.go.id/uploads/produk_hukom/PMK_No._52_Tahun_2016_Tentang_Standar_Tarif_Pelayanan_Kesehatan_Dalam_Penyelenggaraan_JKN_.pdf](http://hukor.kemkes.go.id/uploads/produk_hukum/PMK_No._52_Tahun_2016_Tentang_Standar_Tarif_Pelayanan_Kesehatan_Dalam_Penyelenggaraan_JKN_.pdf))). Payments depend on the type of facility, yet are irrespective of whether the insured individual actually makes use of the insurance. If certain performance indicators are not met, BPJS can adjust the payments downward by up to 10% (Sambodo et al., 2021; World Bank Group, 2018). By the time the capitation rate was set (2014), the US\$ - Indonesian Rupiah exchange rate was about 12,000. In 2022, the US\$ - Indonesian Rupiah exchange rate is about 14,000.

imbursement payment by the facility and the amount finally granted from BPJS were recorded. This rich data source allows for an extraction of the number of disease-specific visits per day within each of the 514 Indonesian districts. To ensure comparability across districts and to maintain representation for all JKN members, I calculate the number of disease-specific visits per 100,000 insured individuals, using the sampling weights provided in the data. The member counts underlying this calculation reflect the enrollment status at the end of 2016.⁴ The ICD-10-codes included in the respective disease categories are shown in Table 3.A1 in Appendix 3.A, the twenty most frequent diagnoses in the data sample are presented in Table 3.A2.

A drawback of the data is that it does not allow for a differentiation between a first-time diagnosis and continued treatment of a given diagnosis that happened before 2015. This means that, for example, a patient who was already diagnosed with diabetes prior to the period available in the data and visits a health center because of health issues (whether related to heat or not) will be similarly counted as someone who visits a health center (e.g., due to not feeling well on a day with high temperatures) and is diagnosed with diabetes for the first time. Moreover, if, for example, someone with diabetes suffers from heat exhaustion and seeks health care, such a visit will be coded as a cardiovascular disease diagnosis. This implies that the data will not allow for inference regarding initial- versus ongoing treatments of these conditions, and that I cannot comment on whether high temperatures are more dangerous for undiagnosed or already diagnosed individuals.

3.3.2 Weather data

Temperature data is obtained from the SA-OBS dataset (Version 2.0), a gridded daily meteorological data set for the entire Southeast Asian region. It is provided by the Southeast Asian Climate Assessment & Dataset Project (SACA&D) and combines data from 3,914 meteorological stations throughout Southeast Asia (Van Den Besselaar et al., 2017). Each grid covers an area of $0.25^\circ \times 0.25^\circ$, which corresponds to approximately $27.7 \text{ km} \times 27.7 \text{ km}$ (770 km^2) at the equator. I merge each of these grids with the respective Indonesian district whenever a grid-point falls directly within the district borders, and average the temperature over all grids per day and district. For 88 of the 514 districts (mainly smaller cities⁵), no grid-points fall directly within the respective borders. In these cases, I use inverse

⁴Using the member counts from the end of the year 2016 might imply an underestimation of the number of visits per 100,000 for any previous point in time, since the member rates increased over time. This means that all results presented below should be interpreted as lower-bound estimates. Member counts per district over time are not provided in the data set.

⁵Districts in Indonesia are the second administrative level and are either regencies (*kabupaten*) or cities (*kotas*).

distance weighting and assign the weighted temperature of the four nearest grid-points to the district (for more details see Appendix 3.B).

Other meteorological conditions such as humidity and precipitation also have been shown to affect human health (Barreca, 2012; Maccini and Yang, 2009). Moreover, wind speed can affect the perceived temperature and thereby weather-related morbidity. Consequently, I control for daily humidity measures, precipitation levels and wind speed to identify the pure temperature effect. Data on daily humidity and precipitation levels and wind speed are obtained from the GLDAS Noah Land Surface Model (Beaudoin, H. and Rodell, M., NASA/GSFC/HSL, 2020). Additionally, I control for the amount of sulfur dioxide (SO₂), sulfate particulate matter (SO₄), and black carbon in the air as measures of air pollution, which can also affect health conditions (Liu and Ao, 2021). Data on air pollution is obtained from the Merra 2 Aerosol Diagnostics data provided by the Global Modelling and Assimilation Office (Global Modeling and Assimilation Office, 2020). All variables are available as gridded data with a spatial resolution between $0.25^\circ \times 0.25^\circ$ and $0.5^\circ \times 0.625^\circ$. The grid-point to district assignment procedure is analogous to that for the temperature dataset.

The aggregated dataset is a daily panel for the 514 Indonesian districts over the two years under study, i.e., 375,734 observations. No health visit data is available for five districts, leaving 372,079 observations (509 districts \times 731 days) for the analysis. Panel A of Table 3.1 summarizes the BPJS health insurance data and Panel B shows the resulting aggregated key variables for the panel dataset. Summary statistics for health visits by age categories are shown in Table 3.A3 in Appendix 3.A.

The bottom part of Table 3.1 summarizes the weather data. The temperature variable is specified as a continuous variable and as temperature bins, i.e., a set of dummy variables that are equal to one whenever the mean temperature on a given day falls within the specified 1.5°C temperature range (<21°C, 21-22.5°C, . . . , 28.5°C-30°C, >30°C). Reflecting the tropical climate of Indonesia, the daily mean temperature is high and varies little; the days on which the mean temperature fell below 21°C account for only 1.4% of all days measured. As expected, the average rainfall and humidity levels are also high. On an average day, precipitation levels of 6.49 mm were recorded, with a maximum of 87 mm. Specific humidity levels were on average 16.25 grams of water per 1 kg air.

Table 3.1: Summary statistics

	Unweighted		Weighted	
Panel A: BPJS Data				
# of families	586,969		76,562,952	
# of individuals	1,697,452		192,294,875	
# of individuals with at least 1 health visit	465,017		35,266,632	
# of recorded visits (2015-2016)	1,733,759		135,082,178	
	Mean	SD	Min	Max
Panel B: Panel Data Set				
Health Visits				
<i>All</i>				
All-cause	96.42	97.34	0.00	2659.11
Diabetes	2.50	9.54	0.00	774.64
Cardiovascular Diseases	7.22	16.62	0.00	747.09
Respiratory Diseases	2.22	8.70	0.00	625.64
<i>Female</i>				
All-cause	115.65	128.21	0.00	4195.77
Diabetes	3.07	14.25	0.00	1303.34
Cardiovascular Diseases	9.07	25.48	0.00	1303.34
Respiratory Diseases	2.21	11.93	0.00	1016.01
<i>Male</i>				
All-cause	78.01	95.61	0.00	2714.21
Diabetes	1.96	11.40	0.00	1182.82
Cardiovascular Diseases	5.44	18.75	0.00	1291.98
Respiratory Diseases	2.23	11.89	0.00	1038.61
Weather Data				
Mean Temperature (°C)	26.76	2.10	8.70	32.33
Temperature Bins (°C)				
<20.5°	0.01			
20.5° - 22°	0.02			
22° - 23.5°	0.06			
23.5° - 25°	0.14			
25° - 26.5°	0.25			
26.5° - 28°	0.32			
28° - 29.5°	0.18			
>29.5°	0.02			
Rainfall (mm/day)	6.79	7.99	0.00	87.09
Specific humidity (grams of water/kg air)	16.09	1.67	5.59	20.77
Wind speed (m/s)	2.08	0.97	0.33	12.00
Sulfur dioxide (SO ₂) (μg/m ³)	10.54	13.45	0.00	129.13
Sulfate particulate matter (SO ₄) (μg/m ³)	5.04	6.80	0.01	374.46
Black carbon (μg/m ³)	1.90	1.72	0.00	71.83

Notes: The data for health visits (Panel B) represents the number of daily visits per 100,000 health insurance members per district. Summary statistics are weighted by the population of insured individuals per district. The mean values for the temperature bins represent the share of district-day observations that fall within the respective temperature range.

3.4 Empirical approach

3.4.1 Main specification

The literature suggests that the effect of ambient temperature on health outcomes often exhibits a U- or J-shaped relationship (Li et al., 2014; Lin et al., 2019; Song et al., 2018; White, 2017), i.e., adverse health effects occur at very low and very high temperature levels. I therefore use a semi-parametric specification that allows for a flexible relationship between temperature and health visits; this approach has been widely adopted in the economic health and climate literature (e.g., Barreca, 2012; Deschênes and Greenstone, 2011; Deschênes and Moretti, 2009; Karlsson and Ziebarth, 2018; White, 2017). I specify eight temperature bins which each cover a 1.5°C temperature range and derive eight binary variables that are equal to one whenever the temperature on a given day fell within the respective temperature range. Further, I exploit the panel structure of the data and use a fixed-effects model that allows me to control for re-occurring seasonal variation, for example rain seasons, and regional, across-district heterogeneity in terms of health facility density and access to health care. Specifically, I include a series of year, month, day-of-the-week as well as district fixed-effects, resulting in the following specification

$$Visits_{kd} = \sum_{i=1, i \neq 5}^8 \beta_i Temp_{kd}^i + \sum_{l=1}^7 \sum_{i=1, i \neq 5}^8 \vartheta_{il} Temp_{k, d-l}^i + \gamma \mathbf{X}'_{kd} + \delta_y + \sigma_m + \theta_k + \mu_w + \varepsilon_{kd}, \quad (3.1)$$

where $Visits_{kd}$ is the number of primary health care visits (differentiated by diagnosis) that occurred on day d in district k . $Temp_{kd}^i$ denotes the binary temperature variables; the bin for the mean temperature 25.5°C-27°C is omitted and serves as a reference category. The coefficients therefore represent the effect of a day on which the temperature falls in the respective bin compared to the reference category. I additionally include seven lags for each of the temperature bins to account for serial correlation in weather realizations. The use of such a finite distributed lag model also allows me to investigate the dynamic effect of visit displacement or “harvesting”, which I address in the following section. δ_y , σ_m , θ_k and μ_w are the year, month, district and day-of-the-week fixed-effects, respectively. The error term ε_{kd} is clustered at the district level to account for the possibility that the errors are correlated within districts over time. The vector of controls \mathbf{X}'_{kd} contains daily rainfall and humidity levels, wind speed, all three air pollution measures as well as a dummy variable reflecting whether the current day falls within the fasting month of Ramadan.

3.4.2 Does “harvesting” exist at the primary health care level?

Studies that investigate the heat effect on mortality often also explore the dynamic temperature effect (Anderson and Bell, 2009; Basu and Malig, 2011; Bi et al., 2011; Braga et al., 2001; Deschênes and Moretti, 2009; Karlsson and Ziebarth, 2018; Schwartz et al., 2004). In other words, they investigate whether “harvesting” or mortality displacement occurs, i.e., whether individuals dying on days with extreme temperatures would have died anyway in the course of the following days or weeks. If mortality displacement is occurring, temporary increases in death rates due to extreme heat are followed by days or weeks that see decreased numbers of deaths, sometimes resulting in a zero net-effect. The majority of the aforementioned studies conclude that this harvesting phenomenon is especially present during hot temperatures and heat waves, but less so during cold temperature spells. Hence, the question arises whether the same phenomenon exists for the temperature-morbidity context and at lower health care levels, i.e., whether primary health care visits increase on days of extreme heat but decrease in the days afterwards.

The underlying mechanisms would be as follows. If increasing temperatures lead to a worsening of an already existing health issue, but the respective individual would have sought health care irrespective of the heat event a couple of days or weeks later, then visits would peak during heat events but would be reduced on the days afterwards. In contrast, if high temperatures lead to newly occurring health issues (i.e., they are caused by hot temperatures), then one would observe a spike in visits on a day with hot temperatures, but no reduction during the following days. Situations without harvesting are of major concern as they imply increases in health visits that are not offset over time but persistent.

To advance the discussion on harvesting with respect to heat-morbidity, I assess the dynamic effect of temperature on the current number of primary health visits to explore whether harvesting at this level exists and investigate the lag structure of the main model specification in more detail. Specifically, I test whether there are significantly *negative* lagged effects of a day with a temperature in the top bin ($< 30^{\circ}\text{C}$) and whether the cumulative effect remains significantly *positive* after a period of one, two, three and four weeks, respectively. This cumulative effect is simply derived by summing the coefficients of the highest temperature bin and its respective lags, e.g., $\beta_8 + \sum_{l=1}^7 \vartheta_{8,d-l}$ for the one-week cumulative effect. This effect can be interpreted either as the effect of a hot day one week ago on today’s cumulative number of visits or similarly as the effect that a current hot day will have on the cumulative health visits in a week, given that $\frac{\partial \text{visits}_d}{\partial \text{temperature}_{d-1}} = \frac{\partial \text{visits}_{d+1}}{\partial \text{temperature}_d}$, assuming that on all other days the reference category temperature prevails. To estimate the effect over a period longer than one week, the number of lags in the

model is increased to reflect the period of interest (e.g., 21 lags for the three-week cumulative effect).

3.5 Results

3.5.1 Main results

Table 3.2 presents the results for the semi-parametric temperature bin model. For each of the four outcomes I apply three different models. The first column shows the most parsimonious model, including only the temperature bins and the full set of fixed-effects. In the next column, I add seven lags for each of the temperature bins. The third column displays the results of the preferred specification for each outcome, including all fixed-effects, temperature lags and current and lagged control variables. The coefficients of the temperature bins display the absolute increase, respectively decrease, in (disease-specific) primary health care visits per day per 100,000 insured individuals in comparison to a day with a mean temperature of between 25.5°C and 27°C. For the ease of interpretation, I calculate the corresponding percentage increase for the top bin relative to the mean of the outcome variable in the reference bin, shown on the bottom part of the table.

My preferred specification suggests that on a day with an average temperature realization of above 30°C, the number of all-cause primary health care visits is higher by 7.6 per 100,000 or 8.44% compared to a day with a temperature in the reference category. Columns (1) – (3) clearly reject a U-shaped relationship between temperature and all-cause primary health care visits in favor of a linear relation, with negative effects for the four lower temperature bins. The effects for the top three bins are consistently positive and significant. Controlling for serial correlation in temperature in Column (2) slightly increases the absolute size of the coefficients in comparison to the most parsimonious model in Column (1), while they are again slightly reduced as soon as I control for other weather conditions in Column (3). When upscaled to the insured population in 2016 (172 million individuals), the effect estimated in Column (3) translates to about 13,000 more visits per day.

Columns (4) – (6) also support the linear relationship between temperature and diabetes morbidity. Though the negative effects at lower temperatures are not statistically significant, the coefficients for the upper bins are significantly positive across all three specifications. Quantitatively these effects are sizable. On a very hot day, above 30°C, the number of diabetes visits increases between 20.9% and 24.7% (the latter corresponding to an absolute increase of about 1,000 visits by the insured population). Even at relatively moderate temperatures between 27°C and

28.5°C, visits increase by 7.2% in comparison to a day with a mean temperature between 25.5°C and 27°C.

The effect of temperature on cardiovascular disease visits, shown in Columns (7) – (9), is also statistically and economically significant. The effects are robust across the three specifications and clearly reject the idea of a U-shaped functional form in favor of a linear relationship, with null or significant negative effects for lower temperature realization and large positive effects for high temperatures. The relative increase is somewhat lower than for diabetes (10.73%–14.77%), yet higher than for all-cause visits. This implies that diabetes and cardiovascular disease morbidity increase disproportionately at high temperatures compared to other diseases.

However, Columns (10) – (12) show that there seems to be no positive relationship between heat and respiratory disease visits. If at all, there is a small negative effect for very high temperatures that reduces the number of respiratory disease visits. Yet this effect is not robust across the three specifications and overall the coefficients are not distinguishable from zero.

Conclusively, high temperatures increase the number of primary health care visits and this relationship is linear rather than U-shaped. When differentiated by diagnosis, the effect remains large and significant for diabetes and cardiovascular diseases, while there is no effect on the number of respiratory disease visits.

Table 3.2: Results – Temperature effects on all and by cause visits per 100,000 insurance members

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All-cause			Diabetes			Cardiovascular Diseases			Respiratory Diseases		
<21°C	-4.393 (3.652)	-8.652*** (2.551)	-7.825*** (2.623)	0.141 (0.159)	-0.055 (0.201)	-0.074 (0.210)	-0.846** (0.330)	-0.843*** (0.291)	-0.771** (0.305)	0.034 (0.192)	-0.068 (0.198)	-0.045 (0.206)
21°C - 22.5°C	-1.612 (2.594)	-7.346*** (1.691)	-6.682*** (1.738)	-0.033 (0.176)	-0.189 (0.192)	-0.206 (0.195)	-0.759** (0.354)	-0.862*** (0.310)	-0.798** (0.316)	0.174 (0.136)	0.145 (0.144)	0.158 (0.147)
22.5°C - 24°C	-0.400 (1.328)	-5.299*** (1.210)	-4.795*** (1.214)	0.063 (0.096)	-0.054 (0.100)	-0.060 (0.103)	-0.011 (0.202)	-0.350* (0.206)	-0.306 (0.209)	-0.038 (0.103)	-0.037 (0.120)	-0.025 (0.121)
24°C - 25.5°C	-0.784 (0.640)	-3.215*** (0.605)	-2.916*** (0.601)	-0.023 (0.061)	-0.090 (0.060)	-0.093 (0.060)	-0.020 (0.105)	-0.283** (0.117)	-0.261** (0.117)	0.028 (0.066)	0.008 (0.074)	0.014 (0.075)
25.5°C - 27°C	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
27°C - 28.5°C	2.412*** (0.629)	3.920*** (0.571)	3.735*** (0.582)	0.096 (0.061)	0.165*** (0.063)	0.170*** (0.063)	0.212** (0.093)	0.391*** (0.110)	0.380*** (0.109)	-0.030 (0.056)	-0.004 (0.059)	-0.010 (0.060)
28.5°C - 30°C	3.535*** (0.971)	5.998*** (0.850)	5.533*** (0.878)	0.151** (0.073)	0.284*** (0.084)	0.295*** (0.088)	0.291** (0.128)	0.581*** (0.161)	0.559*** (0.167)	-0.236*** (0.088)	-0.161* (0.091)	-0.176* (0.094)
>30°C	4.974*** (1.557)	8.475*** (1.451)	7.609*** (1.547)	0.494*** (0.164)	0.582*** (0.200)	0.584*** (0.199)	0.750** (0.300)	1.033*** (0.297)	1.001*** (0.299)	-0.499** (0.196)	-0.250 (0.239)	-0.280 (0.247)
Mean of dep. var. in ref. bin	90.16	90.16	90.16	2.36	2.36	2.36	6.99	6.99	6.99	2.13	2.13	2.13
Percentage change (top bin) ^a	5.51%	9.39%	8.44%	20.93%	24.66%	24.74%	10.73%	14.77%	14.32%	-23.42%	-11.73%	-3.14%
Observations	372,069	372,023	372,023	372,069	372,023	372,023	372,069	372,023	372,023	372,069	372,023	372,023
R-squared	0.464	0.464	0.469	0.102	0.102	0.103	0.134	0.134	0.135	0.042	0.042	0.042
Number of districts	509	509	509	509	509	509	509	509	509	509	509	509
Full set of Fixed-effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lags		✓	✓		✓	✓		✓	✓		✓	✓
Controls			✓			✓			✓			✓

Notes: Table 3.2 shows the regression results for the temperature bin model. Robust standard errors (in parentheses) are clustered at the district level. All regressions are weighted by district-populations of insured individuals. ^aThe percentage change is shown for the top bin and indicates the percentage increase in daily primary health care visits for a day with a temperature in the top bin compared to the mean number of visits on a day with a temperature in the reference category ***p<0.01, **p<0.05, *p<0.1.

3.5.2 Robustness checks

In the following, I conduct a series of robustness checks. I start with re-running the main regression with interacted month \times district fixed-effects instead of including district and month effects separately to test whether the main results are driven by district-specific time trends in health care visits. The results, shown in Table 3.C1 in Appendix 3.C, are robust to this change in the specification and the coefficients remain similar in significance and size to those in Table 3.2.

Next, I re-run the main regressions using a single “hot day” indicator instead of the eight temperature bins. This binary variable is equal to one whenever the temperature is higher than the 90th percentile of the mean temperature distribution (averaged over all district-day observations). The results are shown in Table 3.C2 in Appendix 3.C. The coefficients are smaller in size compared to the main results, but still economically large and statistically significant. The numbers of visits on a hot day for all-causes, diabetes and cardiovascular diseases increase by 4, 0.22 and 0.45 per 100,000 respectively; the coefficient for respiratory visits is negative but insignificant. Similar results are obtained when the mean temperature variable enters the specification in a basic linear form (results shown in Table 3.C3, Appendix 3.C).

I also re-estimate the main specification using a Tobit model to account for the fact that the outcomes are zero-censored variables (i.e., for some district-day observations there are no visits recorded in the sample). The results are shown in Table 3.C4 (regression coefficients) and Table 3.C5 (conditional marginal effects) and are in line with the main results. For all-cause, diabetes and cardiovascular disease visits, the coefficients associated with temperature bins above the mean are significantly positive, and those associated with lower bins are either insignificant or significantly negative. There is again no significant relation between temperature and respiratory disease visits.

I also assess whether the results are robust to compositional changes in the sample. Specifically, two aspects need to be considered. First, due to the fast expansion of the insurance scheme in the early years, an aggregation of the visits might lead to non-comparable units over time. Second, mortality can lead to a transition out of the sample. Since mortality can also be related to heat, not accounting for the fact that some individuals in the sample died over the course of the study period might introduce bias. To address these concerns, I re-calculate the number of visits only for those individuals that have at least one family member with a reported visit in 2015 (assuming that families with the first visit in 2016 might not have been enrolled yet in 2015) and second, I drop all individuals from the sample that died in the period under study. The results are shown in Tables 3.C6 and 3.C7. Both compositional changes in the sample do not alter the results.

I also conduct a randomization inference test; I randomly assign the temperature realizations to the daily visiting rate (permuting only within, not across, districts) and re-estimate the main regression with 500 replications. To confirm that the main results are valid and do not result from statistical coincidence, the coefficients associated with temperature bins in the randomization inference test should be indistinguishable from zero and statistically different from the coefficients in the main model (whenever they are significantly different from zero). This is indeed the case; Figure 3.C1 in Appendix 3.C shows the kernel density plots for the 500 estimates of the top three temperature bins for each of the four outcomes. The straight line in each of the graphs represents the point estimate from the original model. The estimates derived from the randomization inference are, with no exceptions, not distinguishable from zero. Moreover, for all-cause, diabetes and cardiovascular disease visits, I can reject that the point estimates of the top three temperature bins obtained in the main results lie within the estimate distribution obtained from the randomization inference. This further consolidates that the main results indicate a robust relationship between temperature and primary health care visits and are not only significant by statistical chance.

Lastly, I conduct a falsification test to confirm that the number of daily NCD visits does indeed rise due to higher temperatures and not as a result of other factors inherent to these days. To do so, I use the number of health care visits which should reasonably not be affected by temperature and weather realizations, namely, “contraceptive management”, “dental caries” (e.g., tooth decay) and “other soft tissue disorder” (e.g., pain in limbs or muscles). The results are shown in Table 3.C8 in Appendix 3.C. All three specifications do not show significant changes in the number of visits with rising temperatures.

3.5.3 Heterogeneity

Thus far, the results have characterized the temperature-morbidity relation for both genders and all ages jointly. In the following, I assess the effects separately for men and women and by age categories.

Figure 3.1 shows that for all-cause and cardiovascular disease visits, the impact of high temperatures, i.e., of the top three bins, is consistently greater in absolute terms for women, represented by the blue lines. While for cardiovascular disease visits, the effects are too imprecisely measured to conclude that they are statistically different from each other, for all-cause visits, this difference is statistically significant for the temperature bins 27° - 28.5° and 28.5° - 30° (see Table 3.D1 in Appendix 3.D). Granted, this greater effect could also arise from women simply seeking care more often than men, yet when I assess the heat effect on visit severity, proxied by whether the patient was referred to a hospital or higher health care level, I also find

these effects to be greater for women (see Table 3.D2 in Appendix 3.D). This indicates that women are indeed also more severely affected at the intensive margin with respect to all-cause and cardiovascular diseases. For diabetes visits, the effects for men and women are almost identical in size and significance (and also not statistically different from each other); yet interestingly, men are more often referred to a higher health care level, indicating that at the intensive margin, men are more severely affected with respect to diabetes. Respiratory disease visits, contrarily, do not increase with temperature for either gender.

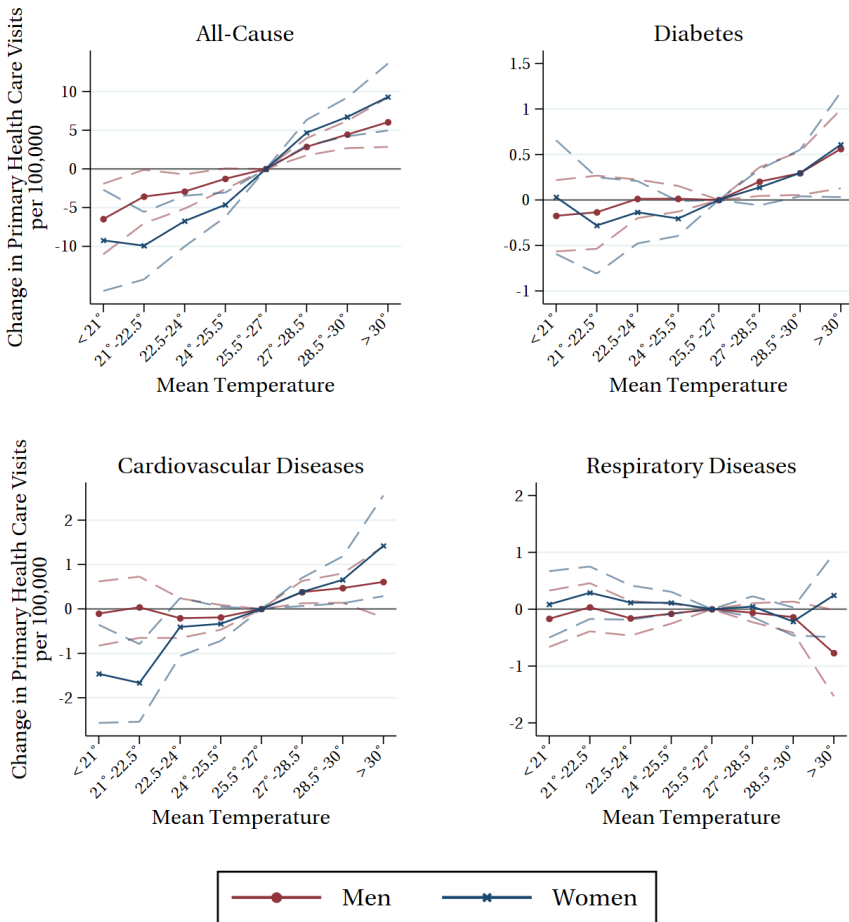


Figure 3.1: Gender heterogeneity - Figure 3.1 presents the temperature effects separately for men and women for each of the four outcome variables. Blue lines represent the female effect, red lines the male effect. Solid lines display the point estimates while the dashed lines represent the upper and lower 95% confidence interval.

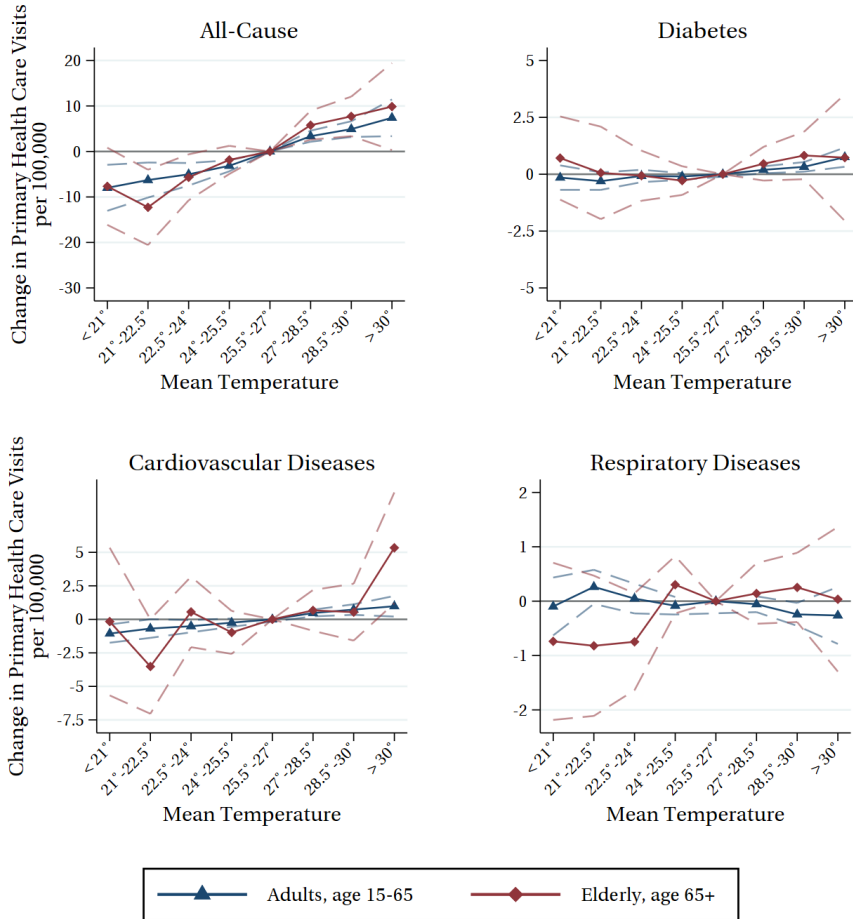


Figure 3.2: Age heterogeneity - Figure 3.2 presents the temperature effects separately for two age categories for each of the four outcome variables. Blue lines represent the effect for adults (age 15-65), red lines the effect for elderly (65+ years). Solid lines display the point estimates while the dashed lines represent the upper and lower 95% confidence interval.

Figure 3.2 shows the temperature effect separately for adults between the ages of 15 and 65 and for persons older than 65 years (regression results are presented in Table 3.D3 in Appendix 3.D). The findings are well in line with previous studies that concluded that elderly are most severely affected by high temperatures (e.g., Agarwal et al., 2021; Karlsson and Ziebarth, 2018). Especially for cardiovascular diseases, the number of visits for the elderly spikes remarkably. Nevertheless, also for adults between 15 and 65 the effect for all-cause, diabetes and cardiovascular disease visits is large and significant; and for diabetes and cardiovascular disease visits (for temperatures between 27°C and 30°C) the point estimates are very similar for both age groups. Of course, increasing morbidity is reason for concern at all ages, but if the adult working population is likewise severely affected by increases in temperature with respect to cardiovascular diseases and diabetes, it may imply a potentially large productivity loss for the Indonesian economy in the coming decades.

3.5.4 Harvesting

As discussed in Section 3.4.2, I assess the dynamic effect of temperature to investigate whether harvesting also exists for visits at the primary health care level or whether the increases found in the main results can be interpreted as permanent increases. Specifically, I test whether a day with a temperature in the top bin (<30°C) leads to a significant *decrease* in visits on the days after the heat event. Moreover, I test whether the cumulative effect remains significant for a period of up to four weeks.

Figure 3.3 presents the results graphically for each of the four disease categories. The circles in each graph indicate the point estimates of a hot day on the number of visits on the same day and for seven days in the future. The four red squares on the right in every graph depict the cumulative effect after one, two, three and four weeks, respectively.

Overall, the harvesting hypothesis can be rejected. With a single exception (t+2 for all-cause visits), none of the lagged effects for any of the disease types is significantly negative, while the cumulative effects of a single hot day above 30°C remain significant up to three weeks for all-causes and cardiovascular diseases and even up to four weeks for diabetes. For respiratory diseases, in contrast, the cumulative effects confirm the findings above, i.e., a decreasing impact of high temperatures for this specific disease category.

Conclusively, the findings speak strongly against the harvesting hypothesis for all-cause, diabetes and cardiovascular disease visits; the increase in primary health care visits is permanent and not offset by visit displacement.

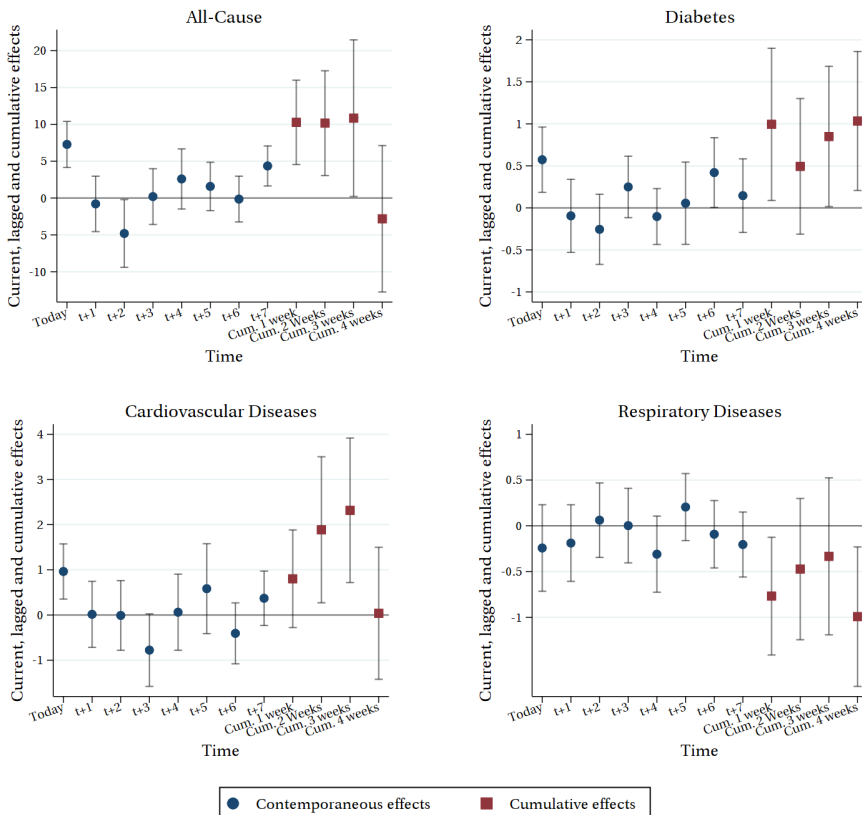


Figure 3.3: Harvesting - The circle point estimates represent the effect of a day with a temperature in the top bin ($<30^{\circ}\text{C}$) relative to the reference bin (25.5°C – 27°C) on the number of daily visits today and up to seven days in the future. The squares show the cumulative effects after one, two, three and four weeks, respectively. Whiskers represent the 95% confidence interval. To estimate the effect over a period longer than one week, the number of lags in the model presented in Equation (3.1) is increased to the reflect the period of interest (e.g., 21 lags for the three-week cumulative effect).

3.6 Visit and cost predictions under various climate change scenarios

Heat-induced illness comes not only with individual health-related consequences but also imposes costs on the economy through losses in productivity, as well as impacting the health care system due to increased costs for acute and long-term care. Several studies have assessed the cost of heat waves for the overall economy (e.g., Cheng et al., 2018; Karlsson and Ziebarth, 2018) or, taking on the insurer perspective, heat-related costs for hospitalization rates (Agarwal et al., 2021). I expand these estimates to the costs that occur for less acute health consequences at the primary health care level and calculate the yearly financial burden for the Indonesian health insurance scheme that might occur under various climate change scenarios by the end of the century.

Since the implementation of JKN, the managing social security agency (BPJS) has faced substantial financial deficits, primarily due to member contribution rates that are too low to cover the costs arising from comprehensive benefit packages (Aidha and Chrisnahutama, 2020; Prabhakaran et al., 2019). Primary health care services should be entirely free for insured members, with health services paid for by BPJS – either indirectly via capitation payments or directly via reimbursement payments. Given that payments are determined by the number and type of visits a facility manages and given that the current height of the capitation rate is already considered to be substantially too low to finance the actually demanded health services, increases in visits will further lead to increases in the required payments (Jo and Setiawan, 2019; Nugraheni et al., 2020). This, in turn, will further deteriorate the financial sustainability of the scheme, assuming that the financial burden is not transferred into higher member contribution rates.

To shed light on the extent of potential additional costs caused by increasing temperatures, I simulate the increases in the number of primary health care visits up to the end of the current century (2060-2080), applying various climate change scenarios and relate these predictions to official cost estimates per visit. Data on climate change predictions are drawn from the CNRM-CM6-1 model, provided by the National Center for Meteorological Research (Voldoire, 2018).⁶ It is one of nine models that are used within the World Climate Research Program's Coupled Model Intercomparison Project Phase 6 (CMIP6), which is the database on which the Intergovernmental Panel on Climate Change builds its regular climate assessment reports. The predictions are provided as monthly means for 20-year averages, with a spatial resolution of about 18.5 km × 18.5 km and for several Shared Socioeconomic Pathways (SSPs, previously Representative Concentration Pathways), i.e., climate

⁶A downscaled and ready-to-use version of the data is provided at the WorldClim database: https://www.worldclim.org/data/cmip6/cmip6_clim10m.html.

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change scenarios. From the available year-averages and emission scenarios, I use the 2060-2080 monthly average with an intermediate (SSP2-4.5) and high-emission (SSP5-8.5) scenario. The former describes a scenario in which CO₂ emissions stagnate at current levels until 2050 and the global mean temperature increases by about 2.7°C by the end of the century compared to the pre-industrial level. The latter describes a scenario in which CO₂ emissions continue to rise and the global mean temperature increases by about 4.4°C (Intergovernmental Panel on Climate Change, 2022).

I transform the temperature predictions to temperature bins at the daily-district level by adding the predicted difference in monthly-district means to the current daily temperature realizations, thereby keeping the variation at the daily level. Figure 3.E1 in Appendix 3.E presents the population-weighted yearly temperature bin distribution resulting from this procedure for the 2015/2016 data and the two climate change scenarios. While in 2015/2016 on average only seven days per year experienced a temperature above 30°C, by the end of the century this number is predicted to climb to 32 and 108 under the intermediate and high-emission scenario, respectively. In both climate scenarios, the number of days falling into temperature bins below 28.5°C is substantially reduced and only the upper two bins with temperatures above 28.5°C experience increases in the number of days per year.

Simulating the increase in primary health care visits and the corresponding costs is then a simple back-of-the-envelope calculation exercise and similar to the linear combination method used in comparable studies (e.g., Agarwal et al., 2021; White, 2017): I calculate the change in the population-weighted number of days per year that fall in each bin and multiply this change with the respective coefficient that was estimated in the main model, i.e., $\sum_i \beta_i * \Delta Temp_i$. Since this depicts the additional yearly visit per 100,000 insured individuals, I further upscale these numbers to the national level, using the current population size of 270 million Indonesians and assuming that the goal of universal insurance coverage will be reached in the coming years and thereby the whole population should be enrolled by 2060.

In an additional prediction model, I also consider population growth jointly with population aging and the resulting changing age structure in Indonesia. In this model, I predict the visit increases and related costs by using the estimated age-specific coefficients and upscale them with the predicted Indonesian population size and age distributions for 2060-2080 which I derive from the UN World Population Prospects (United Nations, Department of Economic and Social Affairs, Population Division, 2019).

The final additional visits per year can then be related to the unit cost per visit. To be precise, capitation payments from BPJS to *Puskesmas* are in the short term

independent of the number of visits that are made by a single patient. Hence, the assumption underlying the following calculations is that capitation payments have to be adjusted in the long run to finance increases in health care visits. The respective unit costs are derived from an evaluation and costing study that was conducted by the BPJS Health Research & Development Group (Kurniawan et al., 2016) to calculate the average unit cost per *Puskesmas* visit.⁷ Based on a random sample of 400 *Puskesmas* from 20 districts, the study calculated an average unit cost of Rp120,000 (US\$8.90⁸).

Table 3.3 shows the resulting visit and cost predictions under both climate change scenarios in the second half of the current century (2060-2080). In contrast to former studies (e.g., Agarwal et al., 2021; White, 2017), I find the increases in visits to be statistically and economically significant – again with the exception of respiratory diseases.

Under the intermediate-emission scenario, the Indonesian health care system is likely to face one million additional primary health care visits a year and a corresponding additional financial burden of US\$9.68 million. Under the high-emission scenario, these numbers increase to 2.8 million additional yearly visits and an additional financial burden of US\$25 million. In both scenarios, primary health care visits related to diabetes or cardiovascular diseases together account for about 17% of the increase in visits and costs. If population growth and the shift in the population structure toward an older population are considered, this share climbs by another 5 percentage points to 22%. This indicates that the shift in the population-structure will also lead to a shift in the disease-burden structure, with a higher burden due to non-communicable diseases. The related yearly costs under this scenario amount to US\$32 million.

Compared to BPJS's annual expenditures for primary health care services, which constituted approximately 14% of total expenditures and averaged US\$0.72 billion over the period 2015-2017 (Aidha and Chrisnahutama, 2020; Sambodo et al., 2021), this implies an increase between 1.3% and 4.3% for the expenditures allocated to primary health care services.

While this is a sizable burden, it most likely captures only a fraction of the total

⁷As described in Section 3.3.1., some of the primary health care visits are not covered by the capitation payments and cost for such visits are reimbursed from BPJS directly. Yet, claims for reimbursements occur at the primary health care level only in a limited number of cases. The major share of primary health care visits is reimbursed via the monthly capitation payments. Overall, only for 4% of the 1.73 million visit observations in the data, a cost claim was made, of which 55% are related to delivery, post-partum care and contraceptive management. Hence, only for a very limited number of visits related to NCDs a cost claim was made, which are, however, not representative for the visits that do not result in cost claims. Therefore, the unit cost per visit was derived from Kurniawan et al. (2016) who estimate the cost for an average visit at Rp120,000. Using the cost claims from the BPJS data would have resulted in a unit cost of almost three times the amount (Rp317,365) which would have resulted in a substantial over-estimation of the cost predictions.

⁸Using the 2016 US\$-Rp exchange rate with Rp13,436 being equal to US\$1.

3.6 Visit and cost predictions under various climate change scenarios

financial burden that might be caused by climate change, since it does not include costs that might arise in hospitals, nor does it include monetized deaths or productivity losses. Moreover, it should be noted that this simple extrapolation method does not account for any form of human adaptation, intensification of climate effects or general equilibrium effects, which are also vital to comprehensively model health effects in the long run (Dell et al., 2014).

Table 3.3: Visit and cost predictions under various climate change and population scenarios

Scenario	(1) Additional yearly visits by 2060-2080			(4) Additional yearly costs by 2060-2080		
	(2) SSP2-4.5	(2) SSP5-8.5	(3) SSP5-8.5 + population growth and aging	(4) SSP2-4.5	(5) SSP5-8.5	(6) SSP5-8.5 + population growth and aging
All-cause	1,084,433*** (155,002)	2,797,376*** (466,318)	3,569,337*** (47,818)	Rp130.13 billion (\$9.69 million)	Rp336.41 billion (\$24.98 million)	Rp428.32 billion (\$31.88 million)
Diabetes	65,713*** (18,426)	185,178*** (58,302)	270,982*** (83,331)	Rp7.86 billion (\$0.59 million)	Rp22.33 billion (\$1.65 million)	Rp32.52 billion (\$2.42 million)
Cardiovascular Diseases	122,270*** (28,057)	338,672*** (86,964)	524,243*** (153,443)	Rp14.67 billion (\$1.09 million)	Rp40.99 billion (\$3.02 million)	Rp62.91 billion (\$4.68 million)
Respiratory Diseases	-36,119 (23,245)	-97,153 (73,910)	-88,224 (65,590)	Rp-4.33 billion (\$-0.32 million)	Rp-11.85 billion (\$-0.88 million)	Rp-10.58 billion (\$-0.78 million)

Notes: Table 3.3 displays the predicted increases in yearly primary health care visits (all-cause and by diagnosis) in comparison to the 2015/2016 data. A single visit is assumed to lead to additional costs to the amount of Rp120,000 (US\$8.90). *** p<0.01, ** p<0.05, * p<0.1.

3.7 Conclusion

This study explored the relationship between high temperatures and NCD morbidity in Indonesia. The results confirm that high temperatures increase the health burden at the primary health care level as heat-induced morbidity significantly increases health care usage. Hence, even though Indonesia is a country where high temperatures prevail and residents are used to heat and high humidity, the heat-morbidity relationship is a relevant factor in people's health care seeking behavior. Using daily health and weather data at the district level, I show that the number of all-cause and NCD-related primary health care visits substantially increases on days when the daily mean temperature exceeds the average mean temperature. Specifically, I find that on days with a mean temperature above 30°C, the numbers of daily all-cause, diabetes and cardiovascular disease visits increase by 8%, 25% and 14%, respectively, compared to a reference day with a mean temperature between 25.5°C and 27°C. These increases are permanent and not offset by visit displacement or "harvesting".

Given rising temperatures and an increasing occurrence of heat waves, the findings also imply an increasing financial burden for the Indonesian national health insurance agency BPJS. Under a high-emission scenario, the insurance system could face an additional financial burden of US\$25 million per year from primary health care services alone, even before accounting for emergency costs and more severe health consequences. Seventeen percent of this burden can be attributed solely to diabetes and cardiovascular diseases. Increasing rates of NCDs and their risk factors, such as obesity, smoking and high blood pressure, further jeopardize the system's sustainability. Higher efforts for the prevention and control of such diseases would have to be made to counteract this trend.

Moreover, to prevent the surge in visits on days with extreme temperatures, action could be taken by health care providers as well as by affected individuals. First, the primary health care sector could establish links with local meteorological services to receive early information and warnings of impending heat events. This would allow a timely response by physicians and general practitioners in the form of increased and disease-specialized staff during days with excessive temperatures. Second, individuals affected by a chronic disease could be sensitized to the risks of heat. Possible interventions could include the provision of educational material or targeted counseling for individuals at risk. Third, individual early warning systems, for example in the form of alerting weather apps, could provide a useful complementary tool for patients to prevent personal exposure to heat. Early notifications of heat waves and hot days would then allow patients to re-organize outdoor activities and delay them until cooler evening hours. Special attention could be given to women and the elderly, as they seem to be more severely affected by heat.

As in any typical low- and middle-income country, the primary health care sector forms the backbone of the health care system in Indonesia. The finding that the primary health care sector experiences an increasing burden when temperatures rise also has potentially important implications for the management of the overall health care system. If, for example, the surge in visits in the primary health care sector leads to bottlenecks in human or resource capacities, an efficient and fast interaction between the various health care levels is required to prevent a locally overloaded health care system. What such interactions and synergies could look like is therefore of great interest for future research.

My findings not only contribute to a better understanding of the relationship between temperature and chronic, non-communicable diseases in Indonesia, but may possibly be more broadly applied to other low- and middle-income countries with a similar tropical climate. Especially for other Southeast Asian countries, which face a similar surge of non-communicable diseases and comparable meteorological conditions, the results might be equally applicable.

Appendices

Appendix 3.A: Details on BPJS sampling procedure and the sample population

Details on BPJS sampling procedure

The families included in the sample were selected based on a stratified sampling procedure. At the time of sampling, there were 22,024 primary health care facilities registered as “gatekeeper” with BPJS. Within each of the 22,024 facilities functioning as gatekeeper, families were stratified into three categories: (i) families that had not yet utilized any health care services, (ii) families that had utilized only primary health care services and (iii) families that had utilized primary health care services and were referred to higher-level health facilities. From each of the three strata, ten families were randomly selected and data on all family members were included in the sample. If there were fewer than ten families in one stratum, all families were automatically included in the sample. This procedure led to a sample of 1,697,452 individuals from 586,969 selected families.

The dataset consists of five distinct data files. The first one includes administrative membership and demographic data, such as an individual insurance number, age, gender, marital status, working status, class of insurance, province and district of residence, the type and location of their gatekeeping health facility, as well as a sampling weight to ensure representativeness for all insurance members. The second file contains information about all inpatient and outpatient primary health care visits conducted by the sampled individuals in the years 2015 and 2016. Due to the sampling procedure, at least one primary health care visit was recorded for about 27% of the individuals (465,017). However, this share drops to 18.3% if sampling weights are applied. The third file contains complementary information about non-capitation-based services for the visits recorded in the second file. File four and five include data for cases referred to higher health care facilities, i.e., district and province hospitals. All data files cover the two-year observation window 2015-2016.

Tables 3.A1, 3.A2 and 3.A3 below present additional descriptive statistics of the data. Table 3.A1 displays the ICD-10 codes and diseases that were included in the respective disease category for this study. Table 3.A2 shows the distribution of the twenty most frequent diagnoses in the data sample. Table 3.A3 displays the summary statistics of primary health care visits by age categories.

Details on the sample population in comparison to the total Indonesian population in early years of the insurance

The insurance scheme differentiates between four enrollment segments: 1) individuals classified as poor with premiums being subsidized by either the national or local government (“PBI”), 2) working individuals in the formal private sector or formal public sector with premiums being deducted directly from salaries (“PPU”), 3) working individuals in the informal sector, who have to enroll and pay premiums individually (“PBPU”), and 4) all remaining non-working individuals that do not fall under the other three segments, such as retired civil servants, for whom premiums are deducted from pension, or non-working individuals, who also have to pay premiums individually (“BP”). Whereas the enrollment for subsidized individuals and formal workers was largely automatically enforced from 2014 onward by the incorporation of previous insurance schemes, the coverage for individuals in the informal sector who had to self-enroll was harder to enforce (Agustina et al., 2019). This implied that in its early years, the scheme was confronted with the problem of the “missing middle class”, whereas those that worked in the informal sector but were not classified as poor were largely not covered by the insurance, who, however, form a significant share of Indonesia’s working population (Agustina et al., 2019; Muttaqien et al., 2021). Muttaqien et al. (2021) estimated that by 2017, only 43% of Indonesia’s 69 million informal workers were covered (compared to a country-wide enrollment rate of 72%). By the end of 2015, 62% of covered individuals belonged to the subsidized segment (“PBI”), 24% to the segment of formal workers (“PPU”), only 10% to the segment of informal workers (“PBPU”), and the remaining 3% to the non-working segment (“BP”). By the time of May 2022, the shares for the respective segments were 60%, 25.2%, 13% and 1.8% (Dewan Jaminan Sosial Nasional, 2022). Hence, while the presented analyses are representative for the insured population in the years 2015/2016, it needs to be kept in mind that a certain social segment was largely underrepresented in the scheme back then (and to some extent still is today).

Table 3.A1: ICD-10-codes and diseases

Diabetes

- E10 Type 1 diabetes mellitus
- E11 Type 2 diabetes mellitus
- E12 Malnutrition-related diabetes mellitus
- E13 Other specified diabetes mellitus
- E14 Unspecified diabetes mellitus

Cardiovascular diseases

- I00 Rheumatic fever without mention of heart involvement
- I01 Rheumatic fever with heart involvement
- I02 Rheumatic chorea
- I05 Rheumatic mitral valve diseases
- I06 Rheumatic aortic valve diseases
- I07 Rheumatic tricuspid valve diseases
- I08 Multiple valve diseases
- I09 Other rheumatic heart diseases
- I10 Essential (primary) hypertension
- I11 Hypertensive heart disease
- I12 Hypertensive renal disease
- I13 Hypertensive heart and renal disease
- I15 Secondary hypertension
- I20 Angina pectoris
- I21 Acute myocardial infarction
- I22 Subsequent myocardial infarction
- I23 Certain current complications following acute myocardial infarction

Cardiovascular diseases - continued

- I24 Other acute ischemic heart diseases
- I25 Chronic ischemic heart disease
- I26 Pulmonary embolism
- I27 Other pulmonary heart diseases
- I28 Other diseases of pulmonary vessels
- I30 Acute pericarditis
- I31 Other diseases of pericardium
- I32 Pericarditis in diseases classified elsewhere
- I33 Acute and subacute endocarditis
- I34 Nonrheumatic mitral valve disorders
- I35 Nonrheumatic aortic valve disorders
- I36 Nonrheumatic tricuspid valve disorders
- I37 Pulmonary valve disorders
- I38 Endocarditis, valve unspecified
- I39 Endocarditis and heart valve disorders in diseases classified elsewhere
- I40 Acute myocarditis
- I41 Myocarditis in diseases classified elsewhere
- I42 Cardiomyopathy
- I43 Cardiomyopathy in diseases classified elsewhere
- I44 Atrioventricular and left bundle-branch block
- I45 Other conduction disorders
- I46 Cardiac arrest
- I47 Paroxysmal tachycardia
- I48 Atrial fibrillation and flutter
- I49 Other cardiac arrhythmias
- I50 Heart failure

Table continues next page

Table 3.A1: ICD-10-codes and diseases - continued

<i>Cardiovascular diseases - continued</i>	
I51	Complications and ill-defined descriptions of heart disease
I52	Other heart disorders in diseases classified elsewhere
I60	Subarachnoid hemorrhage
I61	Intracerebral hemorrhage
I62	Other nontraumatic intracranial hemorrhage
I63	Cerebral infarction
I64	Stroke, not specified as hemorrhage or infarction
I65	Occlusion and stenosis of precerebral arteries, not resulting in cerebral infarction
I66	Occlusion and stenosis of cerebral arteries, not resulting in cerebral infarction
I67	Other cerebrovascular diseases
I68	Cerebrovascular disorders in diseases classified elsewhere
I69	Sequelae of cerebrovascular disease
I70	Atherosclerosis
I71	Aortic aneurysm and dissection
I72	Other aneurysm and dissection
I73	Other peripheral vascular diseases
I74	Arterial embolism and thrombosis
I77	Other disorders of arteries and arterioles
I78	Diseases of capillaries
I79	Disorders of arteries, arterioles and capillaries in diseases classified elsewhere
I80	Phlebitis and thrombophlebitis
I82	Other venous embolism and thrombosis
I83	Varicose veins of lower extremities
I85	Esophageal varices
I86	Varicose veins of other sites
I87	Other disorders of veins
I88	Nonspecific lymphadenitis
I89	Other noninfective disorders of lymphatic vessels and lymph nodes
I95	Hypotension
I97	Postprocedural disorders of circulatory system, not elsewhere classified
I98	Other disorders of circulatory system in diseases classified elsewhere
I99	Other and unspecified disorders of circulatory system
<i>Respiratory diseases</i>	
J30	Vasomotor and allergic rhinitis
J31	Chronic rhinitis, nasopharyngitis and pharyngitis
J32	Chronic sinusitis
J33	Nasal polyp
J34	Other disorders of nose and nasal sinuses
J35	Chronic diseases of tonsils and adenoids
J36	Peritonsillar abscess
J37	Chronic laryngitis and laryngotracheitis
J38	Diseases of vocal cords and larynx, not elsewhere classified
J39	Other diseases of upper respiratory tract
J40	Bronchitis, not specified as acute or chronic
J41	Simple and mucopurulent chronic bronchitis
J42	Unspecified chronic bronchitis
J43	Emphysema
J44	Other chronic obstructive pulmonary disease
J45	Asthma
J46	Status asthmaticus
J47	Bronchiectasis
J60	Coal worker pneumoconiosis
J62	Pneumoconiosis due to dust containing silica
J64	Unspecified pneumoconiosis
J65	Pneumoconiosis associated with tuberculosis

Table continues next page

Table 3.A1: ICD-10-codes and diseases - continued*Respiratory diseases continued*

J66	Airway disease due to specific organic dust
J67	Hypersensitivity pneumonitis due to organic dust
J68	Respiratory conditions due to inhalation of chemicals, gases, fumes and vapors
J69	Pneumonitis due to solids and liquids
J70	Respiratory conditions due to other external agents
J80	Adult respiratory distress syndrome
J81	Pulmonary edema
J82	Pulmonary eosinophilia, not elsewhere classified
J84	Other interstitial pulmonary diseases
J85	Abscess of lung and mediastinum
J86	Pyothorax
J90	Pleural effusion, not elsewhere classified
J91	Pleural effusion in conditions classified elsewhere
J92	Pleural plaque
J93	Pneumothorax
J94	Other pleural conditions
J95	Postprocedural respiratory disorders, not elsewhere classified
J96	Respiratory failure, not elsewhere classified
J98	Other respiratory disorders
J99	Respiratory disorders in diseases classified elsewhere

Notes: Table 3.A1 displays the ICD-10 codes and diseases that were included in the respective disease category for this study.

Table 3.A2: Distribution of diagnosis frequency (ICD-10 Codes) in BPJS insurance data (capitation services)

ICD-10 Code	Diagnosis Name	Sample frequency (weighted)	Population frequency	Percentage
J06	Acute upper respiratory infections of multiple and unspecified sites	179,273.30	13,967,699	10.34%
J00	Acute nasopharyngitis [common cold]	116,893.20	9,107,484	6.74%
I10	Essential (primary) hypertension	94,368.59	7,352,530	5.44%
M79	Other soft tissue disorders, not elsewhere classified	73,117.16	5,696,770	4.22%
K29	Gastritis and duodenitis	69,746.40	5,434,144	4.02%
K30	Functional dyspepsia	55,143.92	4,296,422	3.18%
R50	Fever of other and unknown origin	53,220.84	4,146,590	3.07%
K04	Diseases of pulp and periapical tissues	46,804.05	3,646,639	2.70%
J02	Acute pharyngitis	44,383.06	3,458,012	2.56%
A09	Other gastroenteritis and colitis of infectious and unspecified origin	41,458.42	3,230,145	2.39%
R51	Headache	40,823.80	3,180,700	2.35%
Z30	Contraceptive management	34,914.56	2,720,294	2.01%
E11	Type 2 diabetes mellitus	33,979.08	2,647,409	1.96%
J11	Influenza, virus not identified	33,560.07	2,614,762	1.94%
R05	Cough	25,497.82	1,986,609	1.47%
K02	Dental caries	25,287.31	1,970,207	1.46%
L30	Other dermatitis	21,029.44	1,638,464	1.21%
O80	Single spontaneous delivery	18,987.38	1,479,362	1.10%
L23	Allergic contact dermatitis	17,790.01	1,386,071	1.03%
A01	Typhoid and paratyphoid fevers	17,319.03	1,349,376	1.00%

Notes: Table 3.A2 shows the distribution of the 20 most frequent diagnoses from the BPJS insurance data over the years 2015-2016. The column “sample frequency” shows the weighted distribution in the data; the column “Population Frequency” refers to the frequency upscaled to the national level using the provided population weights in the data sample.

Table 3.A3: Summary statistics of primary health care visits by age

	Mean	SD	Min	Max
<i>All-Cause</i>				
All ages	96.42	97.34	0.00	2659.11
Age <15	95.85	147.03	0.00	5930.57
Age 15-65	96.01	102.52	0.00	4011.96
Age 65+	104.09	257.21	0.00	16584.00
<i>Diabetes</i>				
All ages	2.50	9.54	0.00	774.64
Age <15	0.03	2.96	0.00	771.55
Age 15-65	2.75	11.63	0.00	1168.74
Age 65+	6.45	61.47	0.00	6465.48
<i>Cardiovascular Diseases</i>				
All ages	7.22	16.62	0.00	747.09
Age <15	0.23	6.27	0.00	1696.80
Age 15-65	7.06	18.73	0.00	1127.18
Age 65+	25.86	119.30	0.00	6738.34
<i>Respiratory Diseases</i>				
All ages	2.22	8.70	0.00	625.64
Age <15	2.66	19.18	0.00	1696.80
Age 15-65	1.96	9.63	0.00	811.04
Age 65+	3.42	43.19	0.00	4891.47

Notes: Table 3.A3 shows summary statistics for the number of daily primary health care visits by age categories. The values correspond to daily visits per 100,000 individuals within the respective age category. All summary statistics are population weighted.

The summary statistics shown in Table 3.1 and Table 3.A3 reveal three facts worth discussing. First, visits related to cardiovascular diseases account for about 7.2% of the total number of primary health care visits that were recorded in the years 2015-2016. Visits with the primary diagnosis of hypertension alone make up as much as 5.4% of all diagnoses in the two years under study (see Table 3.A2 for a summary of the 20 most frequent diagnoses). Remarkably, this share is larger than the share recorded for the US, where in 2016 only 3.8% of all visits to a physician's office resulted in a primary diagnosis of hypertension (Rui and Okeyode, 2016). Second, except for chronic respiratory diseases, women have a higher visiting rate than men. For cardiovascular disease visits alone, the rate is over 60% higher. Granted, this could also be driven by women seeking care more often than men, yet, as I have shown in Section 3.5.3, cardiovascular disease severity is also higher in women – a result that is well in line with the findings from the latest Indonesian Basic Health Research (Riskesdas) (Badan Penelitian dan Pengembangan Kesehatan, 2019), in which higher prevalence rates for hypertension and heart diseases were detected in women. Third, considering that Indonesia has one of the highest male smoking rates in the world, it is somewhat surprising that the number of visits related to respiratory diseases is similar for male and female patients, as several respiratory diseases are caused by smoking.

Appendix 3.B: Details on gridded weather data

Figure 3.B1 graphically displays the matching of the gridded weather data with the respective district. For districts A and B, there are 4 and 5 grid points, respectively, that fall directly within the borders of the districts. The daily mean temperature for district A is, hence, constructed as the arithmetic mean of the four grid points displayed in black, whereas the daily mean temperature for district B is constructed as the arithmetic mean of the five grid points displayed in white.

Due to the small size of District C, no grid points fall within it. The daily mean temperature is consequently derived via inverse distance weighting of the four nearest grid points to the district's centroid, as shown in the part of the figure on the right.

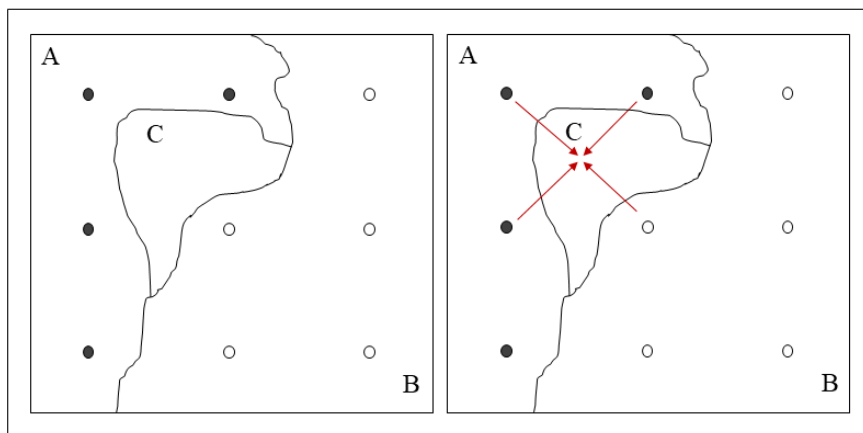


Figure 3.B1: Assignment of gridded weather data to districts

Appendix 3.C: Robustness checks

Table 3.C1: Robustness checks – Interacted month × district fixed-effects

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<21°C	-7.973** (3.103)	-0.049 (0.227)	-0.758** (0.330)	-0.055 (0.231)
21°C - 22.5°C	-6.347*** (1.926)	-0.174 (0.213)	-0.697** (0.335)	0.160 (0.146)
22.5°C - 24°C	-4.481*** (1.353)	-0.014 (0.106)	-0.225 (0.212)	-0.015 (0.119)
24°C - 25.5°C	-2.919*** (0.678)	-0.064 (0.065)	-0.196* (0.117)	0.007 (0.074)
25.5°C - 27°C	ref.	ref.	ref.	ref.
27°C - 28.5°C	3.927*** (0.609)	0.168** (0.065)	0.394*** (0.113)	0.004 (0.060)
28.5°C - 30°C	5.348*** (0.895)	0.269*** (0.091)	0.545*** (0.170)	-0.160* (0.095)
>30°C	6.291***	0.563***	0.856***	-0.316
Mean of dep. var. in ref. bin	90.16	2.36	6.99	2.13
Observations	372,023	372,023	372,023	372,023
R-squared	0.484	0.117	0.150	0.059
Number of districts	509	509	509	509
District × month fixed-effects	✓	✓	✓	✓
Year fixed-effects	✓	✓	✓	✓
Day-of-the-week fixed-effects	✓	✓	✓	✓
Lags	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Table 3.C1 shows the results for a re-estimation of the main specification with the inclusion of month × district fixed-effects. All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C2: Robustness checks – Hot day specification

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
Hot Day ($1 \geq 90^{\text{th}}$ perc.)	4.000*** (0.922)	0.219** (0.089)	0.449*** (0.163)	-0.100 (0.0.093)
Mean of dep. var.	96.42	2.50	7.22	2.22
Observations	372,023	372,023	372,023	372,023
R-squared	0.468	0.103	0.135	0.042
Number of Districts	509	509	509	509
Full set of fixed effects	✓	✓	✓	✓
Lags	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Table 3.C2 shows the results for a re-estimation of the main specification in which, instead of eight temperature bins, a single binary variable is used to indicate a “Hot day”, which is equal to one for temperatures above the 90th percentile of the mean temperature distribution. All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C3: Robustness checks – Linear temperature specification

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
Mean Temperature	2.577*** (0.253)	0.086*** (0.025)	0.270*** (0.050)	-0.025 (0.028)
Mean of dep. var.	96.42	2.50	7.22	2.22
Observations	372,023	372,023	372,023	372,023
R-squared	0.469	0.103	0.135	0.042
Number of Districts	509	509	509	509
Full set of fixed effects	✓	✓	✓	✓
Lags	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Table 3.C3 shows the results for a re-estimation of the main specification in which, instead of eight temperature bins, the mean temperature enters the specification as a linear variable. All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C4: Robustness checks – Tobit model, regression coefficients

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<21°C	-9.821*** (2.569)	-1.626 (1.827)	-1.880 (1.347)	-1.305 (2.045)
21°C - 22.5°C	-7.993*** (2.114)	-0.648 (1.762)	-3.208*** (0.965)	0.710 (1.292)
22.5°C - 24°C	-5.892*** (1.320)	-1.025 (0.793)	-1.037* (0.601)	-0.895 (0.864)
24°C - 25.5°C	-3.258*** (0.650)	-0.993** (0.477)	-1.028*** (0.343)	0.137 (0.454)
25.5°C - 27°C	ref.	ref.	ref.	ref.
27°C - 28.5°C	3.755*** (0.639)	0.600 (0.377)	0.953*** (0.288)	0.104 (0.372)
28.5°C - 30°C	5.453*** (0.929)	1.546*** (0.506)	1.183*** (0.405)	-0.986* (0.514)
>30°C	7.583*** (1.674)	3.004*** (0.982)	2.621*** (0.690)	-0.562 (1.084)
Mean of dep. var. in ref. bin	90.16	2.36	6.99	2.13
Observations	372,023	372,023	372,023	372,023
Number of Districts	509	509	509	509
Full set of fixed effects	✓	✓	✓	✓
Lags	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Pseudo R-squared	0.077	0.283	0.159	0.250

Notes: Table 3.C4 shows the results for a re-estimation of the main specification using a Tobit model. All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C5: Robustness checks – Tobit model, marginal effects

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<21°C	-5.995*** (1.557)	-0.250 (0.281)	-0.435 (0.312)	-0.220 (0.344)
21°C - 22.5°C	-4.879*** (1.276)	-0.100 (0.271)	-0.742*** (0.223)	0.119 (0.217)
22.5°C - 24°C	-3.597*** (0.793)	-0.158 (0.122)	-0.240* (0.139)	-0.151 (0.145)
24°C - 25.5°C	-1.988*** (0.391)	-0.153** (0.073)	-0.238*** (0.079)	0.023 (0.076)
25.5°C - 27°C	ref.	ref.	ref.	ref.
27°C - 28.5°C	2.292*** (0.386)	0.092 (0.058)	0.220*** (0.067)	0.018 (0.063)
28.5°C - 30°C	3.329*** (0.560)	0.238*** (0.078)	0.274*** (0.094)	-0.166* (0.087)
>30°C	4.629*** (1.022)	0.463*** (0.151)	0.606*** (0.159)	-0.095 (0.182)

Notes: Table 3.C5 shows the conditional marginal effects for the Tobit model in Table 3.C4. Marginal effects are calculated at the sample means on uncensored observations. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C6: Robustness checks – Members with recorded visits in both years

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<21°C	-8.176*** (1.970)	-0.161 (0.178)	-0.551* (0.281)	-0.041 (0.171)
21°C - 22.5°C	-7.790*** (1.510)	-0.209 (0.167)	-0.856*** (0.308)	0.081 (0.143)
22.5°C - 24°C	-5.536*** (1.113)	-0.114 (0.087)	-0.459** (0.215)	-0.075 (0.108)
24°C - 25.5°C	-3.019*** (0.489)	-0.083 (0.055)	-0.292*** (0.107)	0.021 (0.072)
25.5°C - 27°C	ref.	ref.	ref.	ref.
27°C - 28.5°C	3.332*** (0.511)	0.166*** (0.062)	0.369*** (0.098)	-0.014 (0.056)
28.5°C - 30°C	5.631*** (0.765)	0.291*** (0.081)	0.568*** (0.154)	-0.150* (0.083)
>30°C	9.536*** (1.317)	0.529*** (0.187)	1.178*** (0.267)	-0.193 (0.213)
Mean of dep. var. in ref. bin	74.72	2.10	5.98	1.84
Observations	371,292	371,292	371,292	371,292
R-squared	0.448	0.098	0.129	0.040
Number of districts	509	509	509	509
Full set of fixed-effects	✓	✓	✓	✓
Lags	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Table 3.C6 shows the results for a re-estimation of the main specification for a sample that includes only visits of individuals for which it can be verified that they were insured in both years of the study period, i.e., for individuals that have at least one family member with a reported visit in 2015 (assuming that families with the first visit in 2016 might not have been enrolled yet in 2015). All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C7: Robustness checks – Accounting for mortality

	(1) All-cause	(2) Diabetes	(3) Cardio-vascular	(4) Respiratory
<21°C	-7.762*** (2.615)	-0.064 (0.210)	-0.736** (0.305)	-0.042 (0.207)
21°C - 22.5°C	-6.667*** (1.746)	-0.189 (0.194)	-0.771** (0.322)	0.160 (0.149)
22.5°C - 24°C	-4.766*** (1.221)	-0.061 (0.101)	-0.307 (0.208)	-0.021 (0.122)
24°C - 25.5°C	-2.900*** (0.603)	-0.094 (0.061)	-0.257** (0.117)	0.016 (0.076)
25.5°C - 27°C	ref.	ref.	ref.	ref.
27°C - 28.5°C	3.814*** (0.585)	0.184*** (0.063)	0.396*** (0.111)	-0.007 (0.060)
28.5°C - 30°C	5.624*** (0.882)	0.310*** (0.089)	0.571*** (0.168)	-0.177* (0.095)
>30°C	7.740*** (1.553)	0.601*** (0.201)	1.047*** (0.308)	-0.286 (0.249)
Mean of dep. var. in ref. bin	90.54	2.35	6.99	2.14
Observations	372,023	372,023	372,023	372,023
R-squared	0.469	0.103	0.135	0.042
Number of districts	509	509	509	509
Full set of fixed-effects	✓	✓	✓	✓
Lags	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Table 3.C7 shows the results for a re-estimation of the main specification after dropping individuals that died during the observation period from the sample. All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

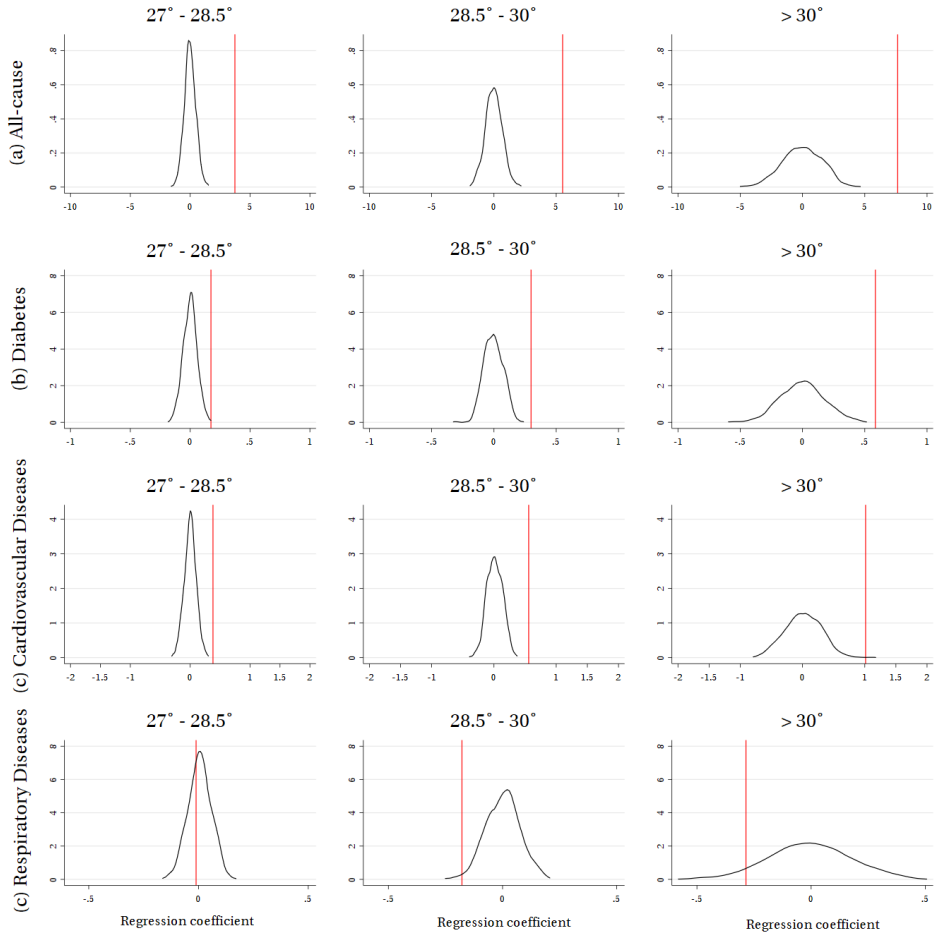


Figure 3.C1: Randomization inference test - Figure 3.C1 shows the kernel density distribution for the placebo estimates of the three highest temperature bins for each disease outcome obtained from 500 random permutations of the daily number of visits and temperature realizations and the subsequent estimation of the main model. The red straight line displays the point estimate from the main results.

Table 3.C8: Robustness checks – Falsification test

	Contraceptive management (1)	Dental caries (2)	Other soft tissue disorders (3)
<21°C	0.058 (0.234)	-0.104 (0.159)	-0.443* (0.242)
21°C - 22.5°C	-0.144 (0.214)	-0.058 (0.158)	-0.326 (0.216)
22.5°C - 24°C	-0.173 (0.147)	-0.011 (0.090)	-0.261 (0.178)
24°C - 25.5°C	-0.125 (0.090)	0.023 (0.059)	0.062 (0.106)
25.5°C - 27°C	ref.	ref.	ref.
27°C - 28.5°C	0.019 (0.058)	-0.013 (0.048)	-0.044 (0.080)
28.5°C - 30°C	0.100 (0.084)	-0.000 (0.081)	0.065 (0.140)
>30°C	0.042 (0.128)	0.108 (0.179)	0.005 (0.318)
Mean of dep. var. in ref. bin	2.04	1.31	3.83
Observations	372,023	372,023	372,023
R-squared	0.057	0.032	0.094
Number of districts	509	509	509
Full set of fixed effects	✓	✓	✓
Controls	✓	✓	✓
Lags	✓	✓	✓

Notes: Table 3.C8 shows the results for a re-estimation of the main specification for placebo outcomes that should reasonably not be affected by temperature to conduct a falsification test. All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 3.D: Gender and age heterogeneity in visits and referrals

Table 3.D1: Gender heterogeneity in temperature effects on all and by cause visits

	(1) All- cause Male	(2) All- cause Female	(3) p-value Male= Female	(4) Diabetes Male	(5) Diabetes Female	(6) p-value Male= Female	(7) Cardio- vascular Male	(8) Cardio- vascular Female	(9) p-value Male= Female	(10) Respiratory Male	(11) Respiratory Female	(12) p-value Male= Female
<21°C	-6.475*** (2.319)	-9.230*** (3.327)	0.212	-0.174 (0.199)	0.031 (0.318)	0.517	-0.104 (0.369)	-1.462*** (0.563)	0.058	-0.168 (0.252)	0.085 (0.297)	0.488
21°C - 22.5°C	-3.575** (1.760)	-9.919*** (2.216)	0.001	-0.135 (0.205)	-0.280 (0.269)	0.593	0.037 (0.351)	-1.666*** (0.445)	0.001	0.033 (0.216)	0.289 (0.235)	0.452
22.5°C - 24°C	-2.923*** (1.125)	-6.741*** (1.668)	0.008	0.012 (0.108)	-0.135 (0.175)	0.464	-0.209 (0.227)	-0.407 (0.332)	0.602	-0.160 (0.155)	0.116 (0.153)	0.155
24°C - 25.5°C	-1.271* (0.682)	-4.633*** (0.802)	0.000	0.013 (0.072)	-0.204** (0.097)	0.069	-0.191 (0.142)	-0.335* (0.195)	0.558	-0.079 (0.089)	0.112 (0.098)	0.085
25.5°C - 27°C	ref.	ref.		ref.	ref.		ref.	ref.		ref.	ref.	
27°C - 28.5°C	2.858*** (0.567)	4.671*** (0.845)	0.027	0.202** (0.080)	0.138 (0.101)	0.625	0.379*** (0.128)	0.383** (0.162)	0.985	-0.062 (0.085)	0.045 (0.093)	0.415
28.5°C - 30°C	4.442*** (0.896)	6.713*** (1.276)	0.082	0.294** (0.122)	0.296** (0.130)	0.993	0.470*** (0.168)	0.655** (0.268)	0.524	-0.139 (0.139)	-0.216* (0.126)	0.684
>30°C	6.040*** (1.627)	9.294*** (2.202)	0.153	0.561** (0.221)	0.608** (0.294)	0.887	0.608 (0.408)	1.422** (0.577)	0.303	-0.771** (0.387)	0.243 (0.374)	0.081
Mean of dep. variable in reference bin	71.91	109.24		1.76	2.99		5.23	8.84		2.19	2.08	
Observations	372,023	372,023		372,023	372,023		372,023	372,023		372,023	372,023	
R-squared	0.349	0.378		0.059	0.069		0.070	0.093		0.026	0.025	
Number of districts	509	509		509	509		509	509		509	509	
Full set of fixed-effects	✓	✓		✓	✓		✓	✓		✓	✓	
Lags	✓	✓		✓	✓		✓	✓		✓	✓	
Controls	✓	✓		✓	✓		✓	✓		✓	✓	

Notes: Table 3.D1 shows the temperature effects on the number of all and by-cause visits by gender. The results are displayed graphically in Figure 3.1 in section 3.5.3. Regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.D2: Temperature effects on the number of referred patients (per 100,000) by gender

	(1) All- cause Male	(2) All- cause Female	(3) p-value Male= Female	(4) Diabetes Male	(5) Diabetes Female	(6) p-value Male= Female	(7) Cardio- vascular Male	(8) Cardio- vascular Female	(9) p-value Male= Female	(10) Respiratory Male	(11) Respiratory Female	(12) p-value Male= Female
<21°C	-0.470 (0.525)	-0.878 (0.697)	0.635	-0.021 (0.101)	0.121 (0.146)	0.311	-0.071 (0.156)	-0.168 (0.212)	0.729	-0.032 (0.056)	-0.075 (0.085)	0.645
21°C - 22.5°C	-0.453 (0.423)	-0.630 (0.618)	0.779	-0.031 (0.088)	0.016 (0.145)	0.769	-0.006 (0.139)	-0.123 (0.177)	0.606	-0.014 (0.055)	-0.005 (0.080)	0.917
22.5°C - 24°C	-0.255 (0.262)	-0.586* (0.345)	0.308	-0.046 (0.065)	-0.074 (0.109)	0.839	-0.029 (0.129)	-0.026 (0.144)	0.988	-0.063 (0.045)	-0.016 (0.050)	0.454
24°C - 25.5°C	0.062 (0.171)	-0.383** (0.169)	0.022	0.012 (0.031)	-0.023 (0.051)	0.575	0.014 (0.056)	0.013 (0.070)	0.995	-0.012 (0.035)	0.018 (0.033)	0.526
25.5°C - 27°C	ref.	ref.		ref.	ref.		ref.	ref.		ref.	ref.	
27°C - 28.5°C	0.297** (0.147)	0.441** (0.192)	0.500	0.057* (0.029)	0.014 (0.046)	0.442	0.093* (0.055)	0.047 (0.053)	0.560	0.010 (0.032)	0.050* (0.028)	0.333
28.5°C - 30°C	0.462* (0.254)	0.757*** (0.285)	0.414	0.073 (0.045)	0.044 (0.062)	0.737	0.114 (0.080)	0.253*** (0.096)	0.528	0.000 (0.041)	0.018 (0.034)	0.722
>30°C	-0.336 (0.593)	1.349** (0.685)	0.085	0.444*** (0.133)	-0.070 (0.129)	0.004	0.068 (0.184)	0.661** (0.333)	0.064	-0.010 (0.100)	0.072 (0.092)	0.576
Mean of dep. variable in reference bin	6.56	9.14		0.34	0.52		0.85	0.94		0.26	0.24	
Observations	372,023	372,023		372,023	372,023		372,023	372,023		372,023	372,023	
R-squared	0.122	0.148		0.024	0.025		0.032	0.029		0.011		
Number of districts	509	509		509	509		509	509		509	509	
Full set of fixed-effects	✓	✓		✓	✓		✓	✓		✓	✓	
Lags	✓	✓		✓	✓		✓	✓		✓	✓	
Controls	✓	✓		✓	✓		✓	✓		✓	✓	

Notes: Table 3.D2 shows the temperature effects on the number of referred patients (per 100,000) to proxy for disease severity. All regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.D3: Age heterogeneity in temperature effects on all and by cause visits

	(1) All- cause Adults (15-65)	(2) All-cause Elderly (65+)	(3) p-value Adults= Elderly	(4) Diabetes Adults (15-65)	(5) Diabetes Elderly (65+)	(6) p-value Adults= Elderly	(7) Cardio- vascular Adults (15-65)	(8) Cardio- vascular Elderly (65+)	(9) p-value Adults= Elderly	(10) Respiratory Adults (15-65)	(11) Respiratory Elderly (65+)	(12) p-value Adults= Elderly
<21°C	-7.985*** (2.573)	-7.656* (4.316)	0.942	-0.149 (0.274)	0.712 (0.931)	0.101	-1.061*** (0.346)	-0.164 (2.803)	0.344	-0.098 (0.271)	-0.739 (0.736)	0.240
21°C - 22.5°C	-6.279*** (1.959)	-12.283*** (4.214)	0.081	-0.305 (0.195)	0.060 (1.034)	0.275	-0.687* (0.353)	-3.516* (1.793)	0.000	0.263* (0.159)	-0.821 (0.657)	0.001
22.5°C - 24°C	-5.018*** (1.261)	-5.685** (2.574)	0.749	-0.076 (0.138)	-0.065 (0.560)	0.968	-0.510** (0.232)	0.556 (1.338)	0.031	0.048 (0.139)	-0.747 (0.454)	0.003
24°C - 25.5°C	-3.144*** (0.620)	-1.851 (1.574)	0.223	-0.097 (0.075)	-0.281 (0.321)	0.222	-0.246 (0.158)	-0.975 (0.815)	0.047	-0.084 (0.082)	0.302 (0.268)	0.011
25.5°C - 27°C	ref.	ref.		ref.	ref.		ref.	ref.		ref.	ref.	
27°C - 28.5°C	3.355*** (0.619)	5.778*** (1.620)	0.028	0.193** (0.078)	0.462 (0.377)	0.098	0.473*** (0.127)	0.668 (0.774)	0.495	-0.056 (0.074)	0.142 (0.283)	0.203
28.5°C - 30°C	4.914*** (0.882)	7.716*** (2.211)	0.074	0.324*** (0.107)	0.825 (0.531)	0.020	0.732*** (0.200)	0.539 (1.079)	0.646	-0.243** (0.108)	0.253 (0.324)	0.018
>30°C	7.398*** (2.054)	9.867** (4.863)	0.555	0.750*** (0.215)	0.730 (1.416)	0.963	0.978** (0.390)	5.338** (2.102)	0.000	-0.263 (0.266)	0.035 (0.677)	0.564
Mean of dep. variable in reference bin	90.51	98.78		2.55	6.28		6.74	24.78		1.90	3.33	
Observations	372,023	372,023		372,023	372,023		372,023	372,023		372,023	372,023	
R-squared	0.414	0.128		0.084	0.036		0.096	0.056		0.028	0.017	
Number of districts	509	509		509	509		509	509		509	509	
Full set of fixed-effects	✓	✓		✓	✓		✓	✓		✓	✓	
Lags	✓	✓		✓	✓		✓	✓		✓	✓	
Controls	✓	✓		✓	✓		✓	✓		✓	✓	

Notes: Table 3.D3 shows the temperature effects on the number of all and by-cause visits separately for two age groups. The results are displayed graphically in Figure 3.2 section 3.5.3. Regressions are population-weighted. Robust standard errors (in parentheses) are clustered at the district level.*** p<0.01, ** p<0.05, * p<0.1.

Appendix 3.E: Temperature bin distribution - current and predicted temperatures

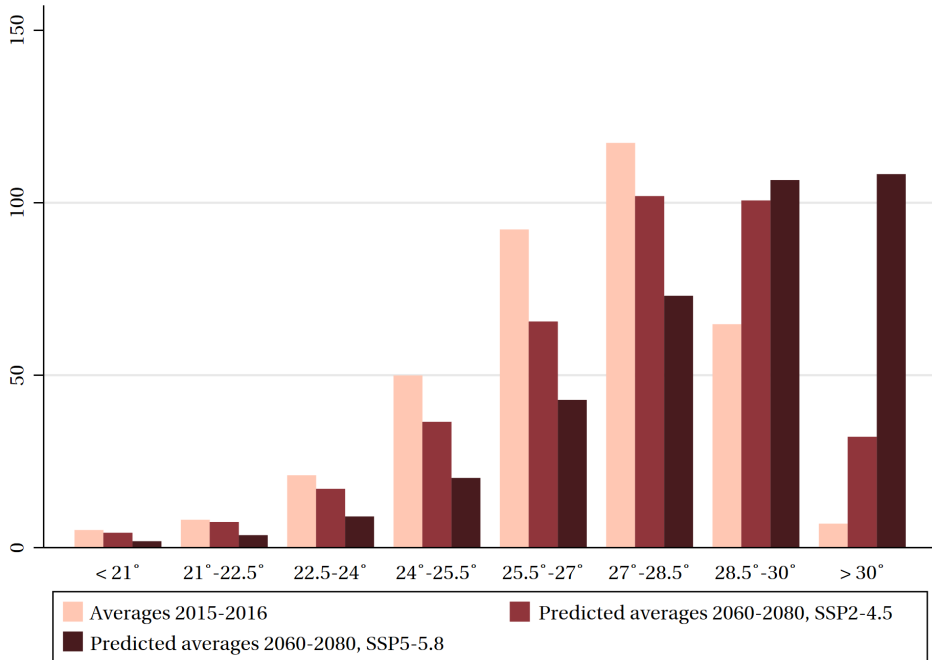


Figure 3.E1: Temperature bin distribution - current and predicted temperatures - Figure 3.E1 presents the population-weighted distribution of temperature bins for the 2015/2016 temperature data and for two climate change scenarios (SSP2-4.5 and SSP5-8.5) derived from the CNRM-CM6-1 model.

4 **Uncover your risk! Using Facebook to increase personal risk awareness and screening of type 2 diabetes in Indonesia** ^{††}

With Michael Grimm, Ingmar Weber, Elad Yom-Tov & Benedictus Praditya

Abstract: We assess whether social media – in particular Facebook – can serve as an efficient and cost-effective instrument to increase type 2 diabetes awareness and encourage risk screening activities in Indonesia, where the prevalence of the disease and with it the rates of undiagnosed cases have dramatically increased in the last decade. We use Facebook’s advertisement function to randomly distribute graphical ads related to the risk and consequences of diabetes to Facebook users above the age of 35 in Jakarta and Yogyakarta. The ads differ in their message (“theme”) and graphical design, but equally invite viewers to visit an information website on which they can participate in a diabetes self-screening activity. Depending on their determined risk score, participants receive a recommendation to contact a physician and ask for an in-depth screening. We find that the ad themes that we label “information” and “shock” outperform all other themes in terms of creating link clicks and completed screening questionnaires. A follow-up survey six weeks after the online screening suggests that approximately 28% of high-risk respondents plan to schedule (or already have scheduled) an appointment for a professional screening. The complementary cost-effectiveness analysis shows that such an online public health campaign can be very cost-effective with a cost of approximately US\$9 per newly diagnosed person with type 2 diabetes.

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4.1 Introduction

The global number of people living with diabetes has risen sharply in the last decades and has reached 537 million by 2021, with more than 90% being attributed to type 2 diabetes (International Diabetes Federation, 2021). Approximately 80% of affected individuals nowadays live in low- and middle-income countries, where not only the absolute number of cases but also prevalence rates have been rising more rapidly than in high-income countries (International Diabetes Federation, 2021; World Health Organization, 2021). To counteract this trend, the 2011 United Nation High-Level Meeting on Non-Communicable Diseases (NCDs) has set the global target to halt the increase in diabetes by 2025 (World Health Organization, 2013a; Zhou et al., 2016), which, however, is currently far away from being reached. Most low- and middle-income countries face a double burden of infectious diseases, that are still among the leading causes of death, and rising numbers of death due to non-communicable diseases, hence expenditures to curb the number of diabetes cases compete with many other priorities in the public health sector. Low cost and easy to implement interventions to prevent and control diabetes could therefore be of great help in many of these countries. When diabetes is sufficiently early detected, it can be effectively treated by medicinal, lifestyle and dietary changes. If undetected and untreated, however, it can have detrimental health consequences, such as eye and kidney damage, neuropathy and, in the most severe cases, stroke and death. The unawareness of the disease and its related risk factors and symptoms and the belated or never occurring diagnosis are therefore major obstacles in the fight against diabetes.

In this study, we design and introduce an online awareness campaign implemented via the social media platform Facebook and analyze whether it can serve as a cost-effective solution to increase the risk awareness of type 2 diabetes and to encourage individuals to complete a self-screening risk test similar to the diabetes risk test of the American Diabetes Association (American Diabetes Association, 1993, 2019) and the diabetes FINDRISC questionnaire (Lindstrom and Tuomilehto, 2003). Specifically, we randomly distribute advertisements that differ in their message (“theme”), framing and graphical design via Facebook, which encourage viewers to click on the ad and thereby being directed towards a website. On this website, we provide informational material about diabetes, its risk factors, symptoms and consequences and individuals are invited to complete the self-screening questionnaire. After completion, participants received an assessment of their personal risk together with recommendations for keeping a low risk or how to encounter a medium or high risk, including the recommendation to contact a physician or a primary health care facility to undergo a professional diabetes screening.

As a showcase of our campaign we use Indonesia, yet we argue that such a cam-

campaign can be equally well implemented in other low- and middle-income countries. In Indonesia, diabetes currently presents the third leading cause of death (Centers for Disease Control and Prevention, 2020) and the country ranks fifth in the list of absolute numbers of diabetes cases worldwide (International Diabetes Federation, 2021). More concerningly, Indonesia ranks third among the countries with the highest undiagnosed cases worldwide. By the end of 2019, more than 10 million individuals were estimated to live with the disease in Indonesia with more than 70% of the cases remaining undiagnosed (International Diabetes Federation, 2021).

With our campaign we target all Indonesian male and female Facebook users above the age of 35, which live either in the city Jakarta or in the Special Region of Yogyakarta (*Daerah Istimewa Yogyakarta*) – the two regions with the highest diabetes prevalence rates in the country (Kementerian Kesehatan Republik Indonesia, 2018). The population of the two regions amounts to 14.23 million and thereby represents 5.4% of the total Indonesian population and almost 10% of the urban population. In Indonesia's urban areas, which also have higher diabetes prevalence rates than rural areas, internet penetration rates and usage of social media platforms are high, suggesting that an online awareness campaign about diabetes could indeed be a very cost-effective instrument to increase diabetes awareness and encourage screening activities. As of January 2022, the internet penetration rate in Indonesia stood at 76.3%, with 94% of all users accessing the internet via smartphones (Internet World Stats, 2022; Kepios, 2022). The social media platform Facebook is especially widely used in the country and therefore offers the great potential to serve as platform for information sharing and spreading. By mid-2021, Facebook had 176 million Indonesian users – corresponding to 64% of the entire population (Internet World Stats, 2022).

With this campaign and the accompanying study, we aim to answer the following research questions: First, can informational ads distributed via Facebook encourage viewers to visit an information website about diabetes and to conduct a self-screening diabetes risk test? Second, which type of ad (with respect to the graphical design and theme) is most effective in encouraging viewers to visit an information website about diabetes and to conduct a self-screening diabetes risk test? Third, what are the characteristics of those who participate in the screening questionnaire compared to the universe we target and what is their diabetes risk score? Fourth, what is the cost per view, per generated website visit and per completed screening questionnaire and can such a campaign be considered a cost-effective public health intervention? Fifth, what is the compliance rate with respect to the received recommendation to schedule an appointment for a professional screening?

We contribute to the literature in several ways. First, we contribute to the lit-

erature that focuses on awareness raising, prevention and uptake of screening for NCDs in low- and middle-income countries, especially in Southeast Asia (Capuno et al., 2021; de Vries Mecheva et al., 2021; Dukpa et al., 2015; Marcus et al., 2022). This literature is of special policy relevance, given that health care systems in low- and middle-income countries are still to a large extent focalized on infectious, maternal, neonatal and nutritional diseases, despite an ever-increasing health burden due to NCDs (Dans et al., 2011; Kostova et al., 2017; Manne-Goehler et al., 2019). Second, we contribute to the growing literature that shows that Facebook is a promising tool for health-related information campaigns (e.g., Parackal et al., 2017; Pereira da Veiga et al., 2020), for health-related research study recruitment (Thornton et al. (2016) provide a comprehensive review) as well as an increasingly relevant tool for scientific research especially in terms of implementing randomized controlled trials (RCTs) and field experiments (Breza et al., 2021; Gordon et al., 2019; Levy, 2021; Orazi and Johnston, 2020). Our study, however, stands out as one of the very first to implement a health-related field experiment via Facebook in a middle-income country context. Lastly, we contribute to a literature mainly rooted in psychology that explores what kind of framings or pictorial contents drive health-related decisions (Gallagher and Updegraff, 2012; Hall et al., 2022; Krishnamurthy et al., 2001; Kuehnle, 2019; Rothman and Salovey, 1997) and whether exposure to information improves health behavior (Dammert et al., 2014; Kim et al., 2019; Slade, 2012). Specifically, we provide evidence about which psychological channels can effectively incentivize individuals to learn about their risk of having or developing diabetes in a country where the general awareness of the disease is low.

The remainder of this article is structured as follows. Section 4.2 summarizes the contextual background about diabetes in Indonesia. Section 4.3 presents the experimental design of the Facebook health campaign and the different ads in detail. Section 4.4 describes the data that we collected, while Section 4.5 presents the empirical strategy and results. Section 4.6 discusses cost-effectiveness and Section 4.7 concludes.

4.2 Contextual background

Indonesia currently faces a public health problem with diabetes that has reached epidemic proportions. The latest Indonesian Basic Health Research from 2018 (RISKESDAS) revealed that the diagnosed diabetes prevalence rate for individuals above the age of 35 was 3.5%, while the rate of individuals with diabetes according to blood sugar testing was 14%. These numbers imply that the prevalence rate increased by almost 25% since the previous RISKESDAS in 2013 and that about 75% of all cases remain undiagnosed. Additionally, the RISKESDAS data show that one

in three adults (30.6%) suffers from impaired glucose tolerance, i.e., pre-diabetes, and therefore has an increased risk of developing type 2 diabetes in the future (Kementerian Kesehatan Republik Indonesia, 2018).

The high number of undiagnosed cases is driven by a low awareness of diabetes in the general public as well as among health care workers and policy makers. With respect to the general population, several studies report that low levels of knowledge about diabetes symptoms, risk factors and treatment possibilities prevail. For example, Kristina et al. (2020) in their study in rural Yogyakarta find that 46% of respondents have poor knowledge of diabetes risk factors, and even worse knowledge in terms of diabetes management and treatment possibilities. Bakti et al. (2021) conducted a study on public knowledge of diabetes and hypertension in metropolitan cities in Indonesia and found that on average 35% of the knowledge questions regarding diabetes symptoms and risk factors were answered incorrectly. On the health care provider side, especially the awareness of and adherence with diabetes screening guidelines as well as knowledge about the disease seems to remain low. Widyahening et al. (2014) conducted a study with 400 general practitioners and found that even though health care professionals do know the risk factors and symptoms of the disease, a high share of them is unaware of the recommendation that patients at risk should regularly be screened for high blood sugar levels. Ligita et al. (2018) provide an extensive literature review on the profile of diabetes healthcare professionals in Indonesia and conclude that they often lack skills and knowledge in providing diabetes education and care. Further, Widyaningsih et al. (2022) present evidence that health workers in the national community-based screening program for diabetes and hypertension (*POSBINDU*) suffer from unsatisfactory knowledge about the disease and lack the required abilities for health screening and education. These findings imply that individuals need to be aware of their individual risk status to demand a professional screening. Hence, raising individual awareness of diabetes is an important first step in the process of disease prevention and treatment in the given context.

The high prevalence rate of diabetes comes not only with an immense health burden but also implies immense costs and substantial economic losses. A modeling study by Bloom et al. (2015) estimates that the expected economic output loss for Indonesia due to diabetes will amount to US\$11 billion per year for the period 2012-2030. Additionally, in light of limited governmental health expenditure (less than 3% of GDP) and a national health insurance scheme (BPJS/JKN) that has suffered from financial deficiencies ever since its implementation, cost-effective health interventions could help to ensure the financial sustainability of the scheme (BPJS Kesehatan, 2015, 2016; Deloitte Indonesia, 2019; Prabhakaran et al., 2019; World Bank, 2022). While Indonesia's current NCD policy encompasses preventive diabetes and hypertension screening activities at the community level,

this policy has been found to suffer from sub-optimal implementation and targeting, low participation rates, inadequate coverage and lack of human and financial resources, which undermine its cost-effectiveness (Alfiyah and Pujiyanto, 2019; Rattanavipapong et al., 2016; Widyaningsih et al., 2022).

With our campaign and study, we aim to address both aspects, awareness and cost-effectiveness, by assessing whether Facebook can serve as instrument to distribute health-related information on a large scale with limited financial resources.

4.3 Experimental design

From March 15 until April 5 2022, we ran a diabetes health campaign entitled “Ada Gula, Ada Diabetes”¹ via Facebook’s advertisement function, which allows to distribute self-designed ads and videos to Facebook users while using specific demographic and geographic targeting criteria. This advertisement tool was originally developed for businesses to boost their customer base and increase sales, yet, it is increasingly also used by scientific researchers to recruit survey participants (Ananda and Bol, 2021; Choi et al., 2017; Grow et al., 2020; Kosinski et al., 2015; Thornton et al., 2016). While using the tool for the recruitment of survey participants is indisputable practical, it does offer an even more sophisticated and scientifically valuable function that allows to implement randomized controlled trials. Facebook’s A/B split test allows to randomly distribute two or more ads to evenly split and statistically comparable audiences to test which ad performs best in terms of a pre-specified campaign target (Meta, 2022a). Hereby, the ads can differ in their design or placement, depending on which variable is sought to be tested. This A/B test design also ensures that the same budget is allocated to each ad and hence avoids that Facebook’s algorithm determines the budget allocation which could generate unbalanced Facebook user exposure rates across ads.

We designed five different ads that each referred to a different theme and psychological channel to test which type of ad content performs best in the given context. We entitled these themes “family”, “geography”, “information”, “religion” and “shock”. The themes and ads are described in more detail below and all graphics are displayed in Figure 4.A1 to Figure 4.A6 in Appendix 4.A.

1. Family: The family ad pictured an Indonesian family of three generations and contained the message that every family can be affected by diabetes.

¹The title of the campaign is related to the traditional Indonesian saying “Ada gula, ada semut”, which literally means “When there is sugar, there must be ants”. Figuratively, the saying means that for every action there is an equal and opposite reaction. Our adapted campaign name hence figuratively interprets diabetes as the reaction to too much sugar – also in relation to the fact that diabetes is known as “Sakit Gula” (“sugar disease” or “sugar sickness”) in Indonesia. Several Facebook comments that were posted below our ads indicated that ad viewers understand this adaptation of the original saying.

2. Geography: One geography ad was designed for each of the two regions in our study (Jakarta and Yogyakarta). The graphics showed a landmark of each of the two cities (the National Monument in Jakarta and the Yogyakarta Monument in Yogyakarta, respectively) covered in sweets. The message referred to the local prevalence rates of diabetes in each of the regions.
3. Information: The information ad contained a statement about the possible health consequences of diabetes. The graphic showed a wooden mannequin on which the body parts that can be affected by diabetes were marked.
4. Religion: The religion ad presented a cooking Indonesian woman with Hijab and contained a statement from the Quran that conveyed the message that one should not live a potentially self-harming life.
5. Shock: The shocking ad pictured a man in front of a tomb and contained the message that diabetes can have deadly consequences.

In addition to the messages outlined above, each ad carried the statement “Learn about your diabetes risk now” (“Pelajari tentang risiko diabetes Anda sekarang”) to encourage the ad viewers to click on the ad and visit the campaign website.

Technically, we ran two different campaigns, one for each of the targeted regions, and then pooled the data for the analysis. Each ad received an equal budget of US\$5 per day, summing to a total daily budget of US\$50 for both cities together. In terms of the target population, we restricted the audience demographically to Facebook users above the age of 35 and geographically to users living in either Jakarta or Yogyakarta.

The campaign objective was chosen to optimize “conversions”, with conversion being programmed to be equal to the completion of the screening questionnaire. Setting “conversions” as the campaign objective (instead of the other two possibilities “awareness” or “consideration”) allowed us to focus on possible questionnaire completers which would thus gain from the campaign, while simultaneously preventing to show the ads to seemingly uninterested users. This conversion objective requires the generation of a so-called Facebook Pixel code, which needs to be embedded in the code of the landing website to which the ad viewers are redirected. Thereby, Facebook can track user actions that happen on our website and optimize accordingly. This implies that after a learning phase, Facebook’s algorithm aims to show the ads to individuals more likely to complete the screening questionnaire, based on the characteristics of earlier completers. While this internal algorithm exaggerates the self-selection bias if the conversion objective is used in regular campaigns (Neundorf and Öztürk, 2021), the use of the A/B split test ensures that conditional on being in the target audience the ad version the user sees is random. This

randomization procedure allows to compare the different ads in their effectiveness to generate clicks and conversions, i.e., completed screening questionnaires, and hence to test which kind of thematic approach would be well suited in the context of Indonesia to raise awareness about a health concern and which approach can effectively encourage individuals to search for more information.

After clicking on one of the ads in Facebook, individuals were redirected to the landing page of the campaign website (<https://adagulaadadiabetes.com/>). Before being able to browse further on the website, the participants were informed about our privacy policy and that data generated on the website were used for an academic study. For both they then had to indicate their consent.

On this website, individuals were offered the opportunity to conduct a diabetes risk test similar to the diabetes risk test of the American Diabetes Association and the diabetes FINDRISC (Finnish Diabetes Risk Score) screening test.² The questionnaire version we used is an adapted and translated version specifically for the Indonesian population (the complete questionnaire and scoring system are presented in Appendix 4.B).³ It consisted of eleven questions which can be answered in approximately 90 seconds. Based on the individual answers, a risk score between 0 and 16 points was calculated and participants received an assessment of their personal risk in terms of low risk (0-3 points), medium risk (4-5 points), or high risk (6 or more points). Additionally, the assessment contained recommendations on how to keep the risk low, how the diabetes risk can be reduced and to visit a health center or a physician in case the risk score was too high.

Moreover, the website contained a page with factual information on diabetes in Indonesia including the distribution of prevalence rates across the country and medical risk factors, as well as information about how diabetes can be diagnosed and how it can be treated. Further, we provided detailed information about the institutions involved in the research activities, the aim of the campaign and the notification that the campaign was purely educative and could not replace a professional health visit or screening activity.

We also asked participants to leave their e-mail address so that they could get follow-up information and further be involved in the study. Six weeks after the end of the campaign we sent to all these addresses a follow-up survey to elicit informa-

²The original FINDRISC questionnaire was developed by Lindstrom and Tuomilehto (2003) to identify individuals at risk of diabetes using a Finnish population sample. Since then, the questionnaire has been evaluated and validated many times and has been adjusted to different population and country samples, e.g., the LA-FINDRISC for Latin America (e.g., Muñoz-González et al., 2019; Nieto-Martínez et al., 2017) or the ModAsian FINDRISC for Asia (e.g. Ku and Kegels, 2013; Lim et al., 2020). The original diabetes risk test of the American Diabetes Association dates back to 1993 and has likewise been adapted multiple times (e.g. Fauzi et al., 2022).

³The used version is based on the diabetes risk test of the American Diabetes Association (1993, 2019), the ModAsian FINDRISC for Asia, the FINDRISC Bahasa Indonesia (Rokhman et al., 2022) and the Malay version of the American Diabetes Association diabetes risk (Fauzi et al., 2022).

tion about actual compliance with the recommendations received. Since providing the mail address was voluntary and hence the sub-sample of respondents is subject to a potential self-selection bias, we provide a description of the sample that completed this follow-up survey and contrast it with the profile of the entire sample. Yet, we believe it is not unlikely that among those who did not leave their e-mail address or left their e-mail address but did not respond to the survey, also a sizable share followed up on the recommendation. They may simply not have perceived a need to get follow-up information.

Our study was pre-registered at the AEA RCT Registry (0008781, <https://doi.org/10.1257/rct.8781>) and received ethical approval from the University of Passau Research Ethics Committee (15.03.2022, IRB Approval Number I-07.5090/2022).

4.4 Data

In the following we present and describe the data that we collected through Facebook, the summary statistics derived from the screening questionnaire, and the data we collected through the additional follow-up survey.

4.4.1 Facebook data and screening questionnaire

Table 4.1 presents the Facebook statistics by age, gender and location. This engagement data is provided directly by Facebook to the campaign implementer. With our campaign we reached in total 286,776 individuals, generated 758,977 impressions (distinct views of the ads) and generated 5,278 link clicks. This amounts to a click rate of 1.84% (relative to the reached individuals), which is higher than the rates achieved in studies with a similar set up as, for example, in Choi et al. (2017) (1.4%) or Orazi and Johnston (2020) (0.2%). Overall, we spent approximately US\$1,060 and the campaign resulted in 2,052 started and 1,469 completed screening questionnaires (a conversion-to-reach rate of 0.51% (1,469/286,776) and a conversion-to-click rate of 27.83% (1,469/5,278)).

Due to changes in Apple's data policy, Facebook is unable to track users that opted out of tracking under iOS 14 or users that prohibit tracking in any other form and therefore relies on statistical modeling to estimate the total number of conversions (Meta, 2022c). Moreover, Facebook is unable to differentiate by age or gender, once the users leave the platform and thus only provides aggregated data on conversions. Hence, for the results in terms of conversions (Column (5)), we rely on the more accurate data that were collected directly on our campaign website from which we could extract – without any loss or modeling – the absolute number of completed (and started) screening questionnaires also by age, gender and location.

Table 4.1: Aggregate statistics of the Facebook campaign

	(1) Reach	(2) Impressions	(3) Link clicks	(4) Expenditure (in US\$)	(5) “Conversions” (compl. quest.)
Total	286,776	758,977	5,278	1,066.04	1,469
<i>By Gender</i>					
Male	160,560 (56%)	433,677 (57%)	2,725 (52%)	570.91 (54%)	754 (51%)
Female	126,216 (44%)	325,300 (43%)	2,549 (48%)	495.13 (46%)	715 (49%)
<i>By Age</i>					
Below 45	136,500 (48%)	342,729 (45%)	1,646 (31%)	372.01 (35%)	466 (32%)
45-54	98,060 (34%)	271,914 (36%)	2,091 (40%)	421.23 (40%)	686 (47%)
55-54	32,820 (11%)	90,314 (12%)	978 (19%)	188.42 (18%)	238 (16%)
Above 65	19,396 (7%)	54,020 (7%)	559 (11%)	83.37 (8%)	79 (5%)
<i>By Location*</i>					
Jakarta	145,528 (51%)	321,154 (42%)	2,834 (54%)	526.75 (49%)	876 (60%)
Yogyakarta	141,248 (49%)	437,823 (58%)	2,440 (46%)	539.29 (51%)	567 (40%)

Notes: *The number of completed screening questionnaires by location does add up to 1,443 and not to 1,469 since for 26 completed questionnaires tracking was restricted and the referring ad and thus the location could not be determined.

We used Facebook’s dynamic URL parameters (Meta, 2022b) to generate ad specific referrer links, containing information about the ad id, ad name and ad placement. These URL parameters could then be read out on our campaign website whenever an individual started to fill out the screening questionnaire. However, for those individuals who opted out of tracking, the ad specific URL parameters within the referrer link would not be displayed. Yet, given that a vast majority of smartphone users in Indonesia relies on an Android system, only 26 (out of 1,469) completed screening questionnaires could not be linked to the ad from which users were re-directed to our campaign website.

We did not restrict the possibility to complete the screening questionnaire multiple times. We did so to allow for possible spillover effects, for example when a user after completion of the screening questionnaire re-did the screening for another person. This, however, also implies that the same person could fill out the screening questionnaire multiple times with differing information, for example to check for related changes in the obtained risk score. The individual link id together with the IP address and browser information, however, allows us to identify repeated survey questionnaires that were completed from the same device. We therefore construct a data sample in which we drop the observations that stemmed from repeated questionnaires, i.e., for each link id \times IP address combination, we keep only the first completed observation in our sample. We use this first observation based on the assumption that a person filling out the questionnaire multiple times would

do so first for him- or herself and potentially only afterwards for another person. Similarly, we assume, if it is filled out multiple times out of curiosity, one would enter the true data the first time and hypothetical data only afterwards. This procedure led to a reduction from 1,533 completed questionnaires (with duplicates) to an individual sample containing the 1,469 completed screening questionnaires presented in the summary statistics.⁴ We will use this reduced individual sample throughout the paper as the main sample. This is especially important for the analysis of ad performance – since a repeated questionnaire does not imply a repeated click on the viewed ad, and we thereby prevent to overestimate ad performance.

Table 4.2: Summary statistics of completed screening questionnaires

	(1)	(2)	(3)	(4)
	Mean	SD	Min	Max
Age distribution				
<i>Below 45</i>	0.32		0	1
45-54	0.47		0	1
55-54	0.16		0	1
<i>Above 65</i>	0.05		0	1
Female	0.49		0	1
Ever had high blood glucose	0.50		0	1
Ever diagnosed with high blood pressure	0.33		0	1
Family member with diagnosed diabetes	0.54		0	1
Weight	69.28	17.10	33	185
Height	162.43	7.84	140	195
BMI	26.15	5.61	11	70
Daily physical activity	0.60		0	1
Smoking				
<i>Never smoked</i>	0.66		0	1
<i>Stopped smoking</i>	0.20		0	1
<i>Currently smoking</i>	0.14		0	1
Daily fruit consumption	0.45		0	1
Daily sweet beverages consumption	0.30		0	1
Risk score	6.37	2.57	0	14
<i>Low risk</i>	0.14		0	1
<i>Medium risk</i>	0.25		0	1
<i>High risk</i>	0.61		0	1
Provided e-mail address	0.14		0	1
Number of observations	1,469			

Notes: Table 4.2 displays the summary statistics of the completed screening questionnaires for the main sample without repeated answers.

Table 4.2 presents the summary statistics of the completed screening questionnaires for the main sample. Summary statistics including the information for all started questionnaires and for the sample of completed questionnaires including any duplicates are presented in Table 4.C1 and 4.C2 in Appendix 4.C.

⁴We observe 45 link id × IP address combinations that completed the questionnaire twice, five link id × IP address combinations that completed the questionnaire three times and one link id × IP address combination that completed the questionnaire four times.

The average user completing the diabetes risk screening questionnaire on our campaign website is between 45 and 54 years old, has a BMI of about 26 and a high diabetes risk with an average risk score of 6. Men and women are almost equally represented. Half of the respondents report to have ever been told to have high blood sugar levels and one third has ever been diagnosed with high blood pressure levels. In terms of smoking, 34% of participants report to be ever-smokers, (i.e., either currently smoke or have smoked previously, but stopped now). This average smoking rate, however, obscures a strong gender heterogeneity, with 8% of women and 57% of men in our sample being ever-smokers; a trend that is also well in line with the tobacco consumption pattern in Indonesia observed in RISKESDAS 2018 (with 3.2% female and 65% male ever-smokers, respectively, for the total Indonesian population above the age of 10). Sixty percent of the respondents report to conduct at least 30 minutes of physical activity per day, while only 45% report to consume fruit or vegetables on a daily basis. Thirty percent of the respondents report to consume sugary beverages every day.

The summary statistics of the started screening questionnaires (Table 4.C1 in Appendix 4.C) reveal that a large share of survey starters dropped out after the first question (9%) and another large share before the question about participants' weight and height (10%). Overall, 75% of started screening questionnaires were completed. Of all completers, 205 (14%) left their e-mail address to be contacted for further study activities. To this sub-sample, we sent a follow-up survey six weeks after the end of the Facebook campaign. The full workflow together with the number of observations at each step is presented in Figure 4.1.

4.4.2 Follow-up survey

Of the 205 participants who left their e-mail address and agreed to be recontacted again for further research activities, 53 participated in the follow-up survey. In this follow-up survey, we asked the respondents whether they remembered their risk level from the screening questionnaire and about their plans to comply with the received recommendations. Specifically, we asked whether they plan to schedule a professional medical screening (or have already done so), if yes, when and where they planned to go and if no, what their reasons were for not doing so. We also asked what types of activities (such as conducting more physical activity or eating healthier) they planned to conduct to reduce the risk of diabetes. Moreover, the follow-up questionnaire included several knowledge questions about diabetes risk factors, symptoms and long-term health consequences, a question whether the respondent possesses a health insurance, whether it was the first time conducting a diabetes risk test, and, if they were already aware of their diabetes diagnosis, whether they were currently on medication.

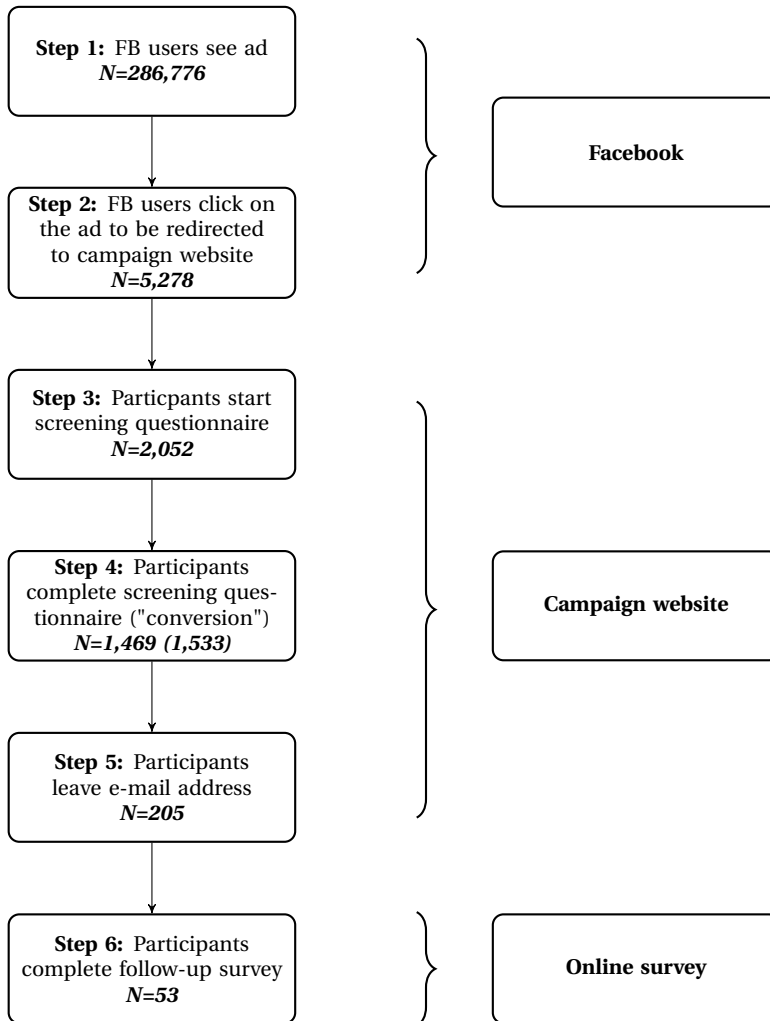


Figure 4.1: Workflow of the experiment - The number 1,533 in parentheses at Step 4 refers to the number of completed questionnaires when duplicated questionnaires are also counted. FB: Facebook

4.5 Empirical specification and results

4.5.1 Empirical specification

We start our empirical analysis with the evaluation of which of the five ad themes is most effective in generating link clicks and conversions. To do so, we estimate the following logistic regressions

$$P(\text{Link click}_i = 1 | \text{Ad theme}_i^j, \mathbf{Z}_i) = \lambda\left(\beta_0 + \sum_{j=1}^4 \beta_j \text{Ad theme}_i^j + \beta \mathbf{Z}_i + u_i\right) \quad (4.1)$$

and

$$P(\text{Conversion}_i = 1 | \text{Ad theme}_i^j, \mathbf{Z}_i) = \lambda\left(\delta_0 + \sum_{j=1}^4 \delta_j \text{Ad theme}_i^j + \delta \mathbf{Z}_i + e_i\right) \quad (4.2)$$

where λ is the logistic function, $\sum_{j=1}^4 \text{Ad theme}_i^j$ is a set of four dummy variables that are equal to one whenever person i saw the ad theme j (the ad theme “family” serves as reference group), \mathbf{Z}_i is a vector of control variables (age, gender, region), and u_i (e_i) is the error term. Note that the coefficients β_j and δ_j can be interpreted as causal effects since the ad themes were randomly assigned to Facebook users.

4.5.2 Main results

Figures 4.2 and 4.3 together with Tables 4.D1-4.D4 in Appendix 4.D display the results for link clicks and conversions for the total sample and separately for men and women. Figures 4.2 and 4.3 show the relative increases in comparison to the “family ad”, which implies a reference click-to-reach-ratio of 1.7% and a reference conversion-to-reach-ratio of 0.4%. Tables 4.D1-4.D2 in the Appendix display the regression coefficients and marginal effects from the logit model; Tables 4.D3-4.D4 present complementary results from an OLS model.

The top graph for the full sample in Figure 4.2 shows that we can establish a clear hierarchy in terms of ad effectiveness for generating link clicks. The ad themes “geography” and “family” are the least performing, while the theme “information” outperforms all four other themes. In terms of the effect size, a user seeing the ad theme “information” was 24% and 25% more likely to click on the ad compared to someone who saw the theme “family” or “geography”, respectively. The ad themes “shock” and “religion” are not significantly different from each other in their effec-

tiveness to generate links, but both perform significantly better than the themes “geography” and “family” (results for pairwise t-tests are shown in Table 4.D1). Differentiating the ad theme effectiveness by gender (graphs b and c) shows that the differential effectiveness is mainly driven by women, while men reacted to all themes in a more similar manner.

In terms of the user characteristics, women were 24% more likely to click on an ad, and the two age groups 55-64 and 65+ were more likely than younger users to click on an ad (see regression results in Tables 4.D1-4.D3).

Turning to conversions, Figure 4.3 (graph a) shows a slightly different picture. While “information” is again the best performing theme in generating conversions, the performance of the “religion” theme is no longer significantly different from the “family” theme. Instead, the “geography” theme is now significantly more effective than the “family” and “religion” themes and equally effective as the “shock” theme in generating conversions. Differentiating by gender (graphs b and c) reveals, however, that the effectiveness of the “geography” ad is solely due to a female response to this theme, while for men the responsiveness to the “information” theme is greatest and the ad performs significantly better compared to all other themes with the exception of the “shock” theme (p-value 0.151).

Women are also more likely (+21%) to complete a screening questionnaire conditional on seeing one of the ads compared to their male counterparts. Yet, given that the number of women seeing an ad on Facebook was lower in absolute terms (since there are generally less female Facebook users than male users in Indonesia (Statista, 2022b)), the sample of completed questionnaires is balanced in the gender distribution. Although the oldest age group (65+) was more likely to click on the ads than users below 45, they are less likely to complete the questionnaire once being re-directed to the website. Specifically, when we regress the probability of attrition on participants’ characteristics (conditional on having started the screening questionnaire), we find that elderly above the age of 65 are 34 percentage points more likely to drop out in the course of the questionnaire compared to the youngest age groups. This effect is larger for elderly men, though not statistically different from the female effect (results shown in Table 4.D5 in Appendix 4.D).

We also find a pronounced difference between the two cities in terms of conversions. While Facebook users in both cities were similarly likely to click on the ads, users based in Jakarta were significantly more likely to complete the screening questionnaire.

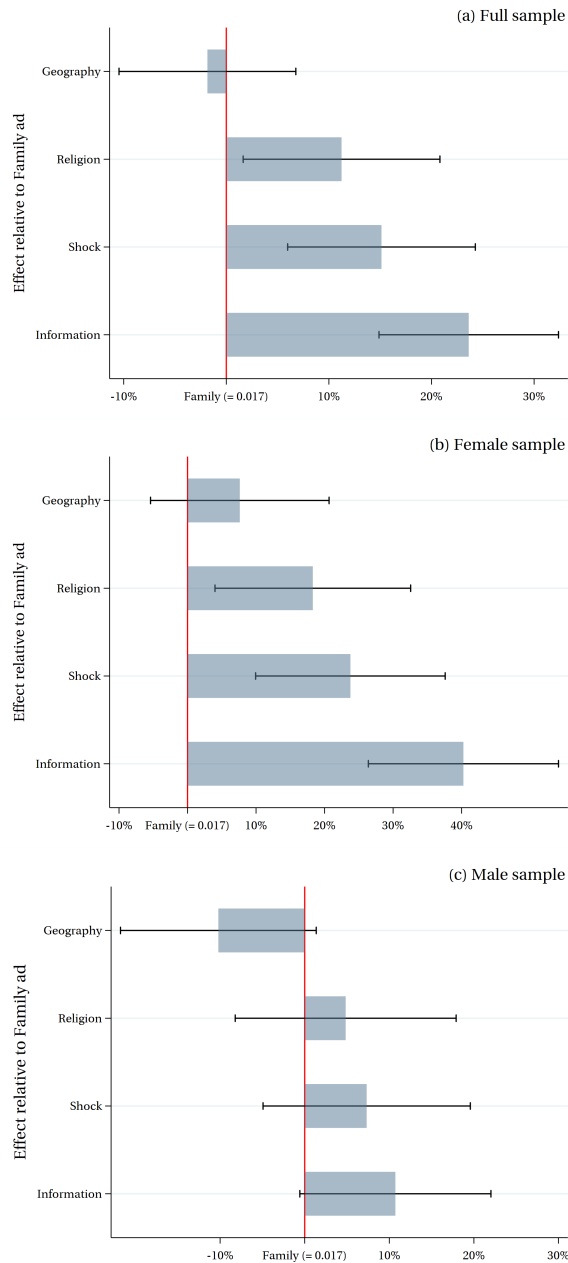


Figure 4.2: Ad effectiveness for link clicks - Figure 4.2 shows the effectiveness of the different ad themes in terms of link clicks. The effects are presented as relative effect to the “family ad”, which serves as reference category. Black whiskers present the 95% confidence intervals.

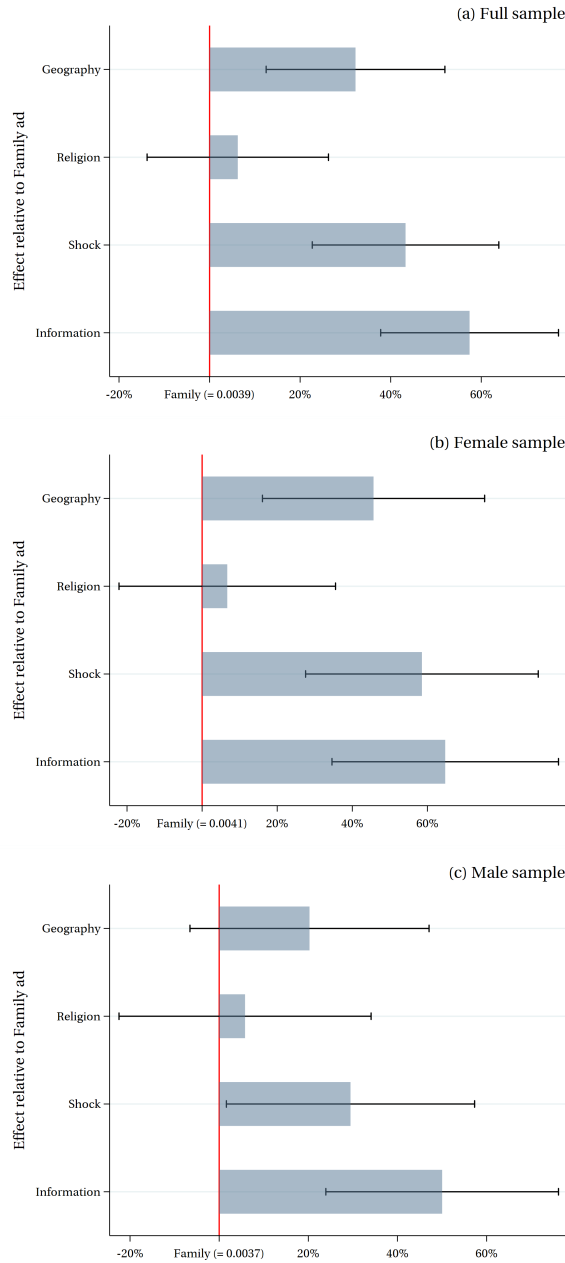


Figure 4.3: Ad effectiveness for conversions - Figure 4.3 shows the effectiveness of the different ad themes in terms of conversions. The effects are presented as relative effect to the “family ad”, which serves as reference category. Black whiskers present the 95% confidence intervals.

4.5.3 Comparison of the sample and a benchmark population

Next, we describe to what extent our generated sample of participants who completed the screening questionnaire differs from the universe of people that meet our eligibility criteria in Jakarta and Yogyakarta. To do so, we rely on different data sources: We use the official population statistics from the Indonesian Statistics Office (BPS) (Badan Pusat Statistik, 2022), we derive health data for prevalence rates of high blood sugar and high blood pressure as well as data on risk factors (smoking, physical activity, diet) for the population above the age of 35 from RISKESDAS 2018 and lastly, we rely on primary survey data from the project SUNI-SEA – a large-scale, international policy and research project that implements NCD interventions in Southeast Asia and in which two of the authors (MF and MG) are involved. From this project, we use data collected in the two urban regions Kota Surakarta (Central Java) and Kota Kediri (East Java) on the topic of NCD screening activities. Although this sample does not present a representative sample for the cities Jakarta and Yogyakarta, it covers a randomly selected sample of individuals living in two urban areas on the same island as Jakarta and Yogyakarta (Java), and therefore provides an urban-Java-specific benchmark for the information that were not available in the representative sample of the RISKESDAS data.

Table 4.3 compares the data collected in the screening questionnaire with the population benchmark data from BPS, RISKESDAS and the data from SUNI-SEA, depending on the data availability. Column (1) contains the mean of the given variable from our generated data from the screening questionnaire, Column (2) presents the mean of the given variable from the comparison data, Columns (3) and (4) contain the information about the sample size and data source of the comparison data.

In comparison to the age distribution derived from the BPS statistics, the distribution generated in our experiment is slightly skewed towards the age group 45-55 and especially the group above the age of 65 is underrepresented in our sample. This is, however, not surprising, given that Facebook is over-proportionally used by younger cohorts in Indonesia (Statista, 2022a). Yet, it means that a Facebook campaign such as ours is less suited to address older generations as they are less often represented on social media platforms. In contrast, it can very effectively encourage the middle-aged generation in the age span of 45-54 years to conduct a self-screening activity online. This is an important finding, given that the risk of developing type 2 diabetes rises significantly after the age of 45 and regular diabetes screenings are recommended from the age of 45 onward by the Indonesian Endocrinology Association (Soelistijo et al., 2021). In terms of the composition by sex, our generated sample can be considered statistically similar to the total population in Jakarta and Yogyakarta. There are no significant differences in the gender

distribution between our data and the benchmark population.

Fifty percent of the respondents of the screening questionnaire claim to have ever been found to have high blood sugar. Unfortunately, there is no similar question being asked in RISKEDAS for comparison. However, the share of individuals above the age of 35 having ever been diagnosed with diabetes by a doctor is equal to 3.5% in the total Indonesian population and 6% in Jakarta and Yogyakarta, the shares of individuals with diabetes and pre-diabetes according to blood testing in total Indonesia are 14% and 30%, respectively, implying that only 25% of the individual with diabetes are aware of it. The sample from the SUNI-SEA project indicates that 62% have ever been screened for high blood sugar levels.

Certainly, we cannot make a statement about how the term “high blood sugar level” was interpreted by the respondents in our questionnaire and having high blood sugar levels does not always imply (pre-)diabetes. Yet, such a high share implies a certain level of awareness about the possibility of having high blood sugar as well as a comparably higher risk in contrast to the benchmark population. Hence, taken together, it seems that we over-proportionally attract individuals who have at least once been tested for high blood sugar levels and had a positive test outcome. Similarly, the share of individuals having ever been diagnosed with high blood pressure or taking anti-hypertensive medication in our sample is significantly higher than in the benchmark population (33% vs. 16%), even though it is still smaller than the prevalence rate of hypertension according to measurements (44%). The same holds true for the risk factors obesity, daily physical activity and daily fruit consumption. On average the individuals in our sample are more likely to be obese, less likely to have sufficient physical activity and less likely to consume fruits or vegetables on a daily basis compared to the benchmark population. Only the prevalence of current smokers is significantly smaller in our sample than in the overall population.

To conclude, the sample generated by our experiment is skewed towards the age group 45-55 and seems to be significantly more at risk for having or developing diabetes compared to the total population in Jakarta and Yogyakarta. We interpret this self-selection as an indication that our campaign is very effective in reaching out to people at high risk that could potentially benefit from such an online screening activity. It could, of course, also imply that we only attract individuals that are already well aware of their high risk, potentially even have already been tested for (pre-) diabetes and therefore do not profit from the screening questionnaire in terms of new information about their risk status.

To investigate what is more likely, we followed-up on those individuals who agreed to participate in further research activities, and show below that only one third of individuals that self-selected into the survey and were found to have a high risk were already aware of having diabetes.

Table 4.3: Comparison of the sample and a benchmark population

	(1) Mean (sample)	(2) Mean (benchmark)	(3) Sample size (benchmark)	(4) Data source
Demographics				
<i>Age</i>				
35-45	0.32**	0.34	6,503,389	BPS 2022
45-54	0.47***	0.29	6,503,389	BPS 2022
55-54	0.16***	0.21	6,503,389	BPS 2022
Above 65	0.05***	0.16	6,503,389	BPS 2022
Female	0.49	0.50	6,503,389	BPS 2022
Blood glucose				
Ever been found to have high blood sugar levels	0.50	-		
Ever diagnosed with diabetes (Jakarta & Yogyakarta)	-	0.06	10,070	RISKESDAS 2018
Ever diagnosed with diabetes (Indonesia)	-	0.035	418,187	RISKESDAS 2018
Diabetes according to blood test ¹	-	0.14	25,767	RISKESDAS 2018
Pre-diabetes according to blood test ¹	-	0.30	18,876	RISKESDAS 2018
Ever had blood sugar measured by health worker	-	0.62	775	SUNI-SEA 2021
Blood pressure / hypertension				
Ever diagnosed with high blood pressure	0.33***	0.16	10,062	RISKESDAS 2018
Hypertension according to measurement ²	-	0.44	6,079	RISKESDAS 2018
BMI				
Weight	69.25***	64.31	775	SUNI-SEA 2021
Height	162.36***	158.61	775	SUNI-SEA 2021
BMI ³	26.14**	25.61	775	SUNI-SEA 2021
Underweight (BMI < 18.5)	0.03***	0.07	11,215	RISKESDAS 2018
Normal (BMI ≥ 18.5 - < 25.0)	0.44**	0.47	11,215	RISKESDAS 2018
Overweight (BMI ≥ 25.0 - < 27)	0.18*	0.16	11,215	RISKESDAS 2018
Obesity (BMI ≥ 27)	0.35***	0.29	11,215	RISKESDAS 2018
Risk factors				
Daily physical activity	0.60***	0.68	11,598	RISKESDAS 2018
<i>Smoking</i>				
Never smoked	0.66***	0.57	11,778	RISKESDAS 2018
Stopped smoking	0.20***	0.15	11,778	RISKESDAS 2018
Currently smoking	0.14***	0.28	11,778	RISKESDAS 2018
Daily fruit consumption	0.45***	0.93	11,791	RISKESDAS 2018

Notes: ¹The data for the diabetes and pre-diabetes prevalence rates come from the full Indonesian sample above the age of 35, since data per province and age category was not available. ²The prevalence rate for hypertension comes only from the Jakarta sample, since data for Yogyakarta per age category was not available. ³The BMI classifications are those provided in RISKESDAS. They differ from the scale used in the screening questionnaire, which relies on the risk-scale for BMI cut-off points for Asian populations provided by the World Health Organization Expert Consultation (2004), in which overweight is classified as having a BMI above 23 instead of 25 and obesity as having a BMI above 27.5.

4.5.4 Results from the follow-up survey

The primary aim of the follow-up survey was to elicit whether individuals with a high risk for diabetes complied with the received recommendation to schedule an appointment in a primary health care facility or with their physician to undergo a blood test for diabetes. Also, if they reported not to plan to schedule an appoint-

ment, we were interested in the reasons. In total, 53 individuals participated in this survey, of which around 60% had received a high-risk score in the screening, 29% a medium-risk score and 11% a low-risk score. Obviously, we must assume that the group of respondents is not necessarily representative for the overall sample of 1,469 individuals that participated in the screening as survey participation was voluntary and hence was based on self-selection. Yet, when comparing their observable characteristics with those of the overall sample we did not find any statistically significant differences in their characteristics, as displayed in Table 4.E1 in Appendix 4.E. Power of these tests is of course limited given the small sample size, but even the absolute size of the differences is in most cases surprisingly small. When asking whether the participants could remember their results from the screening, one third answered that they could not, without however any significant correlation between not being able to remember and the respective risk level (see Figures 4.E1, 4.E2 and Table 4.E2 in Appendix 4.E).

We asked about plans for a professional appointment to those individuals that either were at high risk according to their screening results or who mentioned to remember to have had a high risk. Of those individuals, 34% reported that they are already aware that they have diabetes and hence no further professional test was needed, 37% reported that they do not plan to schedule a professional appointment and 28% reported that they already have scheduled an appointment since they participated in our screening or that they intend to do so in the next month (14% each) (Figure 4.4). Hence, almost one third of those deemed to be at high risk, corresponding to 43% of those being unaware of their disease status, seem to comply with the recommendation to request a professional blood test for diabetes. If we extrapolate this share to the full sample, this amounts to 250 complying individuals at high risk. Moreover, these numbers also verify that the campaign does not only attract individuals that are already well aware of having diabetes, but that we achieve to attract a significant share of individuals being at high risk of developing diabetes and being unaware about it.

To account for a potential desirability bias in our survey, i.e., individuals may just report to comply with the received recommendation because they expect that this is the socially desired answer, we randomized two different framings of the same question. One highlighted the importance of scheduling a professional appointment given the possible severe health consequences of diabetes, the other implied that the time that had passed since the screening was probably too short to already have scheduled a meeting (the exact framings are shown in Appendix 4.E). Whereas the first framing should increase the psychological cost of admitting not having made an appointment, the second framing makes it psychologically rather cheap to admit not having made an appointment. If both framings lead to a comparable share of respondents who report to have taken an appointment, we inter-

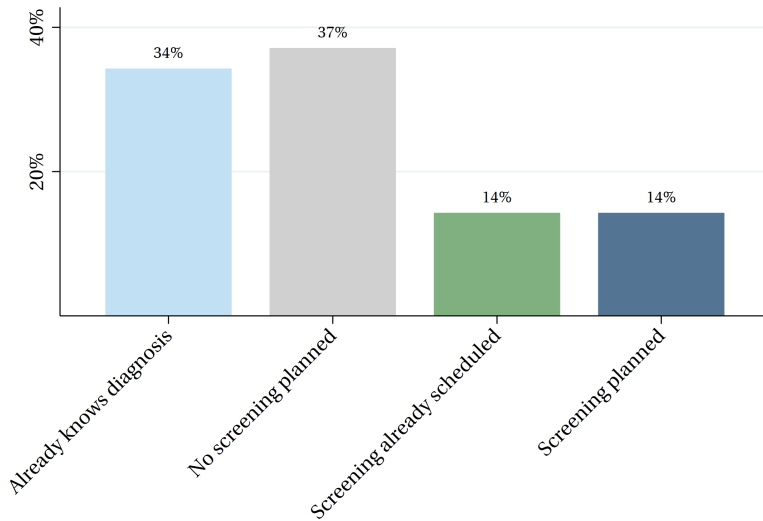


Figure 4.4: Plans for professional follow-up screenings - Figure 4.4 shows the responses of high-risk individuals to the question whether they plan to follow-up with the received recommendation of scheduling a professional diabetes screening.

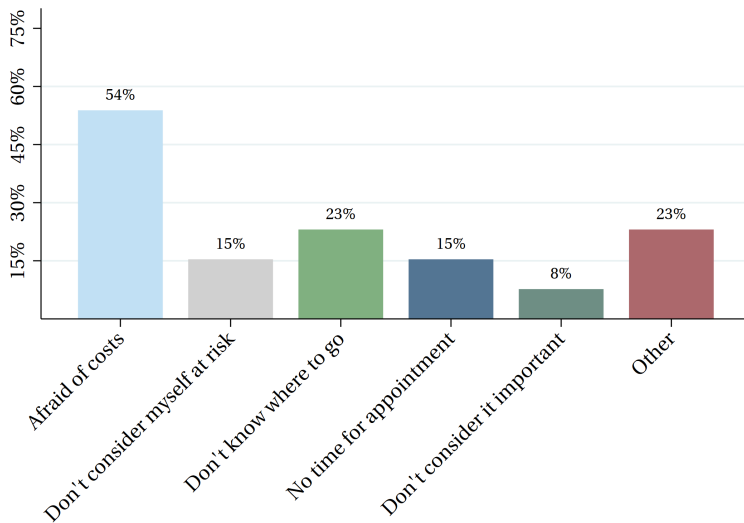


Figure 4.5: Reasons for not planning a professional follow-up screening

pret this as evidence that a desirability bias is not at work. And indeed, we do not find any significant differences in the response pattern to the questions, which increases our trust in the reported answers (Table 4.E3, Appendix 4.E).

Individuals reporting not intending to schedule an appointment for a professional blood test were further asked for the main reasons keeping them from doing so (Figure 4.5). More than half answered to be afraid of the cost that such a test might imply. Given the small sample size for this question, the results have to be interpreted carefully. Yet, since preventive health care visits, including tests for chronic diseases, are free of charge for those covered by the national health insurance JKN (which around 80% in our sample are), a potentially promising strategy to increase screening rates for diabetes could be to distribute detailed information about the services covered in the insurance scheme.

4.6 Cost-effectiveness

In a context of limited public health budgets, identifying cost-effectiveness of health interventions is crucial for the design of a national health strategy. Indonesia had a health budget of less than 3% of its GDP over the last two decades, with which it ranks behind, for example, India, Vietnam and Thailand (World Bank, 2022). The government started to integrate the WHO's Package of Essential Non-communicable Disease (PEN) interventions into its national public health strategy to counteract the surge of NCDs (Rattanavipapong et al., 2016; Widyaningsih et al., 2022; World Health Organization, 2020a). Yet, the country is still in the process of designing a nationwide cost-effective NCD strategy (Rattanavipapong et al., 2016). While the current national policy includes a regular diabetes (and hypertension) screening program at the community level (called POSBINDU), it has been shown to suffer from suboptimal implementation and targeting, low participation rates and inadequate coverage (Alfiyah and Pujiyanto, 2019; Rattanavipapong et al., 2016; Widyaningsih et al., 2022).

In the following, we analyze the cost-effectiveness of our Facebook health campaign, under the assumption that it would be scaled-up to a one-year-running health campaign across the whole Island of Java. This implies a target population of about 25 million Facebook users above the age of 35. We perform a simple cost-effectiveness calculation based on the cost and effectiveness parameters derived from our study and enrich them with a repeated decision-tree model. The final cost parameter of interest is the cost per newly diagnosed person.

Table 4.4, Panel A presents the cost indicators from our Facebook campaign averaged over the sub-groups: ad theme \times gender \times age group \times region. Panel B presents the cost indicators by ad theme. The most relevant indicator is the cost per

completed questionnaire, which is on average US\$0.74, yet with a large variation. The cheapest cost per completed questionnaire was achieved by the “information ad”, targeting females aged 45-55 and living in Jakarta (US\$ 0.24), whereas it was extremely costly to generate conversions, i.e., completed questionnaires, with the “religion ad”, targeting males aged 65+ and living in Yogyakarta (US\$ 3.91). For the further analysis in terms of the campaign cost, we assume that the ad theme “information” would exclusively be used, since it proved most effective in terms of generating conversions (0.6% of Facebook users seeing the ad completed the screening questionnaire) and had on average the lowest cost per conversion (US\$0.49).

Table 4.4: Cost per view, reach, click and conversion (in US\$)

	(1) Mean	(2) SD	(3) Min	(4) Max
Panel A				
Cost per view	0.001	0.000	0.001	0.003
Cost per reach	0.004	0.001	0.002	0.008
Cost per click	0.203	0.056	0.084	0.035
Cost per conversion	0.738	0.385	0.237	3.909
	(1) Cost per view	(2) Cost per reach	(3) Cost per click	(3) Cost per conversion
Panel B				
<i>Ad theme</i>				
Family	0.001	0.004	0.226	0.987
Information	0.001	0.003	0.145	0.488
Geography	0.001	0.004	0.221	0.705
Religion	0.002	0.005	0.255	1.152
Shock	0.001	0.004	0.202	0.700

Notes: Table 4.4, Panel A presents the summary statistics of the cost indicators, averaged over the sub-groups ad theme × gender × age group × region. Panel B presents the cost indicators by ad theme.

We use the average cost for a professional diabetes blood test at an Indonesian primary health care facility drawn from Rattanavipapong et al. (2016), who estimate a cost of US\$2.84 per professional screening. Further, we rely on an assumption regarding the test sensitivity and two assumptions which we derive from the results of the screening questionnaire and our follow-up survey.

First, we assume that the screening questionnaire is adequately sensitive to detect diabetes, and hence we assume that the prevalence rate of diabetes in the “medium risk” and “low risk” group is 0%, whereas the prevalence rate in the “high risk” group is 80%. This sensitivity measure is well in line with that identified by Harbuwono et al. (2021) for the American Diabetes Association risk test in Indone-

sia, who estimate a sensitivity between 68% and 93%, depending on the cut-off level.

Second, we have to acknowledge some form of self-selection, since we do attract a disproportional high share of individuals that has ever been told to have high blood sugar levels (50% of participants) and a significant share that is already aware of the diagnosis. Hence, to reflect the 34% of individuals with a high risk who indicated they do not need to conduct a professional follow-up screening since they already know they have diabetes, we assume that 50% of the 80% of individuals that have diabetes (given the first assumption) are already aware of their diagnosis. This leads to in total 40% of those individuals with high a risk already being diagnosed, which is slightly higher than the 37% identified in our study.

Given this self-selection process into the campaign participation, it also implies that the total prevalence rate of diabetes in the campaign-participating population is slightly higher than in the non-participating population. Since the weighted prevalence rate for both groups (participating and not-participating) must be equal to the overall prevalence rate of 14%, the prevalence rate of diabetes in the non-participating group is reduced to 13.78% and the ratio of diagnosed to undiagnosed cases is slightly lower (24.4%) than in the overall population.

Third, reflecting the results of the follow-up survey, we assume that individuals with a “high risk” which are unaware of their diseases status follow up with a professional diabetes screening in 40% of the cases (slightly less than the 43% found in our study).

We conduct multiple one-way sensitivity analyses below to assess the robustness of our results with respect to the three outlined assumptions.

Integrating the former assumptions, the cost and effectiveness measures and the risk distribution identified in our study as well as the prevalence rates of diagnosed and non-diagnosed diabetes according to the RISKESDAS survey leads to the final decision-tree depicted in Figure 4.6.

We model the decision tree-flow for the total population of 25 million Javanese Facebook users above 35 and as a monthly repeating intervention over the course of one year, i.e., all individuals who do not participate in the online screening questionnaire in the first (second, third etc.) month enter the decision-tree again in the second (third, fourth etc.) month. At the end of the decision-tree, an individual can have one of the following statuses: i) healthy, ii) diagnosed diabetes or iii) undiagnosed diabetes. To be precise, the important difference between the results of the screening vs. the non-screening scenario is the distribution of individuals that have diabetes (14% of the total population) between the two states “diagnosed diabetes” and “undiagnosed diabetes”.

The results of this repeated decision tree simulation are presented in Table 4.5.

The first row presents the results associated with the parameter assumptions outlined above ((i) the sensitivity of the online screening questionnaire, (ii) the share of individuals in the high risk group being aware of their diabetes status, and (iii) the share of individuals with a high risk and being unaware of the diagnosis following up with professional screening). We conduct further sensitivity checks by modifying these three assumptions first one by one and then all together to see how they impact the final cost-effectiveness. The modified parameter is marked in bold in each row.

The main analysis reveals that the hypothetical up-scaling of the intervention to whole Java over the period of one year could lead to about 1.7 million users participating in the online screening, of which about 250,000 would continue with the professional follow-up screening, and finally to the diagnosis of almost 170,000 previously undetected diabetes cases. This corresponds to an increase from 25% to 29% of diagnosed cases relative to all cases, i.e., an increase of 16%. While the share might still seem small, the absolute number is large especially in light of the low cost and low effort needed to implement an online health campaign. This low cost is further confirmed when we look at the total cost of the proposed intervention (including the professional follow-up screening), which is slightly more than US\$1.5 million. Dividing the total cost by the 170,000 newly diagnosed cases, the cost to detect one more previously undiagnosed person amounts to approximately US\$9.

Modifying several of the input parameters shows that the cost per diagnosed person hardly surpasses a threshold of US\$15. Even in the most pessimistic scenario (last row), with an assumed test-sensitivity of only 60%, with 75% of individuals receiving a high-risk score and having diabetes already knowing their diagnosis, and only 20% of individuals following up with the recommendation, the cost for one newly diagnosed person amounts only to US\$37. Contrasting these amounts to the cost of long-term diabetes care in Indonesia suggest a large cost-saving potential. Hidayat et al. (2022) estimate the direct medical cost for a patient with diabetes consequences at US\$930 per person and year in the Indonesian health care system, whereas a patient without consequences accumulates cost of only US\$420. Under the premise that early diagnosis reduces the probability of developing severe diabetic consequences, an online diabetes health campaign offers the possibility to reduce health care expenditures in the long term.

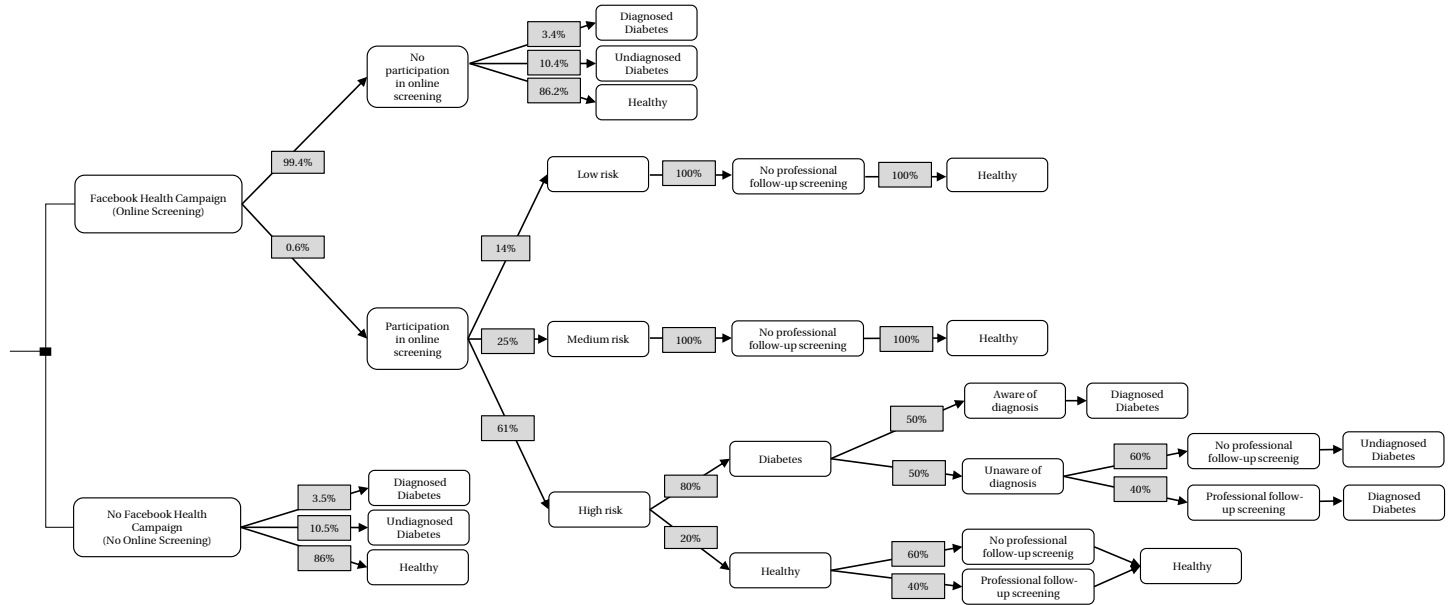


Figure 4.6: Decision tree

Table 4.5: Cost-effectiveness results from the repeated decision tree with sensitivity analysis

	<u>Assumptions</u>			<u>Costs</u>		<u>Results</u>				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sensitivity of online screening questionnaire	Share of individuals in high risk group being aware of diabetes status	Share of individuals with high risk following up with professional screening	Cost per online screening (\$US)	Cost per professional follow-up screening (\$US)	# of online screenings	# of professional follow-up screenings	Total cost (\$US) (4)+(5)+(6)+(7)	Newly diagnosed cases	Cost per newly diagnosed patient (\$US)
Main analysis	80%	50%	40%	0.49	2.84	1,741,772	254,995	1,574,171	169,997	9.26
Sensitivity analysis	60%	50%	40%	0.49	2.84	1,741,772	297,494	1,694,868	127,498	13.29
	70%	50%	40%	0.49	2.84	1,741,772	276,245	1,634,521	148,747	10.99
	90%	50%	40%	0.49	2.84	1,741,772	233,746	1,513,823	191,246	7.92
	80%	25%	40%	0.49	2.84	1,741,772	339,994	1,815,568	254,995	7.12
	80%	75%	40%	0.49	2.84	1,741,772	169,997	1,332,776	84,998	15.68
	80%	50%	20%	0.49	2.84	1,741,772	127,498	1,212,079	84,998	14.26
	80%	50%	60%	0.49	2.84	1,741,772	382,493	1,936,265	254,995	7.59
Best-case scenario	90%	25%	60%	0.49	2.84	1,741,772	494,053	2,253,095	430,305	5.24
Worst-case scenario	60%	75%	20%	0.49	2.84	1,741,772	116,872	1,181,901	31,874	37.08

Table 4.5 shows the results from the repeated decision tree simulations. The first row presents the cost-effectiveness results when the input parameters are set as discussed in Section 4.6. The following rows present the results when the input parameters are modified. The modified parameters are indicated in bold. In the last two rows, all three input parameters as discussed in Section 4.6 are modified to present a best-case and worst-case scenario.

4.7 Conclusion

While diabetes is a preventable disease and can be treated effectively if it is timely diagnosed, it presents currently the sixth leading cause of death in middle-income countries and the third leading cause of death in Indonesia. A major reason for that is the large share of undetected cases; in Indonesia, only one in four persons with diabetes is aware of its diagnosis. To counteract the surging rates, governments across South- and Southeast Asia are striving for (cost-)effective solutions to prevent and control diabetes. Indonesia for example focuses on screening at the community level (POSBINDU), yet so far without sizable success.

Public health campaigns can help to increase the awareness about the disease and to incentivize populations at risk to change unhealthy lifestyle behaviors, to inform them about important preventive health measures, such as screening, and to ensure adequate treatment in case of a positive diagnosis. In this study, we design and evaluate the impact of an online awareness campaign about type 2 diabetes implemented on the social media platform Facebook. Our randomized experiment shows that advertisements that convey factual information about the health consequences of diabetes and those containing a rather shocking message about the deadly consequences of diabetes are most effective in incentivizing viewers to click on the ads and to search for more information. Overall, we were able to reach out to almost 300,000 individuals in only three weeks of time and with a budget of less than US\$1,100. More than 1,400 individuals completed the offered online diabetes risk screening on our campaign website, implying a cost of less than US\$0.75 per person screened in that way.

We find that such a campaign is especially well suited to reach out to the population in the age range 45-55. This is an encouraging finding, given that the risk of diabetes ascends after the age of 45 and a diagnosis of elevated blood sugar at this age offers the opportunity for early treatment to prevent further devastating health consequences. We also find that a large share of participants in the online screening has an over-proportional high risk for diabetes compared to a benchmark population. When we investigate further whether this is driven by a self-selection process of patients already aware of their diagnoses, we find that 34% of individuals with a high risk have already been diagnosed. This, however, leaves a significant proportion of 66% of individuals with a high risk still being unaware of their actual disease status, which can potentially benefit from such a campaign.

Using the cost and benefit parameters derived in our study to perform a cost-effectiveness analysis based on a decision tree model, we find that our campaign – if up-scaled to the Island of Java over a period of one year – offers the potential to detect around 170,000 previously undetected cases. This implies costs per additional person diagnosed of only about US\$9.

Overall, our study suggests that a diabetes health campaign implemented on the social media platform Facebook can reach out to hundreds of thousands of people in a short period of time at a very low cost. We believe that our results have a similar validity for many other middle-income countries, especially in the South-east Asian region.

To the best of our knowledge our study is the first to implement a health-related field experiment via Facebook in a low- or middle-income country context. Naturally, similar Facebook campaigns could also be run for other health issues, such as testing for sexual transmitted diseases, Covid-19 vaccinations or drink-driving. Our study also provides important insights what kind of framings or pictorial contents drive health-related decisions and hence provides evidence about which psychological channels can effectively incentivize individuals to learn about their health risks.

Appendices

Appendix 4.A: Ad themes and design



Figure 4.A1: Ad theme “Family” - English: Diabetes can affect every family. Diabetes can be prevented and controlled. Learn about your diabetes risk now!



Figure 4.A2: Ad theme “Geography: Jakarta” - English: Jakarta is the city with the highest diabetes prevalence rate in Indonesia. Learn about your diabetes risk now!

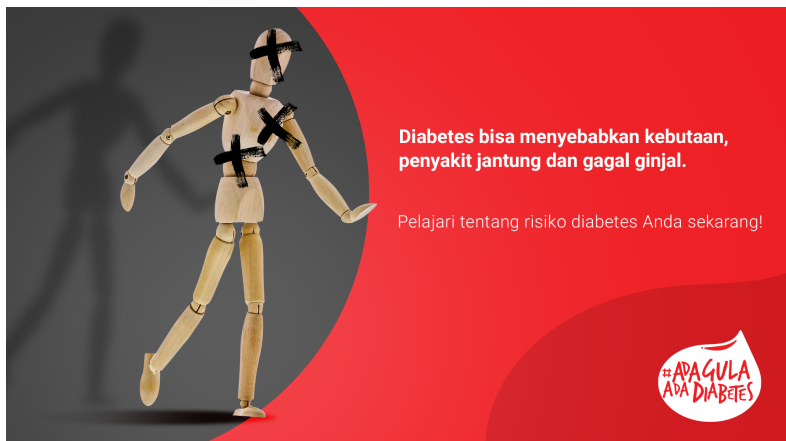


Yogyakarta adalah salah satu kota dengan tingkat diabetes tertinggi.

Pelajari tentang risiko diabetes Anda sekarang!



Figure 4.A3: Ad theme “Geography: Yogyakarta” - English: Yogyakarta is one of the cities with the highest diabetes prevalence rates. Learn about your diabetes risk now!



Diabetes bisa menyebabkan kebutaan, penyakit jantung dan gagal ginjal.

Pelajari tentang risiko diabetes Anda sekarang!



Figure 4.A4: Ad theme “Information” - English: Diabetes can cause blindness, heart diseases and kidney failure. Learn about your diabetes risk now!



Figure 4.A5: Ad theme “Religion” - English: “and do not throw [yourselves] with your [own] hands into destruction” (Q.S. Al-Baqarah, 2:195). Diabetes can be prevented and controlled. Learn about your diabetes risk now!



Figure 4.A6: Ad theme “Shock” - English: Diabetes can have deadly consequences. Diabetes can be prevented and controlled. Learn about your diabetes risk now!

Appendix 4.B: Screening questionnaire

Table 4.B1: Screening questionnaire and scoring system (English)

No.	Question	Alternatives	Score
1	How old are you?	Younger than 45	0
		45-55	1
		56-65	2
		Older than 65	3
2	What is your gender?	Female	0
		Male	1
3	Have you ever been found to have high blood sugar levels? (This could be, for example, in a health examination, during an illness or during pregnancy.)	Yes	3
		No	0
4	Have you ever been diagnosed with high blood pressure or are you taking any anti-hypertensive drugs?	No	0
		Yes	1
5	Do you have a mother, father, sister or brother who was diagnosed with diabetes?	No	0
		Yes	1
6	What is your weight? (in kg)		
7	What is your height? (in cm) <i>BMI calculated from 6 and 7</i>	≤ 23	0
		23 – 27.5	1
		27.5 – 32.5	2
		≥ 32.5	3
8	Do you usually have at least 30 minutes of physical activity per day? (Physical activity means moderate or vigorous activity such as walking, swimming, badminton etc.)	Yes	0
		No	1
9	Do you smoke cigarettes?	No, I never smoked.	0
		No, I stopped smoking.	0
		Yes	1
10	Do you eat fruit or vegetables every day? (Please do not count fruit juices.)	Yes	0
		No	1
11	Do you drink sugary beverages every day? (Examples of these are soft drinks, sweetened tea or fruit juices with sugar.)	No	0
		Yes	1

Scoring

≤ 3	Low risk
4–5	Medium risk
≥ 6	High risk

Notes: Adapted from the American Diabetes Association (1993, 2019), Lindstrom and Tuomilehto (2003), Fauzi et al. (2022) and Rokhman et al. (2022).

Table 4.B2: Screening questionnaire and scoring system (Bahasa Indonesia)

No.	Question	Alternatives	Score
1	Berapa umur Anda?	Di bawah 45 tahun	0
		45-55 tahun	1
		56-65 tahun	2
		Di atas 65 tahun	3
2	Apa jenis kelamin Anda?	Perempuan	0
		Laki-laki	1
3	Apakah hasil pemeriksaan gula darah Anda pernah tinggi? (Contohnya saat tes kesehatan, ketika sakit, atau selama kehamilan.)	Ya	3
		Tidak	0
4	Apakah Anda pernah didiagnosis menderita tekanan darah tinggi atau sedang mengonsumsi obat antihipertensi?	Tidak	0
		Ya	1
5	Apakah Anda memiliki ibu, ayah, saudara perempuan atau saudara laki-laki yang menderita diabetes?	Tidak	0
		Ya	1
6	Berapa berat badan Anda? (dalam kilogram)		
7	Berapa badan tinggi Anda? (dalam sentimeter) <i>IMT berdasarkan 6 dan 7</i>	≤ 23	0
		23 – 27.5	1
		27.5 – 32.5	2
		≥ 32.5	3
8	Apakah Anda biasa melakukan aktivitas fisik, minimal 30 menit per hari? (Aktivitas fisik yang dimaksud adalah aktivitas fisik sedang atau berat seperti berjalan kaki, berenang, bulu tangkis, dll.)	Yes	0
		Tidak	1
9	Apakah Anda merokok?	Tidak, saya tidak pernah merokok.	0
		Tidak, saya berhenti merokok.	0
		Ya	1
10	Seberapa sering Anda mengonsumsi sayur atau buah? (Tidak termasuk jus buah.)	Ya	0
		Tidak	1
11	Seberapa sering Anda mengonsumsi minuman manis? (Contohnya adalah minuman ringan, minuman bersoda, teh manis, atau jus buah dengan gula.)	Tidak	0
		Ya	1

Skor ≤ 3 **Risiko rendah**4-5 **Risiko sedang** ≥ 6 **Risiko tinggi**

Notes: Adapted from the American Diabetes Association (1993, 2019), Lindstrom and Tuomilehto (2003), Fauzi et al. (2022) and Rokhman et al. (2022).

Appendix 4.C: Additional summary statistics of the screening questionnaire

Table 4.C1: Summary statistics of started screening questionnaires (with duplicates)

	(1) Mean	(2) SD	(3) Min	(4) Max	(5) Obs.
Age					2,052
<i>Below 45</i>	0.28				
<i>45-54</i>	0.46				
<i>55-54</i>	0.18				
<i>Above 65</i>	0.08				
Female	0.48				1,873
Ever had high blood glucose	0.50				1,810
Ever diagnosed with high blood pressure	0.34				1,794
Family member with diagnosed diabetes	0.53				1,777
Weight	69.30	16.87	33	185	1,461
Height	162.51	7.86	140	195	1,561
BMI	26.13	5.52	11	70	1,561
Daily physical activity	0.60				1,544
Smoking					1,541
<i>Never smoked</i>	0.65				
<i>Stopped smoking</i>	0.20				
<i>Currently smoking</i>	0.15				
Daily fruit consumption	0.45				1,539
Daily sweet beverages consumption	0.30				1,533
Risk score	6.34	2.58	0	14	1,533
<i>Low risk</i>	0.15				
<i>Medium risk</i>	0.25				
<i>High risk</i>	0.60				

Notes: Table 4.C1 presents the summary statistics for all questionnaires that were started, with duplicates.

Table 4.C2: Summary statistics of completed questionnaires (with duplicates)

	(1)	(2)	(3)	(4)	(5)
	Mean	SD	Min	Max	Obs.
Age					1,533
<i>Below 45</i>	0.32				
<i>45-54</i>	0.46				
<i>55-54</i>	0.16				
<i>Above 65</i>	0.05				
Female	0.48				1,533
Ever had high blood glucose	0.49				1,533
Ever diagnosed with high blood pressure	0.33				1,533
Family member with diagnosed diabetes	0.54				1,533
Weight	69.31	16.95	33	185	1,533
Height	162.51	7.81	140	195	1,533
BMI	26.14	5.55	11	70	1,533
Daily physical activity	0.60				1,533
Smoking					1,533
<i>Never smoked</i>	0.65				
<i>Stopped smoking</i>	0.20				
<i>Currently smoking</i>	0.15				
Daily fruit consumption	0.45				1,533
Daily sweet beverages consumption	0.30				1,533
Risk score	6.34	2.58	0	14	1,533
<i>Low risk</i>	0.15				
<i>Medium risk</i>	0.25				
<i>High risk</i>	0.60				

Notes: Table 4.C2 presents the summary statistics for all questionnaires that were completed, with duplicates.

Appendix 4.D: Additional regression tables and figures (main results)

Table 4.D1: Results – Ad effectiveness (Regression coefficients - Logit model)

	(1)	(2)	(3)	(4)	(5)	(6)
	Link clicks	Link clicks	Link clicks	Conversions	Conversions	Conversions
		men	women		men	women
Reference: Family						
Information	0.221*** (0.042)	0.107* (0.058)	0.348*** (0.061)	0.462*** (0.083)	0.412*** (0.115)	0.502*** (0.121)
Geography	-0.019 (0.046)	-0.113* (0.065)	0.075 (0.066)	0.284*** (0.089)	0.188 (0.127)	0.378*** (0.125)
Religion	0.111** (0.048)	0.050 (0.068)	0.172** (0.068)	0.062 (0.101)	0.057 (0.142)	0.065 (0.142)
Shock	0.147*** (0.045)	0.074 (0.063)	0.219*** (0.065)	0.366*** (0.089)	0.262** (0.127)	0.463*** (0.125)
Female	0.221*** (0.028)			0.216*** (0.053)		
Reference: Below 45						
45-54	0.583*** (0.034)	0.585*** (0.048)	0.576*** (0.047)	0.705*** (0.062)	0.650*** (0.087)	0.758*** (0.087)
55-64	0.931*** (0.041)	0.970*** (0.057)	0.883*** (0.060)	0.752*** (0.081)	0.759*** (0.111)	0.738*** (0.119)
65+	0.913*** (0.050)	0.949*** (0.066)	0.862*** (0.077)	0.221* (0.122)	0.326** (0.152)	0.020 (0.208)
City (Yogyakarta=1)	-0.007 (0.028)	0.044 (0.039)	-0.065 (0.041)	-0.297*** (0.055)	-0.302*** (0.076)	-0.292*** (0.079)
Constant	-4.610*** (0.045)	-4.572*** (0.060)	-4.421*** (0.060)	-5.930*** (0.089)	-5.854*** (0.119)	-5.784*** (0.118)
Observations	286,776	160,560	126,216	286,776	160,560	126,216

P-values of pairwise t-tests:

Information vs. Geography	0.000	0.000	0.000	0.019	0.032	0.256
Information vs. Religion	0.012	0.353	0.005	0.000	0.004	0.000
Information vs. Shock	0.069	0.562	0.031	0.202	0.151	0.722
Religion vs. Geography	0.006	0.017	0.149	0.018	0.330	0.018
Religion vs. Shock	0.443	0.712	0.482	0.001	0.124	0.003
Shock vs. Geography	0.002	0.032	0.025	0.318	0.525	0.452

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of completed survey questionnaires counted as “conversion” are derived from the reduced sample without duplicated questionnaires (N=1,469) of which 1,443 could be linked to the referring ad theme. The missing 26 could not be linked to the referring ad theme due to tracking restrictions.

Table 4.D2: Results – Ad effectiveness (Marginal effects - Logit model)

	(1)	(2)	(3)	(4)	(5)	(6)
	Link clicks	Link clicks	Link clicks	Conversions	Conversions	Conversions
		men	women		men	women
Reference ad: Family						
Information	0.004*** (0.001)	0.002* (0.001)	0.007*** (0.001)	0.002*** (0.000)	0.002*** (0.001)	0.003*** (0.001)
Geography	-0.000 (0.001)	-0.002* (0.001)	0.001 (0.001)	0.001*** (0.000)	0.001 (0.001)	0.002*** (0.001)
Religion	0.002** (0.001)	0.001 (0.001)	0.003** (0.001)	0.000 (0.000)	0.000 (0.001)	0.000 (0.001)
Shock	0.003*** (0.001)	0.001 (0.001)	0.004*** (0.001)	0.002*** (0.000)	0.001** (0.001)	0.002*** (0.001)
Female	0.004*** (0.001)			0.001*** (0.000)		
Reference age: Below 45						
45-54	0.009*** (0.001)	0.008*** (0.001)	0.010*** (0.001)	0.003*** (0.000)	0.003*** (0.000)	0.004*** (0.000)
55-64	0.018*** (0.001)	0.017*** (0.001)	0.019*** (0.002)	0.004*** (0.000)	0.004*** (0.001)	0.004*** (0.001)
65+	0.017*** (0.001)	0.017*** (0.002)	0.018*** (0.002)	0.001* (0.000)	0.001* (0.001)	0.000 (0.001)
Region (Yogyakarta=1)	-0.000 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)
Mean of dependent var.*	0.017	0.017	0.017	0.0039	0.0041	0.0037
Observations	286,776	160,560	126,216	286,776	160,560	126,216

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The number of completed survey questionnaires counted as “conversion” are derived from the reduced sample without duplicated questionnaires (N=1,469) of which 1,443 could be linked to the referring ad theme. The missing 26 could not be linked to the referring ad theme due to tracking restrictions. The table shows the marginal effects from the logit model. *Mean of dependent var. refers to the mean of the dependent variable in the reference group.

Table 4.D3: Results – Ad effectiveness for link clicks (OLS model)

	(1) Link clicks full sample	(2) Link clicks women	(3) Link clicks men	(4) Link clicks with controls	(5) Link clicks gender interactions	(6) Link clicks age interactions
Reference ad: Family						
Information	0.003*** (0.001)	0.007*** (0.001)	0.001 (0.001)	0.004*** (0.001)	0.002* (0.001)	0.004*** (0.001)
Geography	-0.001 (0.001)	0.001 (0.001)	-0.003** (0.001)	-0.000 (0.001)	-0.002 (0.001)	0.001 (0.001)
Religion	0.002** (0.001)	0.003*** (0.001)	0.001 (0.001)	0.002** (0.001)	0.001 (0.001)	0.000 (0.001)
Shock	0.002*** (0.001)	0.004*** (0.001)	0.001 (0.001)	0.003*** (0.001)	0.001 (0.001)	0.002** (0.001)
Reference age: Below 45						
45-54				0.009*** (0.001)	0.009*** (0.001)	0.009*** (0.001)
55-64				0.018*** (0.001)	0.018*** (0.001)	0.015*** (0.002)
65+				0.017*** (0.001)	0.017*** (0.001)	0.020*** (0.003)
Gender (Female=1)				0.004*** (0.001)	0.001 (0.001)	0.004*** (0.001)
Region (Yogyakarta=1)				-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Information#Female					0.005*** (0.002)	
Geography#Female					0.003* (0.002)	
Religion#Female					0.002 (0.002)	
Shock#Female					0.003* (0.002)	
Information#45-54						0.001 (0.002)
Information#55-64						0.003 (0.003)
Information#65+						-0.006 (0.004)
Geography#45-54						-0.002 (0.002)
Geography#55-64						0.003 (0.003)
Geography#65+						-0.006* (0.004)
Religion#45-54						0.002 (0.001)
Religion#55-64						0.010*** (0.003)
Religion#65+						-0.003 (0.004)
Shock#45-54						-0.001 (0.002)
Shock#55-64						0.003 (0.003)
Shock#65+						0.002 (0.004)
Constant	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)	0.009*** (0.001)	0.010*** (0.001)	0.009*** (0.001)
Observations	286,776	126,216	160,560	286,776	286,776	286,776
R-squared	0.000	0.000	0.000	0.003	0.003	0.003

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.D4: Results – Ad effectiveness for conversions (OLS model)

	(1) Conversions full sample	(2) Conversions women	(3) Conversions men	(4) Conversions with controls	(5) Conversions gender interactions	(6) Conversions age interactions
Reference ad: Family						
Information	0.002*** (0.000)	0.003*** (0.001)	0.002*** (0.001)	0.002*** (0.000)	0.002*** (0.001)	0.002*** (0.001)
Geography	0.001*** (0.000)	0.002*** (0.001)	0.001 (0.001)	0.001*** (0.000)	0.001 (0.001)	0.001** (0.001)
Religion	0.000 (0.000)	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)	0.000 (0.001)	-0.000 (0.000)
Shock	0.002*** (0.000)	0.003*** (0.001)	0.001** (0.001)	0.002*** (0.000)	0.001** (0.001)	0.002*** (0.001)
Reference age: Below 45						
45-54				0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.001)
55-64				0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
65+				0.001* (0.001)	0.001* (0.001)	0.002 (0.001)
Gender (Female=1)				0.001*** (0.000)	0.000 (0.001)	0.001*** (0.000)
Region (Yogyakarta=1)				-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Information#Female					0.001 (0.001)	
Geography#Female					0.001 (0.001)	
Religion#Female					0.000 (0.001)	
Shock#Female					0.001 (0.001)	
Information#45-54						0.001 (0.001)
Information#55-64						-0.001 (0.001)
Information#65+						-0.003* (0.001)
Geography#45-54						0.001 (0.001)
Geography#55-64						0.001 (0.002)
Geography#65+						-0.003* (0.001)
Religion#45-54						0.001 (0.001)
Religion#55-64						0.002 (0.002)
Religion#65+						0.001 (0.002)
Shock#45-54						0.000 (0.001)
Shock#55-64						0.000 (0.002)
Shock#65+						0.001 (0.002)
Constant	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.002*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Observations	286,776	126,216	160,560	286,776	286,776	286,776
R-squared	0.000	0.000	0.000	0.001	0.001	0.001

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.D5: Probability of attrition (OLS model)

	(1)	(2)	(3)	(4)
	Attrition	Attrition	Attrition	Attrition
Reference: below 45				
45-54	0.084*** (0.021)		0.034* (0.019)	
55-64	0.175*** (0.029)		0.108*** (0.028)	
65+	0.342*** (0.042)		0.231*** (0.045)	
Gender (Female=1)		-0.006 (0.018)	0.005 (0.018)	
Reference: below 45#male				
45-54#male				0.023 (0.027)
55-64#male				0.096** (0.038)
65+ #male				0.243*** (0.055)
Below 45#female				-0.007 (0.028)
45-54#female				0.039 (0.027)
55-64#female				0.114*** (0.041)
65+ #female				0.190**
Constant	0.155*** (0.015)	0.185*** (0.012)	0.129*** (0.017)	0.135*** (0.020)
Observations	2,052	1,873	1,873	1,873
R-squared	0.046	0.000	0.025	0.025

Notes: Table 4.D5 presents the probability of attrition conditional on having started the screening questionnaire. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 4.E: Additional tables and figures from the follow-up survey

Differences between full sample, e-mail providers and follow-up completers

Table 4.E1: Differences between full sample, e-mail providers and follow-up completers

	(1) Full Sample	(2) E-mail providers	(3) Follow-Up completers	(4) Difference (1)-(2)	(5) Difference (1)-(3)
Age distribution					
35-45	0.32	0.21	0.23	0.13***	0.09
45-54	0.47	0.52	0.60	-0.07	-0.13
55-54	0.16	0.20	0.12	-0.04	0.05
Above 65	0.05	0.07	0.06	-0.02	-0.00
Female	0.49	0.51	0.46	-0.03	0.03
Ever had high blood sugar levels	0.50	0.66	0.60	-0.18***	-0.10
Ever diagnosed with high blood pressure	0.33	0.33	0.37	0.01	-0.03
Family member with diagnosed diabetes	0.54	0.60	0.56	-0.07	-0.02
Weight	69.28	67.82	68.11	1.71	1.22
Height	162.43	161.6	162.33	0.97	0.11
BMI	26.15	25.88	25.80	0.32	0.36
Daily physical activity	0.60	0.61	0.56	-0.01	0.04
Smoking					
<i>Never smoked</i>	0.66	0.66	0.63	0.00	0.02
<i>Stopped smoking</i>	0.20	0.20	0.17	0.00	0.03
<i>Currently smoking</i>	0.14	0.14	0.19	0.00	-0.05
Daily fruit consumption	0.45	0.45	0.44	0.00	0.01
Daily sweet beverages consumption	0.30	0.29	0.37	0.02	-0.06
Risk score	6.37	7.00	6.85	-0.73***	-0.49
<i>Low risk</i>	0.14	0.11	0.12	0.04	0.03
<i>Medium risk</i>	0.25	0.22	0.29	0.03	-0.04
<i>High risk</i>	0.61	0.67	0.60	-0.07*	0.01
N	1,469	205	52		

Notes: Table 4.E1 presents the results of the mean comparisons between the full sample of participants that completed the screening, the e-mail providers and the sample of participants that completed the follow-up survey. *** p<0.01, ** p<0.05, * p<0.1.

Risk distribution and recalled risk of follow-up survey respondents

Figures 4.E1 and 4.E2 display the risk distribution of respondents who participated in the follow-up survey. Figure E1 displays the risk distribution of respondents according to the risk level that was calculated in the screening questionnaire. Figure E2 displays the risk distribution according to the reported risk by the respondent in the follow-up survey.

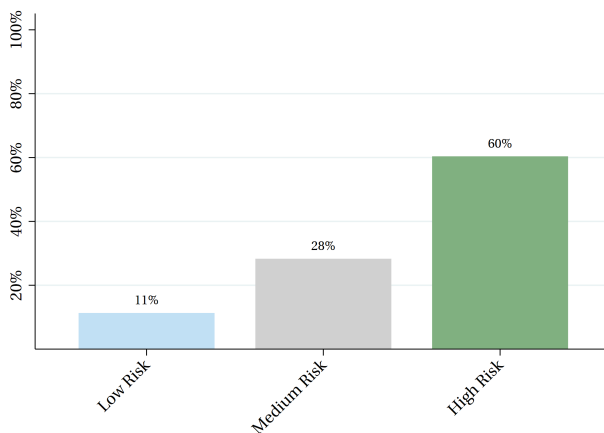


Figure 4.E1: Share of respondents in follow-up survey by risk group according to screening

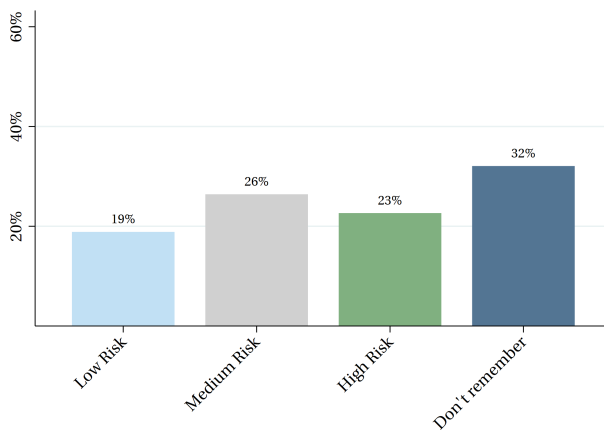


Figure 4.E2: Share of respondents in follow-up survey according to own recall

Table 4.E2 reports the results of a chi-squared test to assess whether the reporting of not being able to remember the risk results from the screening questionnaire differed across the three risk groups. The results suggest that this is not the case, since the null-hypothesis of no significant correlation cannot be rejected (p-value 0.362).

Table 4.E2: Screening risk and recall risk distribution

		Reported Risk (Recall)				Total
		Don't remember	Low Risk	Medium Risk	High Risk	
Screening Risk	Low Risk	1	3	1	1	6
	Medium Risk	4	4	3	4	15
	High Risk	12	3	10	7	32
	Total	17	10	14	12	53

Pearson $\chi^2(6) = 6.9114$ Pr = 0.329

Details on and results of the randomized framing

To account for a potential desirability bias in our survey, i.e. individuals may just report to comply with the received recommendation because they expect that this is the socially desired answer, we randomized two different framings of the same question.

Framing 1:

After the completion of the test you have received the recommendation to meet with a physician or GP to request a professional blood test for diabetes. Since it has already been 6 weeks since the completion of the risk test and given the urgency of a high diabetes risk, we assume that you have already scheduled an appointment with a doctor for a professional diabetes screening.

- Indeed, I have already scheduled an appointment.
- No, but I plan to schedule an appointment.
- I don't plan to schedule an appointment.
- I don't need an appointment since I already know that I have diabetes.

Framing 2:

After the completion of the test you have received the recommendation to meet with a physician or GP to request a professional blood test for diabetes. Since you have completed the online diabetes risk test only 6 weeks ago, we assume that the time might have not been sufficient to schedule an appointment with a doctor for a professional diabetes screening.

- Indeed, but I plan to schedule an appointment
- I don't plan to schedule an appointment.
- I have already scheduled an appointment
- I don't need an appointment since I already know that I have diabetes.

Table 4.E3 reports the results of a chi-squared test to assess whether the response pattern to the question about the professional blood test differs by the two framings presented above. The results suggest that this is not the case, since the null-hypothesis of no significant correlation cannot be rejected (p-value 0.494).

Table 4.E3: Framing experiment

		Plans for scheduling professional blood test				
		Already knows diagnoses	No plans to schedule	Scheduled after screening	Plans to schedule	Total
Framing	Framing 1	4	8	3	3	18
	Framing 2	8	5	2	2	17
	Total	12	13	5	5	35

Pearson $\chi^2(3) = 2.399$ Pr = 0.494

English summary

In the ongoing 21st century, low- and middle-income countries will face two health challenges that are thoroughly different from what these countries have been dealing with in preceding centuries. First, they are confronted with surging rates of non-communicable diseases (NCDs), namely cardiovascular diseases, cancer, chronic respiratory diseases and diabetes, which have overtaken infectious disease as the leading cause of death. Second, climate change will take its toll and is predicted to cause catastrophic health impairments and exacerbate chronic health conditions further. Both will pose a disproportionate health and economic burden on low- and middle-income countries, which are also the countries least able to cope with them. Thereby, increasing rates of NCDs and climate change hinder the progress towards reaching the Sustainable Development Goals. By threatening individual health and socioeconomic improvements, and by putting an immense burden on already constrained health care systems, they impede the progress in poverty reduction and widen health inequities between the rich and the poor.

Against this background, this thesis seeks to contribute to the knowledge of how NCD prevention and control can be enhanced and the economic burden be reduced in the geographical context of Southeast Asia. Specifically, it aims to answer three major research questions in three self-contained articles: First, what type of NCD prevention and treatment interventions promise to be effective in the context of Southeast Asia? Second, to what extent might climate change increase the NCD and financial burden further and thereby counteract the success of such interventions? And third, can social media platforms function as a promising tool for cost-effective interventions to tackle NCDs?

The first article, which is co-authored with Hanna Frommel, synthesizes the evidence of a broad set of NCD interventions in Southeast Asia from the last two decades. We focus on interventions which aim to achieve a reduction in NCD risk factors, an increase in NCD prevention efforts or an improvement in the general practices of health facilities. In the form of a systematic review, which is complemented with a meta-analysis, meta-regression and moderator analysis, we provide evidence about what types of interventions are most promising in the given con-

text. Overall, we extract 204 estimates from 51 studies and sort them into six different intervention categories, with respect to their targeted disease, risk factor or intervention design. In total, we look at a universe of 23 different health outcomes that such interventions can address. We find that especially programs focusing on smoking cessation, on the take-up of preventive screening activities or educating patients on how to cope with NCDs achieve sizable effect sizes. Dietary and physical activity interventions fail to achieve improvements in analyzed health outcomes. In line with the latter, we also show that health outcomes related to weight loss, i.e., BMI and waist circumference, are those that seem hardest to be changed by the interventions under study. We also document evidence of substantial publication bias, which we address with a meta-regression approach to obtain reliable estimates. Lastly, we show that the number of contact moments study participants have with the implementing health authorities strongly relates to the intervention effectiveness. Also, the age of the targeted participants and whether the intervention is implemented in a group design moderate the effect size.

This article contributes to the literature in three aspects. First, we provide an analysis that covers the entire Southeast Asian region and thereby aim to derive conclusions and policy implications that are externally valid for an extensive geographical area. Second, we address the intertwined nature of the four main NCDs and their four main risk factors, and review a wide scope of NCD interventions, which has largely been ignored in the evaluation of interventions' effectiveness so far. We thereby go beyond the common approach of focusing on a single NCD, single risk factor or single country, as the vast literature in the field has done. Lastly, we also make a methodological contribution by addressing several shortcomings that are commonly neglected in conventional meta-analyses with econometrically more sophisticated methods and by using a measure of effect size that accounts for pre-existing differences between treatment and control populations.

The second article zooms into the country context of Indonesia to investigate how climate change, specifically increasing temperatures, raise the NCD burden further. Moreover, it assesses the implications in terms of the financial burden posed on the health care system, specifically the new national health insurance scheme. Individuals affected by NCDs are especially at risk to suffer from rising temperatures, since their already exhausted bodies are less able to cope with further shocks and heat can exacerbate a variety of health conditions. To investigate this link, I concretely study whether the number of health visits related to diabetes, cardiovascular diseases and chronic respiratory diseases in the Indonesian primary health care facilities (*Puskesmas*) increase on days with extremely high temperatures. To do so, I rely on a novel and representative data set from the Indonesian national health insurance scheme *Jaminan Kesehatan Nasional* (JKN). I link the data to several meteorological data sets to extract information on the local tem-

perature and to control for possible confounding factors such as rainfall, humidity, air pollution or wind speed. The final daily-district panel, consisting of more than 370,000 observations, allows to estimate the causal effect of increasing temperatures empirically by relying on a quasi-experimental approach and making use of a semi-parametric specification that includes a series of fixed-effects. The results show that on days with extremely high temperature, the number of visits with a diagnosis of diabetes and cardiovascular diseases increase by 25% and 14%. I find no evidence for an increase in the number of visits related to respiratory diseases. I further assess the existence of so called “harvesting effects”, i.e., whether the increase in health care visits is only temporary or persistent. The analysis shows that the latter is the case. Increases in the number of health care visits related to NCDs are not offset, even after a period of four weeks. This has major implications for the burden that is posed on health facilities and health care workers. Lastly, I rely on different climate change and population growth scenarios to simulate the future increase in NCD-related health care visits and related cost by the end of the current century. The results from this exercise forecast a substantial financial burden for the Indonesian health care system with additional yearly cost up to US\$31 million to be spent on primary health care services.

The major contribution of this article is that it provides first-time evidence for the interplay between increasing temperatures and detrimental health effects on the primary health care level. Previous studies solely investigated the implications for higher level facilities, such as emergency departments or hospitals more generally. Focusing on primary health care visits instead of hospitalization rates and emergency visits provides important information about how global warming will affect the primary health care sector, which is pivotal in many low- and middle-income countries. Further, the article contributes to the literature by using health visit data that represents not only one of the largest countries in the world, but also comes from a middle-income country. Generally, only few studies assess the health impacts of heat in non-western and low- and middle-income countries. Hence, the relationship between temperature and health consequences in countries of the Global South, which tend to have comparably more tropical and humid climate zones as well as poorer health system capacities, has not yet been investigated in detail.

The third article, which is co-authored with Michael Grimm, Ingmar Weber, Elad Yom-Tov and Benedictus Praditya, stays in the country context of Indonesia and focuses specifically on type 2 diabetes. In this study, we assess whether social media can serve as an efficient and cost-effective instrument to increase type 2 diabetes awareness and encourage individual risk screening activities. To do so, we rely on experimental evidence from a diabetes awareness campaign that we implemented on the social media platform “Facebook”. Specifically, we randomly

distributed graphical ads related to the risk and consequences of diabetes to Indonesian Facebook users in the cities of Jakarta and Yogyakarta to test which type of message and graphical design is most effective in incentivizing users to visit an information website and to perform a diabetes self-screening activity. Depending on the result of this screening, participants receive the recommendation to contact a physician and ask for an in-depth screening. Our results suggest that ads with an “information” or “shocking” content are most effective in terms of completed self-screening activities. With a complementary follow-up survey six weeks after the online screening, we provide evidence that approximately 28% of high-risk respondents indeed also comply with the received recommendation for a professional screening. Regarding the cost side of this intervention, we conclude that such an online public health campaign can be very cost-effective with a cost of approximately US\$9 per newly diagnosed person with type 2 diabetes.

This article contributes towards the understanding of how screening rates for NCDs and their risk factors can be increased by making use of a social media campaign. The major innovation of this article is the actual design and implementation of a new awareness campaign on the social media platform Facebook in the form of a randomized controlled trial. Moreover, this study stands out as the very first to implement a health-related field experiment via Facebook in a middle-income country context. Overall, this article contributes to the better understanding of how awareness can be raised and uptake of screening for NCDs in low- and middle-income countries can be enhanced, i.e., in a context where the general awareness of NCDs is low. Lastly, it contributes to a literature mainly rooted in psychology that explores what kind of framing or pictorial content drive health-related decisions and whether exposure to information improves health behavior. We thereby provide evidence about which psychological channels can effectively incentivize individuals to learn about their risk and to engage in essential health screenings.

Together, the three articles presented in this thesis contribute to the understanding of possible pathways towards (cost-)effective solutions for the prevention of NCDs in Southeast Asia and possibly other low- and middle-income countries. Further, the thesis contributes to the understanding of the interplay of climate change and NCDs and how the former might offset some of the efforts undertaken to reduce the NCD burden. Hence, it consolidates a cautious attempt to support low- and middle-income countries in their endeavors to address two major health challenges of the 21st century.

Dutch summary

In de huidige 21e eeuw worden lage- en midden-inkomenslanden geconfronteerd met twee gezondheidsuitdagingen die grondig verschillen van die waarmee deze landen in voorgaande eeuwen werden geconfronteerd. Ten eerste worden zij geconfronteerd met een toenemend aantal gevallen van niet-overdraagbare ziekten (NCD's), namelijk hart- en vaatziekten, kanker, chronische ademhalingsziekten en diabetes, die infectieziekten hebben ingehaald als belangrijkste doodsoorzaak. Ten tweede zal de klimaatverandering haar tol eisen en naar verwachting catastrofale gezondheidsschade veroorzaken en chronische gezondheidsproblemen verder verergeren. Beide zullen een onevenredige gezondheidslast en economische last vormen voor lage- en midden-inkomenslanden, die ook het minst in staat zijn om ze het hoofd te bieden. Daardoor belemmeren de toenemende percentages NCD's en de met de klimaatverandering verband houdende gezondheidseffecten de vooruitgang richting de Duurzame Ontwikkelingsdoelen (SDG's). Door de individuele gezondheid en de economische ontwikkeling te bedreigen, en door een enorme belasting te vormen voor de reeds beperkte gezondheidszorgstelsels, belemmeren zij de vooruitgang met armoedebestrijding en vergroten zij de ongelijkheid in gezondheid tussen arm en rijk.

Dit proefschrift wil daarom een bijdrage leveren aan de kennis over hoe de preventie en bestrijding van NCD's kan worden verbeterd en de economische last kan worden verminderd in de geografische context van Zuidoost-Azië. Concreet beoogt het in drie op zichzelf staande artikelen drie belangrijke onderzoeksvragen te beantwoorden: Ten eerste, welke soorten interventies voor preventie en behandeling van NCD's, met betrekking tot de opzet van de interventie, de setting en de beoogde NCD of risicofactor, beloven effectief te zijn in de context van Zuidoost-Azië? Ten tweede, welke rol zal klimaatverandering spelen met betrekking tot de toekomstige NCD-last en de kosten van de gezondheidszorg in Indonesië? En ten derde, kan een gezondheids campagne via sociale media het bewustzijn en de screening voor diabetes type 2 laten toenemen, en hoe kosteneffectief is een dergelijke campagne?

Het eerste artikel, dat samen met Hanna Frommel is geschreven, geeft een syn-

these van het bewijsmateriaal van een brede reeks NCD-interventies in Zuidoost-Azië uit de laatste twee decennia, die gericht zijn op een vermindering van NCD-risicofactoren, een toename van NCD-preventieve inspanningen of een verbetering van de algemene praktijk van gezondheidsvoorzieningen. In de vorm van een systematische review, aangevuld met een meta-analyse, meta-regressie en moderatoranalyse, leveren wij bewijsmateriaal over welke soorten interventies in de gegeven context het meest veelbelovend zijn. In totaal hebben wij 204 schattingen uit 51 studies gehaald en deze ingedeeld in zes verschillende soorten interventies, naar ziektype, risicofactor of interventieontwerp, en daarbij gekeken naar een universum van 23 verschillende gezondheidsuitkomsten waarop dergelijke interventies zich kunnen richten. Wij stellen vast dat vooral programma's die gericht zijn op stoppen met roken, op het gebruik van preventieve screeningactiviteiten of op voorlichting van patiënten over hoe zij met NCD's moeten omgaan, aanzienlijke effectgroottes bereiken, terwijl interventies op het gebied van voeding en lichaamsbeweging er niet in slagen verbeteringen in de geanalyseerde gezondheidsresultaten te bereiken. In overeenstemming met dit laatste tonen wij ook aan dat gezondheidsuitkomsten die verband houden met gewichtsverlies, dat wil zeggen BMI en tailleomtrek, de uitkomsten zijn die het moeilijkst lijken om te veranderen met de onderzochte interventies. Wij documenteren ook bewijs van aanzienlijke publicatiebias, die wij aanpakken met een meta-regressie benadering om betrouwbare schattingen te verkrijgen. Ten slotte tonen wij aan dat het aantal contactmomenten die de deelnemers aan de studie met de uitvoerende gezondheidsinstanties hebben sterk samenhangt met de doeltreffendheid van de interventie. Ook de leeftijd van de beoogde deelnemers en de vraag of de interventie in groepsverband wordt toegepast, beïnvloeden de effectgrootte.

Dit artikel levert in drie opzichten een bijdrage aan de literatuur. Ten eerste bieden wij een analyse die de gehele Zuidoost-Aziatische regio bestrijkt, zodat wij conclusies en beleidsimplicaties kunnen afleiden die extern valide zijn voor een uitgestrekt geografisch gebied. Ten tweede gaan wij in op de verwevenheid van de vier belangrijkste NCD's en hun vier belangrijkste risicofactoren, en bekijken wij een breed scala aan NCD-maatregelen, die tot dusverre bij de evaluatie van de doeltreffendheid van maatregelen grotendeels buiten beschouwing zijn gebleven. Wij gaan daarmee verder dan de gebruikelijke aanpak waarbij de aandacht wordt toegespitst op één enkele NCD, één enkele risicofactor of één enkel land, zoals in de uitgebreide literatuur op dit gebied het geval is. Ten slotte leveren wij ook een methodologische bijdrage door verschillende tekortkomingen aan te pakken die gewoonlijk in conventionele meta-analyses worden veronachtzaamd, met econometrisch meer verfijnde methoden en door een maatstaf voor de effectgrootte te gebruiken die rekening houdt met reeds bestaande verschillen tussen behandelings- en controlepopulaties.

Het tweede artikel zoomt in op de nationale context van Indonesië, richt zich op de wisselwerking tussen klimaatverandering en NCD's, en beoordeelt de extra gezondheidslasten en financiële lasten voor de nationale gezondheidszorg, met name het nieuwe nationale ziekteverzekeringstelsel. Personen met NCD's lopen een bijzonder risico om te lijden onder de stijgende temperaturen, aangezien hun reeds uitgeputte lichamen beperkt zijn in hun vermogen om verdere schokken op te vangen en hitte een reeks van gezondheidsaandoeningen kan verergeren. Om dit verband te onderzoeken, ga ik concreet na of het aantal gezondheidsbezoeken in verband met diabetes, hart- en vaatziekten en chronische ademhalingsziekten in de Indonesische eerstelijnsgezondheidszorg (Puskesmas) toeneemt op dagen met extreem hoge temperaturen. Daartoe gebruik ik een nieuwe en representatieve dataset van de Indonesische nationale ziektekostenverzekering Jaminan Kesehatan Nasional (JKN) en koppel ik de gegevens aan verschillende meteorologische datasets om informatie over de lokale temperatuur te verkrijgen en te controleren voor mogelijke versturende factoren zoals regenval, vochtigheid, luchtverontreiniging of windsnelheid. Het uiteindelijke panel, met dagelijkse waarnemingen per district en in totaal meer dan 370.000 waarnemingen, maakt het vervolgens mogelijk het causale effect van temperatuurstijgingen empirisch te schatten door gebruik te maken van een quasi-experimentele benadering en een semi-parametrische specificatie met een reeks vaste effecten. Uit de resultaten blijkt dat op dagen met extreem hoge temperaturen het aantal bezoeken met een diagnose van diabetes en hart- en vaatziekten met respectievelijk 25% en 14% toeneemt, terwijl ik geen bewijs vind voor een toename van het aantal bezoeken in verband met ademhalingsziekten. Voorts ga ik na of er sprake is van zogenaamde "oogst-effecten", dat wil zeggen of de toename van het aantal bezoeken aan de gezondheidszorg slechts tijdelijk of blijvend is. Uit de analyse blijkt dat het laatste het geval is. De toename van het aantal bezoeken aan de gezondheidszorg in verband met NCD's wordt zelfs na een periode van vier weken niet gecompenseerd. Dit heeft grote gevolgen voor de belasting van de gezondheidsvoorzieningen en de gezondheidswerkers. Ten slotte simuleer ik aan de hand van verschillende scenario's voor klimaatverandering en bevolkingsgroei de toekomstige toename van het aantal aan NCD-gerelateerde zorgbezoeken en de daaraan verbonden kosten tegen het einde van deze eeuw. De resultaten van deze oefening voorspellen een aanzienlijke financiële last voor de Indonesische gezondheidszorg met extra jaarlijkse kosten tot 31 miljoen dollar voor de primaire gezondheidszorg.

De belangrijkste bijdrage van dit artikel is dat het voor het eerst bewijs levert voor het onderlinge verband tussen stijgende temperaturen en schadelijke gezondheidseffecten op het niveau van de eerstelijnsgezondheidszorg, terwijl eerdere studies vooral de gevolgen voor voorzieningen op een hoger niveau, zoals spoedeisende hulp of ziekenhuizen in het algemeen, onderzochten. Door zich te

richten op bezoeken aan de eerstelijnsgezondheidszorg in plaats van op hospitalisatiecijfers en bezoeken aan spoeddiensten, wordt echter belangrijke informatie verkregen over de gevolgen van de opwarming van de aarde voor de eerstelijnsgezondheidszorg, die in veel lage- en midden-inkomenslanden een centrale rol speelt. Verder levert het artikel een bijdrage aan de literatuur door gegevens over gezondheidsbezoeken te gebruiken van een land, dat niet alleen een van de grootste landen ter wereld is, maar tegelijk ook een midden-inkomensland. Over het algemeen beoordelen slechts weinig studies de gezondheidseffecten van hitte in niet-westerse landen en lage- en midden-inkomenslanden. Daardoor is het verband tussen temperatuur en de gevolgen voor de gezondheid in landen in het mondiale Zuiden, die relatief meer tropische en vochtige klimaatzones en slechtere gezondheidsstelsels hebben, nog niet eerder in detail onderzocht.

Het derde artikel, dat samen met Michael Grimm, Ingmar Weber, Elad Yom-Tov en Benedictus Praditya is geschreven, blijft in de geografische context van Indonesië en richt zich specifiek op type 2 diabetes. In deze studie gaan we na of sociale media kunnen dienen als een efficiënt en kosteneffectief instrument om het bewustzijn over diabetes type 2 te vergroten en individuele risicoscreening aan te moedigen. Daartoe baseren wij ons op experimenteel bewijsmateriaal van een diabetesbewustmakingscampagne die wij op het sociale-mediaplatform “Facebook” hebben uitgevoerd. Meer specifiek hebben wij willekeurig grafische advertenties over het risico en de gevolgen van diabetes verspreid onder Indonesische Facebook-gebruikers in de steden Jakarta en Yogyakarta om te testen welk type boodschap en grafisch ontwerp het doeltreffendst is om gebruikers ertoe aan te zetten een informatiewebsite te bezoeken en een diabeteszelfscreening uit te voeren. Afhankelijk van het resultaat van deze screening krijgen de deelnemers de aanbeveling om contact op te nemen met hun huisarts en te vragen om een grondige screening. Onze resultaten suggereren dat advertenties met een “informatieve” of “schokkende” inhoud het meest effectief zijn in termen van voltooide zelfscreeningsactiviteiten. Met een aanvullende vervolgenquête zes weken na de online screening tonen wij aan dat ongeveer 28% van de respondenten die een hoog risico bleken te hebben, inderdaad de ontvangen aanbeveling opvolgen om contact op te nemen met hun huisarts voor een professionele screening. Wat de kosten van deze interventie betreft, concluderen wij dat een dergelijke online volksgezondheidscampagne zeer kosteneffectief kan zijn met een kostprijs van ongeveer 9 dollar per nieuw gediagnosticeerde persoon met type 2 diabetes.

Deze studie levert verschillende bijdragen. Ten eerste dragen wij bij aan de literatuur die zich richt op bewustwording, preventie en gebruik van screening voor NCD's in lage- en midden-inkomenslanden, met name in Zuidoost-Azië, wat van groot belang is voor lokale beleidsmakers. Verder leveren wij een bijdrage aan de zeer recente literatuur die aantoont dat Facebook een veelbelovend in-

strument is voor gezondheidsgerelateerde informatiecampagnes en een steeds relevanter instrument voor wetenschappelijk onderzoek, met name wat betreft de uitvoering van gerandomiseerde onderzoeken met controlegroep (“RCTs”) en veldexperimenten. Onze studie onderscheidt zich echter als een van de allereerste die een gezondheidsgerelateerd veldexperiment via Facebook uitvoert in een middeninkomensland.

Ten slotte leveren wij een bijdrage aan een literatuur die voornamelijk geworteld is in de psychologie en waarin wordt onderzocht welk soort framing of beeldinhoud gezondheidsgerelateerde beslissingen aanstuurt en of blootstelling aan informatie het preventieve gezondheidsgedrag verbetert. Daarmee leveren wij bewijs over welke psychologische kanalen individuen effectief kunnen stimuleren om te leren over hun risico op het hebben of ontwikkelen van diabetes in een land waar de algemene bekendheid met de ziekte laag is.

Samen dragen de drie in dit proefschrift gepresenteerde artikelen bij tot het inzicht in mogelijke routes naar (kosten)effectieve oplossingen voor de preventie van NCD's in Zuidoost-Azië en mogelijk andere lage- en middeninkomenslanden. Verder draagt het bij tot een beter begrip van de wisselwerking tussen klimaatverandering en NCD's. Daarmee consolideert het een voorzichtige poging om lage- en middeninkomenslanden te ondersteunen bij hun inspanningen om de twee grote gezondheidsuitdagingen van de 21e eeuw aan te pakken.

German summary

Im gegenwärtigen einundzwanzigsten Jahrhundert stehen Länder mit niedrigen und mittleren Einkommen vor zwei gesundheitlichen Herausforderungen, die sich grundlegend von denen unterscheiden, mit denen diese Länder in den vergangenen Jahrhunderten konfrontiert waren. Erstens sehen sie sich mit steigenden Raten nicht übertragbarer Krankheiten (NCDs) konfrontiert, namentlich Herz-Kreislauf-Erkrankungen, Krebs, chronische Atemwegserkrankungen und Diabetes, welche Infektionskrankheiten als Haupttodesursache überholt haben. Zweitens wird der Klimawandel seinen Tribut fordern und wird Prognosen zufolge katastrophale gesundheitliche Beeinträchtigungen verursachen und chronische Gesundheitszustände weiter verschlimmern. Beides wird eine unverhältnismäßig große gesundheitliche und wirtschaftliche Belastung für Länder mit niedrigen und mittleren Einkommen darstellen, welche wiederum nur limitierte Ressourcen zur Verfügung haben, dieser Belastung entgegenzuwirken. Die zunehmenden NCD-Raten, der Klimawandel und die damit zusammenhängenden gesundheitlichen Folgen behindern somit die Fortschritte bei der Erreichung der Ziele für nachhaltige Entwicklung. Indem sie die Gesundheit des Einzelnen und die wirtschaftliche Entwicklung bedrohen und die ohnehin schon eingeschränkten Gesundheitssysteme immens belasten, behindern sie die Fortschritte bei der Armutsbekämpfung und verstärken die gesundheitlichen Ungleichheiten zwischen Arm und Reich.

Vor diesem Hintergrund soll diese Dissertation einen Beitrag zu der Frage leisten, wie die Prävention und Kontrolle von NCD im geografischen Kontext Südostasiens verbessert und die wirtschaftliche Belastung verringert werden kann. Konkret sollen drei Forschungsfragen in drei in sich geschlossenen Artikeln beantwortet werden: Erstens: Welche Art von Präventions- und Behandlungsmaßnahmen für NCDs versprechen im südostasiatischen Kontext wirksam zu sein? Zweitens: Inwieweit könnte der Klimawandel die NCD-Raten und die finanzielle Belastung weiter erhöhen und damit dem Erfolg solcher Maßnahmen entgegenwirken? Und drittens: Können Social-Media-Plattformen als vielversprechendes Instrument für kosteneffiziente Interventionen zur Bekämpfung von NCDs dienen?

Der erste Artikel, der gemeinsam mit Hanna Fromell verfasst wurde, fasst die Erkenntnisse über eine breite Palette von NCD-Interventionen in Südostasien aus den letzten zwei Jahrzehnten zusammen, die auf eine Reduzierung der NCD-Risikofaktoren, eine Erhöhung der NCD-Präventionsmaßnahmen oder eine Verbesserung der allgemeinen Praktiken von Gesundheitseinrichtungen abzielen. In Form einer systematischen Übersichtsarbeit, die durch eine Meta-Analyse, eine Meta-Regression und eine Moderator-Analyse ergänzt wird, liefern wir Evidenz dafür, welche Arten von Interventionen im gegebenen Kontext vielversprechend sind. Insgesamt ziehen wir 204 Schätzungen aus 51 Studien heran und ordnen sie in sechs verschiedene Interventionstypen ein, je nach Art der adressierten Krankheit, des Risikofaktors oder des Interventionsdesigns, und betrachten so ein Universum von 23 verschiedenen Gesundheitsaspekten, auf die solche Interventionen abzielen können.

Unsere Ergebnisse zeigen, dass insbesondere Programme, die sich auf die Raucherentwöhnung, die Inanspruchnahme von Vorsorgeuntersuchungen oder die Aufklärung von Patienten über den Umgang mit NCDs konzentrieren, beträchtliche positive Effekte erzielen. Interventionen in den Bereichen Ernährung und körperliche Betätigung können keine Verbesserungen bei den analysierten Gesundheitsaspekten erzielen. Damit zusammenhängend zeigen wir auch, dass die mit der Gewichtsabnahme korrelierten Gesundheitsaspekte, d.h. BMI und Taillenumfang, bei den untersuchten Interventionen am schwersten zu verbessern sind. Wir dokumentieren auch Hinweise auf eine erhebliche Publikationsverzerrung, die wir mit einem Meta-Regressions-Ansatz adressieren, um zuverlässigere Schätzungen zu erhalten. Schließlich zeigen wir, dass die Anzahl der Kontakte der Studienteilnehmer mit den durchführenden Gesundheitsbehörden stark mit der Wirksamkeit der Intervention korreliert. Auch das Alter der Studienteilnehmer und die Tatsache, ob die Intervention in einem Gruppendesign durchgeführt wird, beeinflussen die Stärke des Effekts.

Dieser Artikel leistet drei wichtige Beiträge zur Literatur. Erstens deckt unsere Analyse die gesamte südostasiatische Region ab, womit wir in der Lage sind, Schlussfolgerungen und Implikationen abzuleiten, die für ein großes geographisches Gebiet gültig sind. Zweitens gehen wir auf die Verflechtung der vier wichtigsten NCDs und ihrer vier Hauptrisikofaktoren ein, was bei der Bewertung der Wirksamkeit von Interventionen bisher weitgehend ignoriert wurde. Damit gehen wir über den üblichen Ansatz hinaus, sich auf einzelne NCDs, einen einzelnen Risikofaktor oder ein einzelnes Land zu konzentrieren, wie dies in einem Großteil der Literatur auf diesem Gebiet der Fall ist. Schließlich leisten wir auch einen methodischen Beitrag, indem wir mehrere Mängel, die in herkömmlichen Meta-Analysen häufig vernachlässigt werden, mit ökonometrisch anspruchsvolleren Methoden beheben. Ebenfalls verwenden wir ein Maß für die Effektgröße, das die bereits vor

der Intervention bestehenden Unterschiede zwischen Behandlungs- und Kontrollgruppen berücksichtigt.

Der zweite Artikel geht spezifisch auf den Länderkontext Indonesiens ein, konzentriert sich auf die Wechselwirkung zwischen Klimawandel und NCDs und bewertet die daraus resultierende gesundheitliche und finanzielle Belastung für das nationale Gesundheitssystem. Personen, die von NCDs betroffen sind, sind besonders gefährdet, unter steigenden Temperaturen zu leiden, da ihre bereits erschöpften Körper nur begrenzt in der Lage sind, weitere Schocks zu verkraften, und Hitze eine Vielzahl von Gesundheitszuständen verschlimmern kann. Um diesen Zusammenhang zu erörtern, untersuche ich, ob die Zahl der Arztbesuche im Zusammenhang mit Diabetes, Herz-Kreislauf-Erkrankungen und chronischen Atemwegserkrankungen in den indonesischen Einrichtungen der medizinischen Grundversorgung (*Puskemas*) an Tagen mit extrem hohen Temperaturen zunimmt. Dabei stütze ich mich auf einen neuen und repräsentativen Datensatz der nationalen indonesischen Krankenversicherung *Jaminan Kesehatan Nasional* (JKN) und verknüpfe die Daten mit mehreren meteorologischen Datensätzen, um Informationen über die lokale Temperatur zu gewinnen und für mögliche Störfaktoren wie Niederschlag, Feuchtigkeit, Luftverschmutzung oder Windgeschwindigkeit zu kontrollieren. Der finale Datensatz, der aus mehr als 370,000 Beobachtungen besteht, ermöglicht es, die kausale Wirkung steigender Temperaturen empirisch zu schätzen. Dafür stütze ich mich auf einen quasi-experimentellen Ansatz und nutze eine semi-parametrische Spezifikation.

Die Ergebnisse zeigen, dass an Tagen mit extrem hohen Temperaturen die Zahl der Besuche mit der Diagnose Diabetes und Herz-Kreislauf-Erkrankungen um 25% bzw. 14% ansteigt, während ich keine Hinweise auf einen Anstieg der Zahl der Besuche im Zusammenhang mit Atemwegserkrankungen finde. Ferner untersuche ich, ob es so genannte "Harvesting-Effekte" gibt, d.h. ob der Anstieg der Zahl der Arztbesuche nur vorübergehend oder dauerhaft ist. Die Analyse zeigt, dass Letzteres der Fall ist. Der Anstieg der Arztbesuche im Zusammenhang mit NCDs wird auch nach einem Zeitraum von vier Wochen nicht nivelliert. Dies hat erhebliche Auswirkungen auf die Belastung der Gesundheitseinrichtungen und des Gesundheitspersonals. Schließlich ziehe ich verschiedene Szenarien des Klimawandels und des Bevölkerungswachstums heran, um den künftigen Anstieg der NCD-bedingten Arztbesuche und der damit verbundenen Kosten bis zum Ende dieses Jahrhunderts zu simulieren. Die Ergebnisse dieser Schätzung prognostizieren eine beträchtliche finanzielle Belastung für das indonesische Gesundheitssystem mit zusätzlichen jährlichen Kosten von bis zu 31 Millionen US-Dollar, die für primäre Gesundheitsdienste ausgegeben werden müssen.

Der wichtigste Beitrag dieses Artikels besteht darin, dass er zum ersten Mal den Zusammenhang zwischen steigenden Temperaturen und negativen gesund-

heitlichen Auswirkungen auf der Ebene der primären Gesundheitsversorgung nachweist, während frühere Studien in erster Linie die Folgen für übergeordnete Einrichtungen wie Notaufnahmen oder Krankenhäuser im Allgemeinen untersucht haben. Die Fokussierung auf Besuche in der primären Gesundheitsversorgung anstelle von Hospitalisierungsraten und Notfallaufnahmen liefert jedoch wichtige Informationen darüber, wie sich die globale Erwärmung auf den primären Gesundheitssektor auswirken wird, der in vielen Ländern mit niedrigen und mittleren Einkommen von zentraler Bedeutung ist. Darüber hinaus leistet der Artikel einen Beitrag zur Literatur, indem er Daten über Gesundheitsbesuche verwendet, die nicht nur für eines der größten Länder der Welt stehen, sondern auch aus einem Land mit mittleren Einkommen stammen. Im Allgemeinen gibt es nur wenige Studien, die sich mit den gesundheitlichen Auswirkungen von Hitze in nicht-westlichen Ländern sowie in Ländern mit niedrigen und mittleren Einkommen befassen. Somit wurde der Zusammenhang zwischen Temperatur und gesundheitlichen Folgen in Ländern des globalen Südens, die tendenziell tropischere und feuchtere Klimazonen sowie schlechtere Gesundheitssystemkapazitäten aufweisen, noch nicht im Detail untersucht.

Der dritte Artikel, der gemeinsam mit Michael Grimm, Ingmar Weber, Elad Yom-Tov und Benedictus Praditya verfasst wurde, bleibt im Länderkontext von Indonesien und konzentriert sich speziell auf Typ-2-Diabetes. In dieser Studie untersuchen wir, ob soziale Medien als effizientes und kostengünstiges Instrument zur Sensibilisierung für Typ-2-Diabetes und zur Förderung individueller Risikovororgemaßnahmen dienen können. Dazu stützen wir uns auf experimentelle Erkenntnisse aus einer Diabetes-Aufklärungskampagne, die wir auf der Social-Media-Plattform "Facebook" durchgeführt haben. Konkret verteilten wir nach dem Zufallsprinzip grafische Anzeigen zu den Risiken und Folgen von Diabetes an indonesische Facebook-Nutzer in den Städten Jakarta und Yogyakarta, um zu testen, welche Art von Botschaft und grafischer Gestaltung am wirksamsten ist, um die Nutzer zum Besuch einer Informations-Website und zur Durchführung eines Diabetes-Selbstscreenings zu bewegen. Je nach Ergebnis dieses Screenings erhalten die Teilnehmer die Empfehlung, sich an ihren Hausarzt zu wenden und nach einem professionellen Diabetes-Screening zu fragen. Unsere Ergebnisse deuten darauf hin, dass Anzeigen mit "informativem" oder "schockierendem" Inhalt im Hinblick auf die Durchführung von Selbstscreenings am effektivsten sind. Mit einer ergänzenden Folge-Befragung sechs Wochen nach dem Online-Selbstscreening konnten wir nachweisen, dass etwa 28% der Befragten, bei denen ein hohes Risiko festgestellt wurde, tatsächlich der erhaltenen Empfehlung nachkamen, ihren Hausarzt für ein professionelles Screening zu kontaktieren. Mit Blick auf die Kosten dieser Maßnahme kommen wir zu dem Schluss, dass eine solche Online-Gesundheitskampagne mit Kosten von etwa 9 US-Dollar pro neu di-

agnostizierter Person mit Typ-2-Diabetes sehr kosteneffizient sein kann.

Diese Studie leistet mehrere Beiträge. Erstens leisten wir einen Beitrag zur Literatur, die sich mit der Bewusstseinsbildung, der Prävention und der Inanspruchnahme von Vorsorgeuntersuchungen für NCDs in Ländern mit niedrigen und mittleren Einkommen, insbesondere in Südostasien, befasst, was für die politischen Entscheidungsträger vor Ort von größter Bedeutung ist. Darüber hinaus leisten wir einen Beitrag zu der sehr aktuellen Literatur, die zeigt, dass Facebook ein vielversprechendes Instrument für gesundheitsbezogene Informationskampagnen und ein zunehmend relevantes Instrument für die wissenschaftliche Forschung ist, insbesondere im Hinblick auf die Durchführung von randomisierten kontrollierten Studien und Feldexperimenten. Unsere Studie ist jedoch eine der ersten, die ein gesundheitsbezogenes Feldexperiment über Facebook in einem Land mit mittleren Einkommen durchführt. Schließlich leisten wir einen Beitrag zu einer hauptsächlich in der Psychologie verwurzelten Literatur, in der untersucht wird, welche Art von "Framing" oder bildlichen Inhalten gesundheitsbezogene Entscheidungen beeinflussen und ob die Exposition gegenüber Informationen das Gesundheitsverhalten verbessert. Damit liefern wir Hinweise darauf, welche psychologischen Aspekte Personen wirksam dazu anregen können, sich über ihr Diabetes-Risiko zu informieren, in einem Land, in dem das allgemeine Bewusstsein für diese Krankheit gering ist.

Gemeinsam tragen die drei in dieser Dissertation vorgestellten Artikel zum Verständnis möglicher Wege zu (kosten-)wirksamen Lösungen für die Prävention von NCDs in Südostasien und möglicherweise in anderen Ländern mit niedrigen und mittleren Einkommen bei. Außerdem trägt sie zum Verständnis des Zusammenspiels von Klimawandel und NCDs bei. Auf diese Weise wird ein vorsichtiger Versuch unternommen, Länder mit niedrigen und mittleren Einkommen in ihren Bemühungen zu unterstützen, die beiden großen gesundheitlichen Herausforderungen des einundzwanzigsten Jahrhunderts anzugehen.

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