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Keywords

health screening, hypertension, non-communicable diseases, regression discontinuity design, matching estimator, low income countries, Malawi

Disciplines

African Studies | Demography, Population, and Ecology | Diseases | Inequality and Stratification | Medicine and Health | Rural Sociology | Social and Behavioral Sciences

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Evidence for the effectiveness of population health screenings to reduce the burden of non-communicable diseases in low income countries remains very limited. We investigate the sustained effects of a health screening in Malawi where individuals received a referral letter if they had elevated blood pressure. Using a regression discontinuity design and a matching estimator, we find that receiving a referral letter reduced blood pressure and the probability of being hypertensive by about 22 percentage points four years later. These lasting effects are explained by a 20 percentage points increase in the probability of being diagnosed with hypertension. There is also evidence of an increase in the uptake of medication, while we do not identify improvements in hypertension-related knowledge or risk behaviors. The health screening had some positive effects on mental health. Overall, this study suggests that population-based hypertension screening interventions are an effective tool to improve health in low-income contexts.

Keywords: Health Screening, Hypertension, Non-communicable Diseases, Regression Discontinuity Design, Matching Estimator, Low Income Countries, Malawi

JEL: C21, I12, I18

1 Introduction

Individuals often have very imperfect knowledge about their own health (Foot *et al.* 2014). This lack of knowledge can inhibit critical health decision making and result in preventable elevated mortality and morbidity (Kenkel 1991; Ruhm 2016). Limited knowledge about own health is of particular concern when severe medium/long-term health risks do not manifest itself in instantaneous disease symptoms. Examples include: HIV infection, with infected individuals facing significantly elevated morbidity and mortality as the disease progresses, while experiencing virtually no specific indications of being HIV+ for a prolonged period of time (Tomar 1994); diseases with well-defined genetic risk factors but delayed manifestation of symptoms, including breast cancer or some inherited disorders

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such as Huntington's disease (Müller *et al.* 2018; Oster *et al.* 2013); or conditions such as insulin resistance where early detection and intervention can reduce cumulative organ damage and delay disease progression to adult-onset diabetes (American Diabetes Association 2002). In this category of illnesses is also cardiovascular disease (CVD), an eminent emerging disease burden in low- and middle-income countries (LMICs) where individuals with high blood pressure generally experience few noticeable indications of hypertension, while at the same time, face heightened morbidity and mortality risks through stroke, heart attacks, metabolic syndrome, memory loss or dementia (Geldsetzer *et al.* 2019; Lackland and Weber 2015; Wang *et al.* 2006).

Improving individuals' knowledge about their own health has the potential to reduce morbidity and mortality in the above cases, as informed individuals can respond to latent health risks through appropriate prevention and/or risk-reduction strategies. For example, HIV testing is a pathway to access antiretroviral treatment (ART), a diagnosis of hypertension can be followed up by behavioral changes or biomedical treatment to reduce CVD risks, women may opt to undergo mastectomy if they are identified as carriers of BRCA1 or BRCA2 genes, etc. Because of the basic insight that knowledge is key to prevention and treatment, ***health screenings*** have been promoted and implemented in many contexts as a tool to improve population health and enhance individuals' ability to effectively invest in heath across the life course. In high-income countries, health screenings are routinely conducted as part of regular health care visits (Swenson and Ebell 2016). In countries affected by the HIV epidemic, HIV testing has become an essential component of pre-natal care, and door-to-door HIV testing, widespread screening as part of National HIV Testing Days, and HIV self-testing have all been promoted as effective health policy (CDC 2020; Ganguli *et al.* 2009; WHO 2016). Demand for such testing services is often high (Thornton 2008). In contrast to these well established screening programs, currently very limited NCD screening is conducted in LMICs, which is in striking contrast to the rapidly rising NCD disease burden (GBD Collaborators 2018; NCD-RisC Collaboration 2017). As a result, poor and rural populations are likely to have a high prevalence of undiagnosed risk factors (Geldsetzer *et al.* 2019; Islam *et al.* 2014).

Population-based health screenings have been promoted in LMICs to address this rising NCD-related morbidity and mortality (Benziger *et al.* 2016; Greenberg *et al.* 2011). Screening for hypertension is particularly relevant as the prevalence of hypertension in LMICs ranges between 20% and 40% (Ibrahim and Damasceno 2012). Yet, important concerns remain as to whether NCDs-screening in LICs is effective for improving population health for several reasons. *First*, individuals need to have basic NCDs-related health literacy in order to be able to act based on obtaining knowledge about hypertension or similar NCDs-risk factors. Even if the health screening is accompanied by the respective health information about the determinants, behavioral and biomedical risk reduction strategies, because of limited health literacy and knowledge individuals may not be able to respond to the provided health information in ways that results in longer-term morbidity and mortality benefits. *Second*, prevention and treatment guidelines for NCDs and CVDs specifically in LICs are often based on established guidelines for higher-income contexts. However, individuals' ability to effectively respond to NCDs-related information revealed during heath screenings is made more complex in LICs by the fact that CVD and certain other NCDs are partially driven by a different set of risk factors than in higher-income contexts (WHO 2013a). *Third*, health systems in LICs are often inadequately prepared and equipped in terms of staffing, equipment, guidelines and medications to diagnose, manage and/or treat NCDs (Cappuccio and Miller 2016; Nulu *et al.* 2016). Individuals who present themselves to the health system based on NCD-related health screenings, therefore, often may not be able to receive treatment or guidance that allows them to reduce their underlying health risks.

The existing evidence about the effectiveness of NCDs-related health screenings is mixed, including the one generated in high-income countries with sophisticated health systems and relatively good NCDs-related health literacy (Krogsbøll *et al.* 2012). While there is some evidence about the effectiveness of NCDs-related health screenings in high and middle-income populations (Chen *et al.* 2019; Rodriguez-Lesmes *et al.* 2017), to date, no population-based evidence exists about its effectiveness in rural LICs contexts. Moreover, the effectiveness of NCDs-related health screenings in poor and/or rural LMICs populations cannot be inferred by relying on research evidence generated in higher-income countries, given the distinctly different health systems, distinct risk factors for common NCDs, and low NCDs-related health literacy in the population. The experience in LICs with HIV testing however provides useful guidance on how the benefits of population-based screening multiply once access to the respective health care is made available. Prior to the widespread availability of antiretroviral treatment (ART), the benefits of widespread population-based HIV testing were controversial (Denison *et al.* 2008). Once access to ART became widely available, HIV testing outside of clinical settings has became the gateway to accessing ART and the benefits of testing are widely accepted (CDC 2020).

This paper fills an important gap in the research on the effectiveness of population-based screening for NCDs in LICs by evaluating the *long-term effects* of a simple and inexpensive population-based health screening for hypertension in Malawi. Specifically, we investigate if screening for high blood pressure among mature adults with high prevalence of hypertension can lead to significant long-term gains in hypertension-related health outcomes such as reductions in blood pressure levels, or uptake in diagnosis and medication. The causal identification of these effects exploits a study design feature that provided "*at-risk*" study participants with a referral letter for further assessment by a health care provider if they were measured with blood pressure above a specific threshold (160 mmHg systolic or 110 mmHg diastolic blood pressure). We pursue two empirical strategies to evaluate the effects of the referral letter. Using a sharp regression discontinuity design (RDD), we compare the outcomes for individuals who are right above the cutoff for receiving the referral letter (treatment group) to the outcomes for those who are right below the cutoff (control group). The second strategy, a nearest-neighbor matching estimator, exploits the availability of multiple blood pressure measurements to estimate the causal effects of getting a referral letter on hypertension-related health outcomes away from the cutoff of 160 mmHg systolic blood pressure. This second strategy matches individuals based on their mean blood pressure measurements while the RDD strategy is implicitly matching individuals on their maximum blood pressure measurements. The two methods complement each other: the discontinuity design controls best for selection, while matching allows to explore the results away from the critical cutoff and provides estimates with higher external validity. The results yield very similar estimates across the two different methods, although they vary in some cases in their statistical power.

Overall, our study finds that hypertension health screening was effective, and that providing referral letters to at-risk respondents resulted in a long-term reduction of blood pressure. More specifically, the regression discontinuity local average treatment effect on the change in systolic blood pressure between 2013 and 2017 is around -14.3 units of millimeters of mercury (mmHg), which corresponds to about half a standard deviation in systolic blood pressure. The average treatment effect on the treated measured by the matching estimator is very similar at about -12.6 mmHg. We also find a negative treatment effect of about half a standard deviation for diastolic blood pressure (-6 mmHg) using both methods. As a consequence of this drop in blood pressure levels, individuals in the treatment group ended up being 22% less likely to be hypertensive in 2017. Such sustained long-term effects have not previously been documented for NCD-related health screening in rural LIC populations with low levels of health literacy, high NCD prevalence and limited access to NCDs care through the health system.

The observed drop in blood pressure among at-risk respondents subsequent to the MLSFH-MAC health screening was most likely the consequence of a sharp increase in the rate of diagnosis for hypertension. Individuals who received the referral letter have a 20 percentage points higher chance to have been diagnosed as hypertensive by a medical provider within two years before the follow-up assessment in 2017. The increase in diagnosis rate that resulted from the referral letter also seemed to have lead to a higher share of individuals who were treated for hypertension by taking medication, although the effects are less precisely estimated and are statistically significant only in the matching estimates. The effect on the probability of currently taking medication is 13 percentage points in the matching specification which is rather large considering that the share of people taking medication is very low (9.4%).

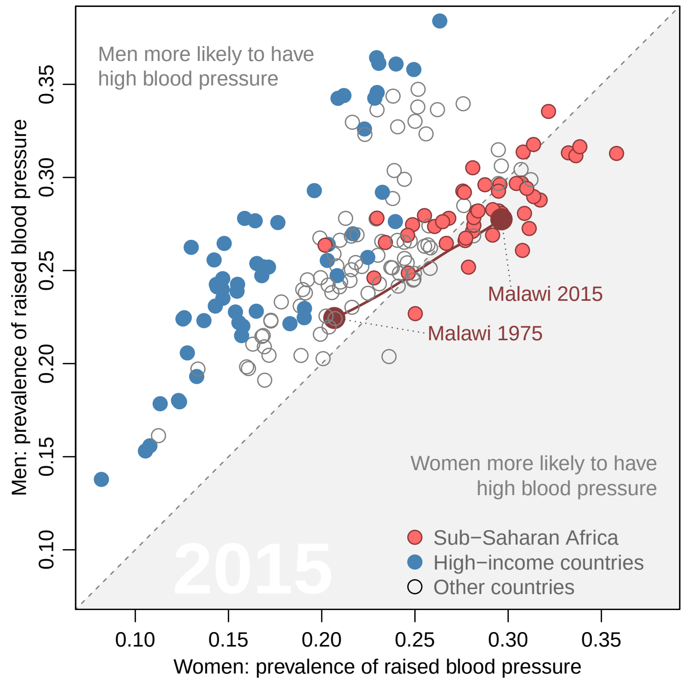
Efforts to reduce blood pressure through medication could be reinforced or hampered by other hypertension-related risk behaviors such as unhealthy diet and lack of physical exercise. We fail to find any positive effects of the referral letter on these risk behaviors. If anything, we find some negative effects, according to Western recommendations, such as an increase in sugar intake and a decrease in physical exercise in the matching estimates only. These counter-intuitive behavioral responses are possibly related to the fact that some risk factors for CVDs in LICs are different from those established in higher-income contexts (our study population, for example, is physically very active, has almost no obesity or consumption of western diets, and nevertheless, is characterized by widespread hypertension Kohler *et al.* 2018b). It is therefore not clear that standard recommendations about how to reduce high blood pressure, which are generally derived based on evidence from Western high-income populations, are pertinent to LIC populations. Individuals in our study population might also aware that their options for changing dietary behaviors or physical activity levels are very limited, and that any such changes might overall have no (or even negative) effects on their health and well-being. We also do not find any effect on improved hypertension knowledge such as knowing the symptoms of hypertension and its treatment options. Finally, we do not find that the referral had negative effects on subjective physical and mental health. If anything, we find some evidence of a positive effect on subjective mental health in the RDD specification.

In summary, our analyses contribute to the literature on health care demand for newly emerging disease burdens in LICs, and more broadly, to the literature on how individuals respond to new information about their own health in terms of life-course decision-making (Dupas and Miguel 2017). Our results are consistent with findings from high- and middle-income countries that evaluated the effects of population-based health screening for hypertension using similar identification strategies (Chen *et al.* 2019; Rodriguez-Lesmes *et al.* 2017), although very few other study—and none in LMICs—have examined sustained population-based effects of health screening during a 4-year period. Our study expands this research by documenting the effects of NCD-related health screening in a very poor LIC context, and by investigating the pathways through which screening resulted in reduced blood pressure and improved hypertension management by affecting knowledge, diagnosis and medical treatment. Our study is also the first to exploit a dual methodological approach for establishing the causal effects of health screening. While the RDD strategy provides valid causal inference at the cutoff and has high *internal validity*, the matching strategy we employ allows to increase the *external validity* of our findings by estimating the effects of the referral for hypertension on different sets of individuals, therefore providing important insights for policies aiming at changing the different cutoffs for screening high blood pressure.

2 Non-communicable diseases (NCDs) and Health Screening in LICs

The prevalence of hypertension in African countries is high (Figure 1). While there have been important steps to improve treatment coverage for communicable diseases such as HIV and malaria (Lozano *et al.* 2012; Murray *et al.* 2012), the health care systems in these countries are ill-prepared to face the emergency of the rapidly increasing burden of hypertension and other NCDs (Beaglehole *et al.* 2008; Kämpfen *et al.* 2018). Moreover, despite the shifting burden of disease in SSA LICs, individuals' knowledge about NCD risk factors,

Figure 1: Prevalence of high blood pressure (systolic), by sex, 2015 (%, age-standardized)



Source: Adapted from The Economist (2017), based on NCD-RisC Collaboration (2017)

the symptoms and the importance of preventive health care to reduce NCD risk factors are generally very limited (Boateng *et al.* 2017; Das *et al.* 2017; Sjørensen *et al.* 2012; WHO 2015). NCD-related healthcare and knowledge is hampered by the fact that adequate information and resources are not provided to sub-populations at greatest risk and/or most affected by chronic conditions. Importantly this includes older populations above age 45, the majority of whom continues to live in rural areas, has very low levels of formal education and has very limited access to adequate NCD-related healthcare (Boateng *et al.* 2017; Kohler *et al.* 2018a; Malawi MOH and WHO 2010).

Policy options for addressing issues related to hypertension and the shifting burden of disease in LICs face formidable implementation challenges due to strained health systems that are coping with a dual burden of infectious and non-communicable diseases, have restricted resources for NCD-related health promotion and prevention, and serve populations with low NCD-related health literacy. Among the various measures that can potentially be put in place to contain the rising epidemic of hypertension and NCDs more generally, access to preventive care, screening interventions and early detection of health conditions are perhaps the ones that are the more efficient and recommended (WHO 2013b). Screening and early detection of health conditions, especially of high-blood pressure, have important benefits (American Heart Association 2019; Siu 2015). Indeed, high-blood pressure screening has no harms and facilitates the detection of associated CVDs diseases at an early stage and thus prevent individuals from going through unaffordable health care and more rigorous treatments that complications would require (Dehmer *et al.* 2017; Howard *et al.* 2010; Sheridan *et al.* 2003; Siu 2015; Wald *et al.* 1999). Given the limited health systems in SSA LICs, understanding the health behaviors and responses of individuals in the face of NCD awareness and screening is therefore crucial to contain the increasing burden of hypertension and NCDs more generally (Dupas 2011).

To date, however, very little evidence exists on the effectiveness of population-based health screening efforts focused on NCDs in LICs countries, in contrast to the extensive literature on screening (testing) for HIV and some other communicable diseases in LICs (e.g., Cohen *et al.* 2015; Delavande and Kohler 2012; Gong 2014; Thornton 2008).[1] A general finding is that households in low-income countries spend a significant portion of their resources on remedial health care but very little in preventive health care (Dupas 2011). A growing research evidence supports interventions to increase investments in preventive health care (Dupas and Miguel 2017), among which health screening is perhaps the most efficient, particularly for newly proliferating NCDs (Strong *et al.* 2005; WHO 2014).

3 Context and Data

3.1 Context

Our study is set in the context of Malawi, a SSA country with one of the lowest income per capita in the world, equal to about 2% of the global average, and a Human Development Index that is ranked 172 out of 189 countries ($HDI_{2018} = .485$). In rural areas, where our study is based and most Malawians (85%) live, the majority of individuals engage in home production of crops, complemented by some market activities. About 60% of the rural population is considered poor in 2016/17, thus having a total consumption that does *not* provide 2,400 calories per day per person plus some basic nonfood items, and 24% is considered ultra-poor (Malawi NSO 2018). The HIV epidemic reached its peak in the 2000s when the availability of antiretroviral treatment (ART) started to reduce the number of HIV-related deaths and initiated rebound of life expectancy (GBD Collaborators 2018; Jahn *et al.* 2008). NCDs have since become the major cause of death, as is also the case in other LMICs. Underlying this shifting disease burden is a high and increasing prevalence of NCD-risk factors such as hypertension (Figure 1). Our study population is no excep-

[1] Specifically, among the studies that have analyzed screening interventions for communicable diseases in Africa, Thornton (2008) finds that a financial incentive substantially increases the likelihood that an individual travels to learn the result of an HIV test in Malawi. Delavande and Kohler (2012) use the same intervention to look at beliefs over transmission risk and risky sexual behavior, and find that receiving an HIV-negative test result implies higher subjective expectations about being HIV-positive after two years, and individuals tend to have larger prediction errors about their HIV status after learning their HIV status. Gong (2014) looks at a randomized HIV testing campaign in Kenya and Tanzania and find that being tested reduce the likelihood of getting an STI, and document behavioral responses to HIV tests when tests provide unexpected information. Cohen *et al.* (2015) randomize access to rapid malaria diagnostic tests in Kenya where overtreatment of malaria is very common, and find that those who learn their status are less likely to buy the antimalarial drug but around half of individuals testing negative still purchase the drug.

tion: more than than 60% of the mature adults in 2013 were at least pre-hypertensive, and 42.30% had Stage 1 or Stage 2 hypertension, exposing more than two-fifth of respondents to substantially elevated CVD risks (Kohler *et al.* 2018b).[2] In Malawi and other LICs, however, the increasing importance of NCDs is not matched with a significant increase in financial and human resources dedicated to NCDs-related health care (Beaglehole *et al.* 2008). Hospitals in Malawi are understaffed and the medical staff is poorly trained to treat NCDs (Malawi Ministry of Health and ICF International 2014). In our study areas, about 85 percent of health facilities do not have staff recently trained to provide services for diabetes or for cardiovascular diseases. As a consequence of limited NCD-related heath care services, people are not routinely screened for NCDs, a situation that is especially pronounced in rural areas. As a result, very few people get tested for hypertension either because they are not aware of the risks associated with high blood pressure or because routine high blood pressure testing is not done as part of health examinations (Msyamboza *et al.* 2012).[3]

3.2 The Mature Adults Cohort of the Malawi Longitudinal Study of Families and Health (MLSFH-MAC)

Our analyses use data from the Mature Adults Cohort of the Malawi Longitudinal Study of Families and Health (MLSFH-MAC), a longitudinal cohort study of individuals (mostly) aged 45 years and older in rural areas in three districts in Malawi (Mchinji, Rumphi and Balaka).[4] The cohort was established in 2012, with follow-up waves in 2013, 2017 and 2018 collecting extensive information on physical, mental and cognitive health, NCDs-related health knowledge and NCDs-related health care utilization, socioeconomic well-being, household production and consumption, household structure and family change. The study population is broadly representative of the 45+ years old rural population in Malawi. The MLSFH and MLSFH-MAC Cohort Profiles provides detailed information on sampling procedures, study design and study instruments (Kohler *et al.* 2015, 2020).

[2]Interestingly, individuals in Malawi and more generally in SSA LICs lack the presence of conventional risk factors such as obesity or lack of physical activity that are associated with hypertension. In the MLSFH-MAC study population, only 15% of study participants are overweight (BMI between 25 to 30) and less than 5% are obese (BMI $\geq$ 30).

[3]For example, the WHO STEPS Survey conducted in 2009 in Malawi found that 75% of the participants never had their blood pressure measured before and 94.9% of the individuals who were tested with high blood pressure were unaware of their hypertensive conditions (Msyamboza *et al.* 2012).

[4]There are no birth certificates and/or other reliable records of when individuals are born in Malawi. MLSFH-MAC makes several attempts to verify age of the study participants. Eligibility for enrollment in MLSFH-MAC was determined by ages reported in 2010 and earlier. A small number of individuals reported ages below 45 at enrollment in 2012. These individuals were nevertheless enrolled in the study and this resulted in small number of respondents below age 45. In our MLSFH-MAC sample used in this analysis includes 12 respondents who are between ages 40 and 45.

3.3 Screening for high blood pressure in the MLSFH-MAC

The MLSFH-MAC screened all respondents for high blood pressure in 2013 and 2017 following the protocol established by the U.S. Health and Retirement Study (HRS) and using a Omron HEM-780 Blood Pressure Monitor (or comparable device). Three measurements were taken on the respondent's left arm, about 45 seconds apart, towards the end of the interview. Data recorded for each measurement included systolic and diastolic blood pressure, pulse, and the time of day the reading was taken.

Respondents who recorded *at least one* systolic blood pressure measurement above 160 mmHg, or *at least one* diastolic blood pressure measurement above 110 mmHg, were given referral letters for further assessment by a health care provider. The referral letter simply stated that the person was measured with high blood pressure surpassing 160 mmHg systolic and/or 110 mmHg diastolic and is referred to further assessment.[5] The referral letter did not provide any additional information, including where and with whom the respondent should go for further assessment. Interviewers were also instructed to inform the respondent only about their blood pressure measurements, and *not* to provide additional information on blood pressure or hypertension, or indicate a diagnosis that a respondent might be hypertensive. The referral letter is included in the Appendix.

In addition, MLSFH-MAC asked the study participants if they have been diagnosed with hypertension by a medical provider (doctor or nurse) in the last 2 years prior to the survey and if they were taking medication for the treatment of hypertension at the time of the interviews in 2013 and 2017. MLSFH-MAC collected also detailed information on respondents' knowledge about risk factors, symptoms and treatment of hypertension.

Table 1 shows the characteristics of our baseline sample in 2013, when blood pressure was measured for the first time in MLSFH-MAC. Specifically, the study sample is restricted to MLSFH-MAC respondents for whom we have three non-missing systolic and diastolic blood pressure measurements both in 2013 and 2017 (N=1,075).[6] The average age of the sample used in this analysis is about 62 years, and women represent 59% of the study population. Respondents are almost equally distributed across the three study areas.

The mean systolic blood pressure of individuals in our sample (based on three measurements) is equal to 134 mmHg in 2013 and 135 mmHg in 2017, and the corresponding mean values for diastolic blood pressure are 86 mmHg and 84 mmHg respectively. The average blood pressure of mature adults is thus close to the thresholds used to classify an individual as hypertensive (i.e., currently these thresholds are 140 mmHg for systolic and 90 mmHg for diastolic blood pressure; Geldsetzer *et al.* 2019). In fact, according to these

[5]Note that the referral letter and the questionnaire mention that respondents were being referred if their systolic or diastolic blood pressure "surpassed" 160 and 110mm/Hg, respectively. In practice, referral letters were given if one of the systolic or diastolic blood pressure measurements was greater or equal to 160 and 110, respectively. As robustness checks, we check that our results hold when dropping individuals who are exactly at the 160 cutoff. Results are available upon request.

[6]The 2013 MLSFH-MAC survey consists of 1,257 completed interviews, among which 1,244 interviews contained three non-missing systolic and diastolic blood pressure measurements.

Table 1: Descriptive statistics of the MLSFH-MAC sample, 2013–2017

	Mean (1)	Std. dev. (2)	10^{th} (3)	90^{th} (4)
Blood pressure, referral letters, health behaviors and literacy				
Mean systolic BP (2017)	135.1	25.21	108	170.7
Mean systolic BP (2013)	134.26	25.31	106.3	170
Mean diastolic BP (2017)	83.67	12.69	69	100
Mean diastolic BP (2013)	85.94	12.49	71.3	102
Hypertensive 2017[a]	.41	.49	0	1
Hypertensive in 2013[a]	.41	.49	0	1
Received a referral letter in 2013	.19	.4	0	1
Being diagnosed in 2017	.16	.37	0	1
Taking medication in 2017	.09	.29	0	0
Know what high BP is (2017)	.82	.39	0	1
Know symptoms of high BP (2017)	.63	.48	0	1
Know will have to take treatment forever (2017)	.78	.41	0	1
Add extra salt to plate (2017)	.54	.5	0	1
Consume at least 1 sweet drink per day (2017)	.24	.43	0	1
Total number of teaspoons of sugar used in tea/coffee per day (2017)	2.71	1.91	0	5
Change in standardized SF12 physical score	0	1.05	-1.4	1.3
Change in standardized SF12 mental score	0	1.24	-1.7	1.6
Control variables				
Female	.59	.49	0	1
Age	62.38	10.69	50	78
Central region	.31	.46	0	1
South region	.34	.47	0	1
North region	.35	.48	0	1
Nb of observations in benchmark sample	1075			

Note: The sample is derived from the MLSFH-MAC 2013 and 2017 waves. Our analysis is based on a sample of 1075 individuals for which we have non-missing systolic and diastolic blood pressure measurements in 2013 and who were interviewed in 2017. The descriptive statistics of some of the variable in Table 1 are derived from a smaller sample because of missing values. Note also that we restricted our analysis to individuals who were 40 years or older in 2017. [a]: We define someone as hypertensive if the mean systolic or diastolic blood pressure measurements was greater or equal to 140 and 90, respectively. 10^{th} and 90^{th} represent the 10^{th} and 90^{th} percentiles of the distributions, respectively.

official guidelines, the prevalence of hypertension in our sample was 41% in both years.

About 19% of the individuals in our sample received a referral letter in 2013 because one of their systolic or diastolic blood pressure measurements was above 160 or 110, respectively. The rate of individuals being diagnosed with hypertension by a medical professional in the two years prior to the 2017 interview is almost as high, 16%, while only a subset of them, 9%, were taking medication for hypertension at the time of the survey.

In 2017, the vast majority of respondents know what hypertension is (82%) and 63% of them know the characteristics of the symptoms of hypertension.[7,8] Moreover, the majority of the respondents is aware that, once diagnosed as hypertensive, they will have to take treatment forever (78%). About 24% of the study participants consume at least one sweet drink per day and on average they add daily about 2.71 teaspoons of sugar to their tea/coffee consumption. More than half of the respondents adds extra salt to their plate (54%).

Figure 2 shows the distribution of mean values of systolic and diastolic blood pressure measurements in our sample. The vertical line along the x-axis represents the threshold that determines whether a respondent receives a referral letter because of a systolic measure above 160 and the horizontal line along the y-axis because of diastolic blood pressure at 110. All study participants who received a referral letter, did so because they had at least one measurement exceeding the threshold of 160 mmHg. Only 2 individuals received the letter because of their diastolic blood pressure exceeding the threshold of 90 mmHg, as represented by the two red x in the plot. In the empirical analysis, we exclude these 2 observations to include only respondents who received a referral letter because of their high level of systolic blood pressure.

4 Methodology

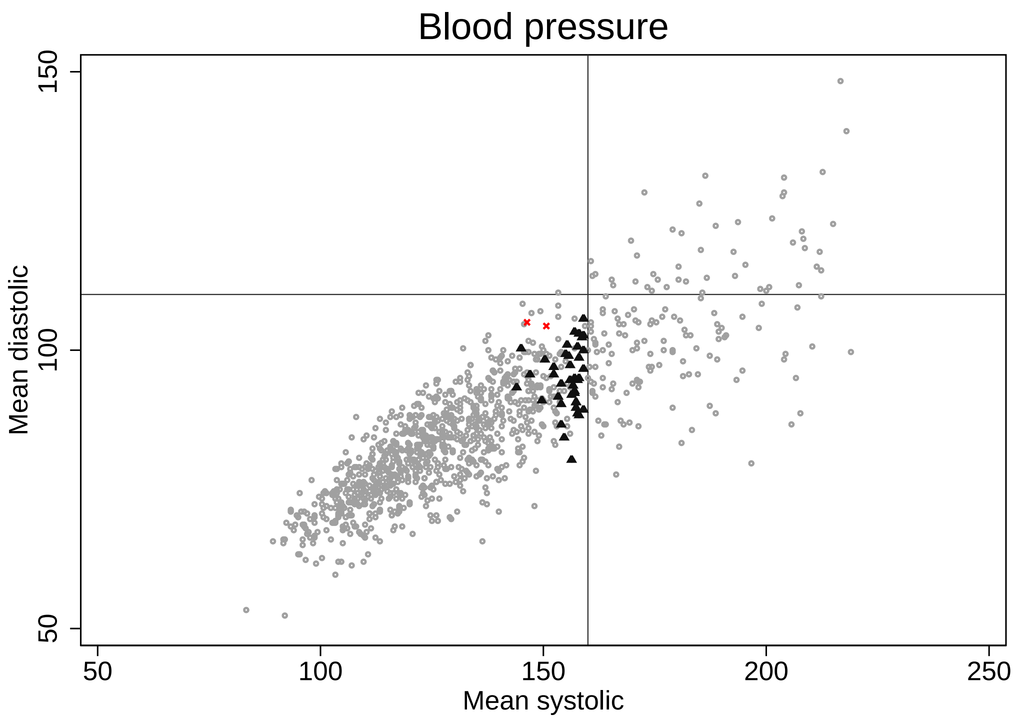
The procedures implemented for providing a referral letter to study participants whose blood pressure measured above a specific threshold suggests the use of a sharp regression discontinuity design (RDD) as an appropriate application to evaluate the effects of the referral letter on hypertension-related outcomes. The method compares individuals whose maximum measurement of blood pressure is right below the cutoff (i.e., 160 mmHg systolic blood pressure) with those whose maximum measurement is right above it, assuming that individuals around the cutoff share similar observable and unobservable characteristics with the exception of having received a referral letter.

The RDD specification benefits from strong internal validity whereas it potentially lacks external validity as it does not reveal much about what is happening away from the cutoff (Wing and Bello-Gomez 2018). The availability of multiple blood pressure measurements for each individual allows however to estimate the causal effects of receiving a referral letter on hypertension-related outcomes away from the critical cutoff. Indeed, one can use a nearest-neighbor matching estimator and match individuals based on similar blood pressure levels but where some had a maximum blood pressure above the criti-

[7]Health knowledge and behaviors were measured differently in 2013. Therefore, we focus on the 2017 measures only.

[8]Hypertension is usually asymptomatic but can result in various symptoms such as shortness of breath and headache in some cases. In our analysis, we consider that an individual knows about the characteristics of the symptoms of hypertension if she either says that hypertension is asymptomatic or can identify at least one of its symptoms.

Figure 2: Blood pressure of respondents of the 2013 MLSFH survey.



Notes: The graphs shows average of the three measures of systolic and diastolic blood pressure for respondents of the 2013 MLSFH-MAC survey. Dots represents mean values of systolic (x-axis) and diastolic (y-axis) blood pressure. Small triangles represent individuals whose maximum systolic blood pressure is at least 160 but their mean systolic blood pressure is below 160. Small red x represent the individuals who were given a referral letter because their diastolic blood pressure is at least 110.

cal threshold and hence received a referral letter and some other who did not fulfill the condition to receive such a referral letter. In particular, the proposed estimator matches individuals on the mean of the three systolic blood pressure measurements, with the average across measurements providing an estimator for the (unobserved) "true" blood pressure of individuals at the time of screening.

Estimating corresponding effects away from the cutoff allows to determine whether our RDD results hold for a different subset of the population (Angrist and Rokkanen 2015; Lee and Lemieux 2010; Mealli and Rampichini 2012), hence increasing the external validity of the findings. This could be particularly relevant and informative to policy makers in the case they would consider lowering the threshold of the cutoff in a screening intervention for instance. Analyzing the effects of getting a referral letter away from the cutoff can also helps in identifying possible heterogeneous effects in the population along the distribution of blood pressure.

4.1 Sharp Regression Discontinuity Design (RDD)

We exploit the discontinuity in the probability of receiving a referral letter—the treatment D—that is assigned based on the maximum systolic blood pressure (= the score X_i). More formally, we observe n individuals, indexed by $i = 1, 2, \ldots, N$ whose systolic blood pressure was measured thrice (s_{1i}, s_{2i}, s_{3i}). Each respondent received a referral letter if $max(s_{1i}, s_{2i}, s_{3i}) = X_i \geqslant 160$, with 160 being the cutoff determining treatment D. Because the assignment rule is $Z_i = \mathbb{1}(X_i \geqslant 160) = D_i$ in our setting, each unit complies perfectly with its assignment and thus treatment corresponds to a deterministic function of the score. Because of this deterministic decision rule at a precise cutoff, a *sharp* RDD design can be used to estimate the causal effects of receiving a referral letter on hypertension-related health outcomes.

The fundamental problem with causal inference in social sciences is that we only observe realized outcomes Y_i and rarely potential outcomes (Holland 1986). In other words, we observe the health outcomes of those who received a referral letter and those who did not but never their counterfactual outcomes. That is, we observe:

$$Y_i = Y_i(1) \cdot D_i + Y_i(0) \cdot (1 - D_i) = \begin{cases} Y_i(0) & \text{if } x_i < 160 = c \\ Y_i(1) & \text{if } x_i \geqslant 160 = c \end{cases} \tag{1}$$

with $Y_i(0)$ the outcomes of those who did not get a referral letter –our control group– and $Y_i(1)$ the outcomes of those who got a referral letter –our treatment group–. However, as discussed in the RDD literature (Calonico *et al.* 2014b, 2019; Hahn *et al.* 2001), one can obtain average treatment effects at the cutoff, by comparing individuals just below and just above it and calculating the vertical distance between $\mathbb{E}[Y_i(1)|X_i]$ and $\mathbb{E}[Y_i(0)|X_i]$. Hahn *et al.* (2001) showed that if the conditional expectation functions of Y_i are continuous in x at $x = c$, then one can derive the average treatment effect at the cutoff $\tau_{rd}(c)$ as:

$$\tau_{rd}(c) = lim_{x\downarrow 160}\mathbb{E}[Y_i(1)|X_i] - lim_{x\uparrow 160}\mathbb{E}[Y_i(0)|X_i] = \mathbb{E}[Y_i(1) - Y_i(0)|X_i = 160] \tag{2}$$

Because the true functional form of $\mathbb{E}[Y_i(1)|X_i]$ and $\mathbb{E}[Y_i(0)|X_i]$ is not known, we follow the recommendations of Skovron and Titiunik (2015) and nonparametrically approximate these regression functions with local polynomials of order 1.[9] Furthermore, in our benchmark analysis, we use triangular weights determined by kernel functions and centered at the cutoff c to put more weights on observations closer to c,[10] and restrict our analysis to observations that are between $160 - h_-$ and $160 + h_+$ with h_- and h_+ representing bandwidths on each side of the cutoff.[11] We allow these optimal bandwidths to be different on

[9] We will show however as robustness checks that our results are consistent when using quadratic polynomials, that is polynomials of order 2.

[10] Note that our results are robust to to using rectangular kernel function and hence giving equal weight to all observations within the range $[160 - h_-; 160 + h_+]$.

[11] These bandwidths are chosen optimally following data-driven techniques developed by Calonico *et al.*

both sides of the cutoff c and present results in the Appendix where we restrict our analysis to use the same optimal bandwidths on both sides of the cutoff.[12]

Although not necessary for identification, we also estimate all our models with a set of exogenous/predetermined control variables to assess the robustness of our findings to the inclusion of covariates and potentially increase the precision of our estimates. The set of control variables consists of sex, age and region dummy variables to control for any systematic differences in the three regions where the MLSFH-MAC data are collected.

4.2 Matching strategy

We exploit the fact that treatment was determined based on the maximum of the three systolic blood pressure measurements, and not on the "true" systolic blood pressure, to estimate the causal effect of getting a referral letter away from the 160 cutoff. We do not observe the “true" blood pressure at the time of the interview but we proxy it with the average of the three measures $R_i = mean(s_1, s_2, s_3)$. Indeed, there are respondents in our sample who were treated and therefore received a letter because $max(s_1, s_2, s_3) = X_i \geqslant 160$, but for whom their “true" blood pressure was lower than the cutoff. These respondents are represented by small triangles in Figure 2. This setup therefore allows us to implement a nearest-neighbor matching estimator (Abadie and Imbens 2002, 2006; Abadie *et al.* 2004) to estimate the causal effect of getting a referral letter on Y_i away from the cutoff, by comparing outcomes of interests of those who were given a referral letter with those who were not, matching respondents with similar values of “true" blood pressure.

More formally, for this specific set of respondents, conditioning on the “true" blood pressure R_i, D_i is random because D_i is based on the maximum of the three measurements and is thus purely error-driven and independent to individual characteristics except R_i. By assuming that R_i, can be measured by the mean of the three systolic measurements, that is $R_i = mean(s_1, s_2, s_3)$, one obtains $\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp D_i \mid R_i$, which implies that that conditioning on R_i, treatment D_i is given at random and is therefore independent to potential outcomes.

It follows that one can estimate the potential counterfactual outcomes of each individual using information from the nearest neighbor in the opposite treatment group. That is, for each i, $\hat{Y}_i(D) = Y_i$ if $D_i = D$, and $\frac{\sum_{j=\Omega_i} Y_j}{|\Omega_i|}$ otherwise, for $D \in \{0, 1\}$. In this relation, Ω_i represents the set of individuals j in the neighborhood of i (as defined below) with $D_j = 1 - D_i$ and $|.|$ the cardinality function. The average treatment effect on treated

(2014a,b, 2015) using Mean Square Error (MSE) optimal bandwidth selector. In addition, the estimates of the standard errors are computed using heteroskedasticity-robust plug-in residuals variance estimator (Calonico *et al.* 2017). Note that the estimates of the variance covariance matrix are very similar when including weights for finite sample adjustments or when using nearest neighbor variance estimator.

[12]For ease of comparisons across the different outcome variables we consider, we will also show results where we impose the bandwidths on both sides of the cutoff to be identical across all the dependent variables we consider in our analysis. Again, our results are very robust to these restrictions as well.

(ATET)[13] can then be expressed as:

$$\tau_m^{ATET} = \sum_{i=1}^{n} D_i(\hat{Y}_i(1) - \hat{Y}_i(0)), \tag{3}$$

where we define, for our our benchmark analysis, Ω_i for each i as $\Omega_i = \{j_1, ..., j_K | D_{j_k} = 1 - D_i, \|R_i - R_{j_k}\|_e \leqslant 10, K \geqslant 4\}$, where $\|.\|_e$ represents the euclidean distance on R which has to be less than 10 mmHg for individual j to be in the neighborhood of individual i and K is the number of matches. [14]

To assess the quality of our matching, we report the average distance between our treated and untreated observations. We estimate our matching model in which individuals are matched based on a vector of characteristics x where x includes 1) only R, 2) R, sex, region dummy variables and age, which is the same set of control variables we use in our RDD specification.[15]

It is possible that people might be different not only in terms on mean blood pressure but also in terms of variance. We may therefore be matching individuals with identical means but with very different variance. Because the mean itself is explained by the maximum value, which may or may not be systematically different across different individual characteristics, the mean systolic blood pressure measurements may not reflect the "true" underlying blood pressure of the individuals, such that the treatment, conditioning on the mean blood pressure, is not random as assumed. We therefore augment the specification in which we include our basic set of control variables by including the standard deviation of the three systolic blood pressure in our matching function. By doing so, we match individuals not only on their mean but also on the variance of their systolic blood pressure, therefore increasing the chance that individuals who are matched with one another are similar in terms of systolic blood pressure characteristics (not only the first but also the second moment of the systolic blood pressure distribution).

As robustness check, we present matching estimates when the "true" blood pressure R

[13] Our main interest is in τ_m^{ATET} as we are more interested in the effects of treatment on the subpopulation of treated units than on the effects on the population as a whole (Heckman *et al.* 1998; Imbens 2004). We will however also present estimates of the average treatment effect (ATE), τ_m^{ATE}, defined as $\tau_m^{ATE} = \sum_{i=1}^{n} \hat{Y}_i(1) - \hat{Y}_i(0)$ in the Appendix.

[14] Selecting the number of matches involves the traditional trade-off between bias and variance, as a lower number of matches decreases bias and increase variance whereas the other way around holds when the number of matches increases (Rosenbaum and Rubin 1985). In terms of the number of matches, it is usually recommended to choose a small number and four matches has been shown to perform well in terms of mean-squared error (Abadie and Imbens 2002). We therefore restrict the number of matches to be at least 4 and show in the Appendix that our results are robust when decreasing and increasing the number of matches to 3 and 5, respectively. In cases of ties, all observations with equal R are used to compute τ_m^{ATE} and τ_m^{ATET}. Note also that we allow the same control unit to be matched to treated unit several times, that is, we are matching observations with replacement. We also explore the robustness of our findings when shrinking the neighborhood around each R_i to 8 and 5.

[15] When matching individuals not only on R but also on a set of covariates x, we impose the same distance restriction as in our benchmark analyses, where, instead of the distance being computed based on the euclidean metric, the distance will be calculated using the mahalanobis metric.

of respondents is based on the median of (s_1, s_2, s_3) instead of the mean of these three measurements and when R is based on the mean of the last two measures Leung *et al.* (2016). In all the results using our matching estimator, we report robust standard errors estimated using the number of matches (4 for our benchmark results, and 3 and 5 as robustness checks) in the neighborhood of each observation.

5 Results

We first present results derived from the application of the RDD approach followed by the corresponding results based on the matching specification. Specifically, we focus on the following effects of receiving a referral letter: (*a*) changes in the average systolic and diastolic blood pressures between 2013 and 2017, the probability of being hypertensive in 2017, the probability of having been diagnosed by a medical professional during a period of two years prior to the follow-up interview in 2017 and on the probability of taking blood pressure medication at the time of the interview; (*b*) corresponding estimates of the effects of referral cards on health behaviors such as diet and physical exercise and on high blood pressure-related knowledge; and (*c*) effects of the referral letter on overall subjective physical and mental health of the study participants.

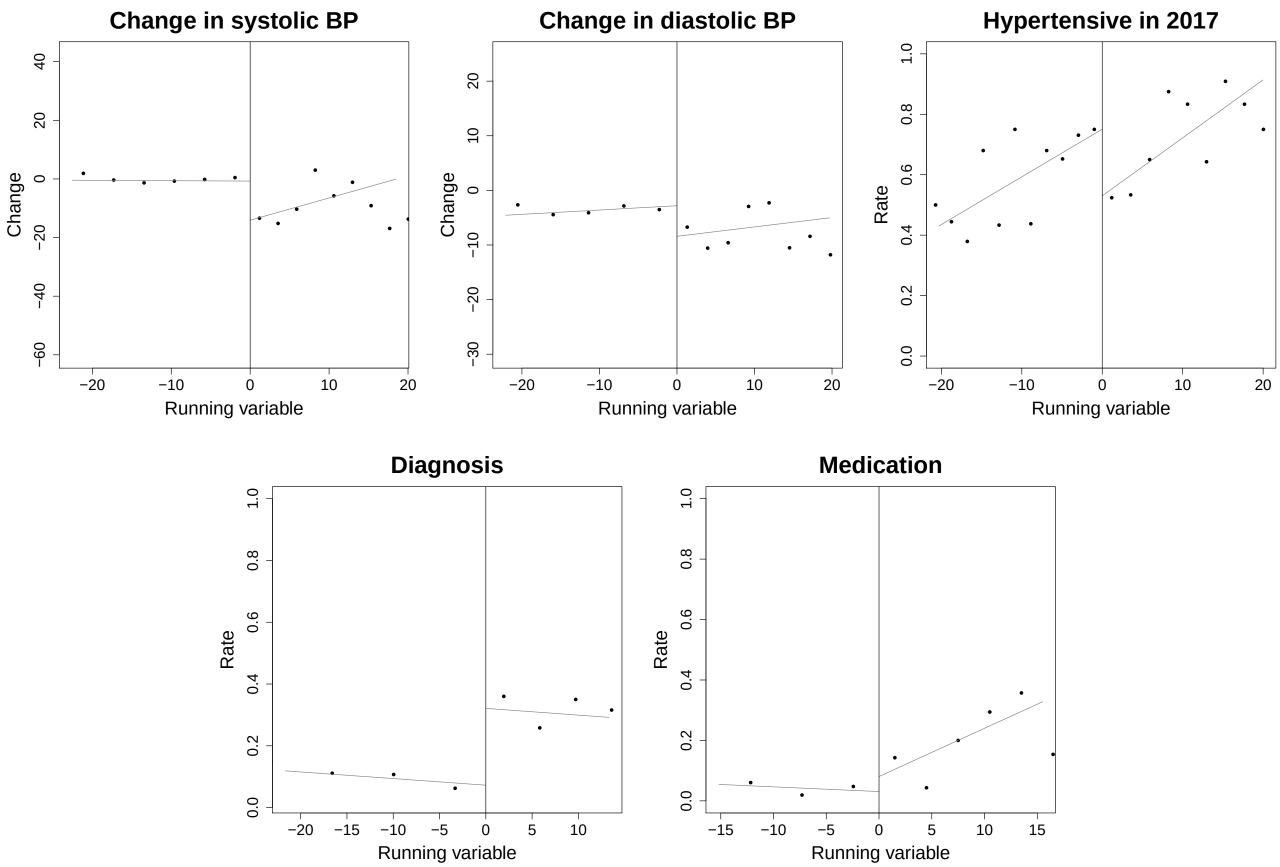
5.1 Effects of receiving a referral letter—RDD estimates

a) Blood pressure and hypertension diagnosis/treatment: The left graph of Figure 3 plots the change in the mean systolic blood pressure between 2013 and 2017 with respect to the running variable, that is the maximum of the three systolic measurements taken in 2013 (x-axis). The bandwidths on both sides of the cutoffs are derived optimally using first order local-polynomials (Gelman and Imbens 2019; Skovron and Titiunik 2015), and triangular kernels to put more weight on observations closer to the cutoff.[16] Each dot represents the averages of the respective outcome in a given bin.[17] The solid line represents the predicted outcome based on those local polynomial regressions.

The causal effects of receiving a referral letter on the outcome variables are represented in Figure 3 by the vertical distance between the two different solid lines at the cutoff (running variable $X_i = 0$). The top-left plot shows a drop of about 13 mmHg in the changes in systolic blood pressure between 2017 and 2013 at the cutoff, reflecting that an individual who received a referral letter and whose maximum systolic blood pressure was just above the cutoff had a mean systolic blood pressure in 2017 that was on average 13 mmHg lower than those who were right below the cutoff. A corresponding drop in blood pressure can also be observed in the changes in diastolic blood pressure (top-middle plot), where individuals at the right of the cutoff appear to have a diastolic blood pressure to be on average

[16]Similar plots but using second order local polynomials can can be found in the Appendix Figure A.1.
[17]Bins are derived optimally using variance evenly-spaced method estimators (Calonico *et al.* 2014a,b, 2015, 2017).

Figure 3: RDD estimates—Effects of receiving a referral letter on 2013–17 changes in blood pressure, on probability of being hypertensive, diagnosed with hypertension, or treated for hypertension in 2017



Notes: The graphs show average blood pressure outcomes conditional on the maximum systolic blood pressure in 2013. Individuals located to the right of the vertical line received the referral card in 2013. The outcome in the top-left graph represent the average changes in systolic blood pressure from 2013 to 2017. The outcome in the top-middle graph is the average changes in diastolic blood pressure from 2013 to 2017. In the top-right graph, we define someone as being hypertensive if the mean of the three systolic or diastolic blood pressure measurements was greater or equal to 140 and 90, respectively. The outcome in the bottom-left graph is whether individuals got diagnosed by a medical professional in the two years prior to 2017. The outcome in the bottom-right graph is whether individuals are currently taking medication during the follow-up survey in 2017. Optimal bandwidths on both sides of the cutoffs are derived using first order local-polynomial and triangular kernels. Bins are derived optimally using variance evenly-spaced method using spacing estimators (Calonico *et al.* 2014a,b, 2015, 2017). Each dot represents the means of the respective outcome in a given bin.

about 5 mmHg lower than their counterparts located on the left of the cutoff. The top-right graph shows that getting a referral letter in 2013 did not only lower blood pressure, but also reduced their probability of being hypertensive in 2017 (hypertension is indicated if the mean of the three systolic or diastolic blood pressure measurements was greater or equal to 140/90). A large discontinuity at the cutoff can also be observed when looking at whether respondents were diagnosed with hypertension during the two years prior to the follow-up interview in 2017. Indeed, the bottom-left plot in Figure 3 shows a discontinuous increase of about 0.24 points in the probability of being diagnosed as a result of receiving a referral letter for those at the cutoff. The effect of the referral card on medication is less pronounced and the discontinuity at the cutoff on whether respondents are currently taking medication is, if any, small (bottom-right plot).

Table 2 presents the corresponding estimated coefficients of the causal effects of receiving a referral letter on our five main outcomes of interests using our RDD specification. The estimates use first order polynomial and allow the sizes of the optimal bandwidths on both sides of the cutoff to be different. The first row of Panel A of Table 2 shows that those who received a referral letter in 2013 had a change in systolic blood pressure (between 2013 and 2017) that was about 12.9 mmHg lower (p-value = 0.03) than those who did not receive a letter. This effect is statistically significant at 95%, and slightly higher (14.3, p-value=0.016) with the inclusion of our basic set of predetermined control variables sex, age and region (second row of each panel). Similar effects on blood pressure can be observed on changes in mean diastolic blood pressure, where individuals who received a letter had an average decrease in diastolic blood pressure of about 5.5 mmHg (p-value=0.053) and 5.8 mmHg (p-value=0.034) depending on whether our set of control variables are included in the specification or not. Panel C of the same table also confirms the results shown in Figure 3: individuals who received a referral letter in 2013 were about 20 percentage points less likely to be hypertensive in 2017 as compared to those who did not receive such letter and whose maximum systolic blood pressure was just below the 160 cutoff. This effect is particularly precisely estimated in the specification in which the set of predetermined controls are included in the model (p-value=0.044)

One possible explanation for the improvement in these blood pressure outcomes is that individuals who received a referral letter indeed followed up with a health care provider regarding their high blood pressure levels. In Panel D of Table 2 we therefore show the effects of getting a referral letter in 2013 on the probability of being diagnosed as hypertensive by a medical professional in the two years preceding the 2017 interview. For individuals located at the cutoff, receiving a referral letter caused an increase in the probability of being diagnosed by about 24.1 percentage points (p-value = 0.023). Again, this effect is significant and robust to the inclusion of various control variables.[18]

[18] We also investigated whether there is a discontinuity at the cutoff in diagnosis in 2013 before the blood pressure screening. Reassuringly, we do not see a statistically significant discontinuity using several different polynomials and controls.

Table 2: RDD estimates—Effect of the referral letter on 2013–17 change in systolic and diastolic blood pressure, and probability of being hypertensive, diagnosed with hypertension, and treated for hypertension in 2017

Specification	Effects	Std. errors	P-values	OB-	OB+	N-	N+
A. Change in systolic blood pressure 2013–17							
Linear	-12.88^{**}	5.947	0.030	23.57	18.43	312	108
Linear with controls	-14.28^{**}	5.952	0.016	21.30	18.72	275	107
B. Change in diastolic blood pressure 2013–17							
Linear	-5.503^{*}	2.849	0.053	22.60	19.32	294	109
Linear with controls	-5.790^{**}	2.730	0.034	20.33	21.66	256	115
C. Probability of being hypertensive in 2017							
Linear	-0.199^{*}	0.114	0.079	20.403	19.734	260	109
Linear with controls	-0.225^{**}	0.112	0.044	20.693	19.981	256	108
D. Diagnosed with hypertension in 2017							
Linear	0.241^{**}	0.106	0.023	22.22	13.29	294	87
Linear with controls	0.201^{**}	0.101	0.046	19.25	14.50	229	90
E. Treated for hypertension in 2017							
Linear	0.045	0.073	0.538	16.15	15.56	192	96
Linear with controls	0.038	0.072	0.598	14.89	15.53	160	95

Notes: The table shows estimates of the effect of receiving a referral card in 2013 on blood pressure related outcomes using a regression discontinuity design. Change in systolic blood pressure is the difference between the average of the three systolic blood pressure measures in 2017 and in 2013. Change in diastolic blood pressure is the difference between the average of the three diastolic blood pressure measures in 2017 and in 2013. We define someone as being hypertensive if the mean systolic or diastolic blood pressure measurements was greater or equal to 140 and 90, respectively. Diagnosis is a dummy equal to 1 if the respondent has been diagnosed by a medical professional in the last two years (2017 survey). Medication is a dummy equal to 1 if the respondent is currently taking medication for blood pressure (2017 survey). All these specifications use triangular weights and first order local polynomials. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. The change in systolic and diastolic blood pressure is $mean(x_1, x_2, x_3)^{2017} - mean(x_1, x_2, x_3)^{2013}$ with $x = \{systolic, diastolic\}$. We use a Mean Square Error (MSE) optimal bandwidth selector. Specifications with controls includes a sex dummy, age and region dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

People who get diagnosed by a doctor or a nurse should in theory receive treatment and advice on how to control their blood pressure with appropriate health behavior changes such as adoption of better diet and increase in physical activity, as is commonly recommended in developed countries. The causal effects of receiving a referral letter on the probability of currently taking medication (Panel E) is about 4.5 percentage points, but fails to be precisely estimated at conventional statistical levels. One possible explanation for this absence of a significant effect is that the study asks whether respondents are *currently* taking medication but we do not know if they have been taking medication at some point in time between 2013 and 2017.

Table A.1 in the Appendix shows that our results are not driven by the choice of the polynomial order we use. Indeed, the effects appear very similar when using local polynomials of order two. The effects on the changes in systolic blood pressure range from -14 to -15 when using a quadratic specification, against -12.9 and -14.3 in our benchmark specification. The effects on the probability of being hypertensive in 2017 are similar in magnitude as well, although less precisely estimated. The effects on diagnosis and on medication when allowing for more flexible specification are also in the ballpark of those obtained in our linear specification. Moreover, while our benchmark specification uses triangular kernels to put more weight on observations closer to the cutoff, Table A.2 in the Appendix shows that our results are robust to using rectangular weights, which weight all observations within the optimal bandwidths equally. Finally, we investigate whether our results hold when we impose the optimal bandwidths on both sides of the cutoff to be equal. Table A.4 in the Appendix shows that this is the case. In the same vein, Table A.3 shows that our results hold when the optimal bandwidth for systolic blood pressure is used for all the other outcomes. These robustness checks show that our results are therefore not driven by the choice of the sample taken into consideration in our analysis.

b) Health behaviors and knowledge: While our RDD strategy suggests some important causal effects of receiving a referral letter on hypertension-related health outcomes, it is of particular interest to better understand the pathways through which these effects operate and especially if health behaviors other than diagnosis and medication play a role. Specifically, we investigate whether receiving a referral letter also had an effect on diet. Changes in health behaviors such as diet and eating habits for instance are possible channels through which the referral letter can have an effect on blood pressure. The consumption of salt and sugar-sweetened beverages for instance have been shown to be strongly associated with higher blood pressure and the incidence of hypertension (Cappuccio and Miller 2016; He and MacGregor 2016; Malik *et al.* 2014).

Table 3 shows that although receiving a referral letter seems to have reduced the probability of adding extra salt to one's plate, this effect is not precisely estimated at conventional statistical levels. Opposite to what one would expect, the referral letter has had positive effects on the probability of consuming sweet drinks in a given day and on the total number of teaspoons of sugar individuals consume in a given day in their tea or cof-

Table 3: RDD estimates—Effect of the referral letter on pathways for changing blood pressure during 2013–17

Specifications	Effects	Std. errors	P-values	OB-	OB+	N-	N+
Pathways 1: Health Behaviors							
A. Extra salt to plate							
Linear	−0.127	0.134	0.345	12.38	21.06	136	117
Linear with controls	−0.130	0.131	0.322	12.70	23.50	133	122
B. Consume sweet drinks							
Linear	0.119	0.111	0.282	20.95	14.69	260	91
Linear with controls	0.127	0.110	0.248	21.94	14.10	275	90
C. Total number of teaspoons of sugar used in tea/coffee per day							
Linear	0.539	0.485	0.267	14.782	23.754	163	123
Linear with controls	0.489	0.457	0.285	14.174	21.616	160	116
D. Change in weekly MET score							
Linear	−60.971	39.124	0.119	12.23	16.43	134	101
Linear with controls	−56.842	37.02	0.125	12.80	17.61	132	102
Pathways 2: Knowledge							
A. Know about HBP							
Linear	−0.025	0.100	0.800	25.03	16.06	336	102
Linear with controls	−0.050	0.102	0.628	24.58	15.70	320	95
B. Know symptoms							
Linear	0.042	0.123	0.729	20.246	13.462	260	87
Linear with controls	0.019	0.127	0.881	18.339	13.621	214	86
C. Know about treatment							
Linear	−0.032	0.121	0.792	18.04	13.72	218	87
Linear with controls	−0.104	0.124	0.400	16.74	12.24	188	82

Notes: The table shows estimates of the effect of receiving a referral card in 2013 on diet and knowledge about hypertension in 2017 using a regression discontinuity design. Extra salt to plate and consumption of sweet drinks are dummies. The knowledge measures are dummies based on whether they know what high blood pressure is, whether they are able to name at least one of its symptoms and whether they know that having high blood pressure required life-long treatment. All these specifications use triangular weights and first order local polynomials. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. We use a Mean Square Error (MSE) optimal bandwidth selector. Specifications with controls includes a sex dummy, age and region dummies. “MET” stands for metabolic equivalent of task and it is a measure of physical activity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

fee. Individuals who received a referral letter were about 12 percentage points more likely to consume a sweet drink in a given day and also consumed about half a spoon more of sugar in their hot beverage per day as compared to others. These effects fail to be statistically significant, which suggests that referral letters have not had any effects on change in diet, possibly because diet recommendations are not given or are difficult to follow by respondents diagnosed with hypertension.

Our analysis further shows a negative causal effects of receiving a referral letter on physical activity, as evidenced in Panel D of Table 3.[19] While negative, these effects again fail to be precisely estimated.

These results suggest that, as opposed to changes in behaviors that are commonly recommended for those with hypertension in developed countries (i.e., increasing physical activities), this is not a likely pathway through which respondents who received a referral letter achieve a reduction in their blood pressure levels. While it is impossible to identify the specific reasons why this is the case, one possible explanation is that the study population is indeed physically quite active, with strenuous agricultural labor present in their daily life and hence little space for improvement in physical activity.

Further analyses show that referral letters did not have any effect on hypertension-related knowledge such as high blood pressure treatments and symptoms. Indeed, the lower part of Table 3 shows that individuals at the cutoff who received a referral letter did not have a higher probability of knowing what high blood pressure was, nor were they more likely to know the characteristics of the symptoms of hypertension and to know that having high blood pressure required life-long treatment. This is not surprising since our descriptive statistics in Table 1 showed that on average this population is aware of what hypertension is and its consequences.

c) Overall subjective health: Table 4 shows the effects of the referral letter on two indicators of respondents overall subjective health: the SF12 subjective physical and mental health score.[20] Our main specification focuses on changes in the standardized SF-12 subjective physical and mental health score between 2013 and 2017, and we observe an increase of about half a standard deviation in both the SF-12 subjective physical and mental

[19]For physical activity, we use "MET" which stands for metabolic equivalent of task. MET is a measure of oxygen consumption generated by physical activities which are ranked according to their level of intensities relative to the standard resting metabolic rate (Ainsworth *et al.* 2000). We create the MET score as a weighted physical activity score based on the number of hours per week of vigorous physical activity multiplied by 7.5 METs and the number of hours per week of moderate physical activity by 4 METs. These two subjective coefficients have been confirmed as being reliable for objective measures of moderate and vigorous physical activities (Brown *et al.* 2008). Table A.5 in the Appendix shows that getting a referral card does not change physical activity when broken down by moderate or vigorous activity, nor does it have any effect on body mass, as measured by BMI and waist to hip ratio.

[20]SF12 subjective physical health score is based on 12 questionnaire items that summarizes the overall physical health status of individuals by asking them to answer questions pertaining to their general health status, mobility and ability to perform daily activities as well as their emotional health. Mental health score uses the same variables but with different weights. The SF-12 has been shown to be valid and reliable and has been widely used in different socio and demographic contexts, including in Sub Saharan African (Allotey and Reidpath 2007; Gandek *et al.* 1998; Jenkinson *et al.* 1997; Nduka *et al.* 2016; Ware Jr *et al.* 1996).

Table 4: RDD estimates—Effect of the referral letter on overall health status

Specifications	Effects	Std. errors	P-values	OB-	OB+	N-	N+
A. Change in standardized SF12 physical score 2013–17							
Linear	0.529	0.323	0.101	21.29	13.49	273	85
Linear with controls	0.510	0.311	0.101	21.98	13.63	273	85
B. Change in standardized SF12 mental score 2013–17							
Linear	0.511*	0.284	0.072	19.04	23.00	227	121
Linear with controls	0.568**	0.279	0.042	19.46	22.21	227	119
C. Change in 5-year survival expectation							
Linear	−0.089	0.096	0.352	21.04	26.82	260	124
Linear with controls	−0.016	0.097	0.872	17.91	25.55	189	121

Note: The table shows estimates of the effect of receiving a referral card in 2013 on health in 2017 using a regression discontinuity design. SF12 subjective physical and mental health scores are constructed using twelve questions about general health status, mobility and ability to perform daily activities as well as emotional health. 5-year survival expectation is the subjective probability of survival in 5 years elicited using a methodology developed by Delavande and Kohler (2009). All these specification use triangular weights and first order local polynomials. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. We use a Mean Square Error (MSE) optimal bandwidth selector. Specifications with controls includes a sex dummy, age and region dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

health scores. These results are very similar when we include the set of predetermined control variables (age, sex and region). The results are statistically significant for mental health (p-value = 0.04 when including controls) and close to be marginally significant for the physical health score (p-value = 0.1). Although our results show no statistically significant effects on changes in diet and negative effects on physical activity, these estimates indicate that individuals either realize that a drop in their blood pressure is a positive improvement in their health or that they are taking steps to improve their health in ways we do not fully observe. Importantly, we do not find a negative effect of giving referral letters on mental health, as measured by the change in PHQ-9 score,[21] which could have been an ex-ante concern of this type of screening. We also do not find any effect on subjective 5-year survival expectations (last rows of Table 4).[22]

Finally, the first panel of Table A.6 in the Appendix shows that individuals who received a referral letter at the cutoff did not have a higher probability of dying between 2013 and 2017.[23] Having received a referral card does not seem to have any impact on

[21]The multi-item Patient Health Questionnaire (PHQ-9) is a widely used and validated depression instrument that assess the presence and severity of depressive symptoms in clinical and general settings as well as large population-based studies (Kroenke *et al.* 2001). These results are available upon request.

[22]Subjective survival expectations are routinely collected in the MLSFH. In particular, the MLSFH asks about the probability of dying in 5 and in 10 years. Delavande and Kohler (2009) developed an elicitation technique ad-hoc for a context with low literacy and numeracy.

[23]Among the 1,240 individuals we consider in our analysis for which we have all blood pressure measure-

attrition either,[24] as we show that receiving a referral letter in 2013 did not increase the probability of not participating in the interview in 2017 due to refusals, hospitalizations or temporarily absence or because of migration. Our analysis therefore does not appear to suffer from sample selection in the follow-up survey.

5.2 Effect of receiving a referral letter—Matching/nearest-neighbor estimates

Our matching/nearest-neighbor approach for estimating the causal effect of a referral letter matches treated and untreated individuals based on the mean of their three systolic blood pressure measurements. A total of 46 individuals had mean systolic blood pressure below 160 the cutoff for receiving a referral letter, but they received one because their maximum recorded blood pressure reading exceeded 160/90. These respondents constitute the "treatment group," and are matched with up to 161 nearest-neighbor respondents as control group. A minimum of 4 matches is used for each individual who received a referral letter and whose mean systolic blood pressure was below 160. The average value of the mean systolic blood pressures of the individuals in our treatment group is equal to 155.4, with a minimum of 144 and a maximum of 159.3; in the control group, corresponding numbers are equal to 146.8, 140 and 157, respectively.[25].

a) Blood pressure and hypertension diagnosis/treatment: Table 5 shows that individuals who received a referral letter experienced a change in systolic blood pressure of about -12 mmHg when including our set of control variables along with the standard deviation of the three measurements (p-value=0.02) and -6.4 mmHg in diastolic blood pressure (p-value=0.01). These effects are rather similar in the specifications in which individuals are matched on their mean systolic blood pressure and our set of basic predetermined control variables only, although they are less precisely estimated. Similarly, our results indicate negative effects on the probability of being hypertensive in 2017 and these effects are along the lines to those reported in our RDD specification, albeit smaller and again not precisely estimated in the specifications in which standard deviation is excluded from the matching score. When it is included, the effect appears to be larger than our RDD estimates and precisely estimated however. The effects on the probability of having been diagnosed

ments in 2013, we know the survival status of 1,216 of them in 2017. Out of these 1,216 individuals, 104 have died between 2013 and 2017. This constitutes a mortality rate of about 8.6%.

[24]Among those who were still alive in 2017, 6 individuals refused to participate, 1 was hospitalized, 9 were temporarily absent and 11 have migrated.

[25]Note that in our benchmark specification, we drop respondents whose mean systolic blood pressure is below 140 to restrict our study sample of treated and untreated individuals to have a relatively common support within the matching tolerance. As detailed in the methodology section, we restrict the distance between the mean blood pressure between treated and untreated individuals to be less than 10 units in order to compare individuals with similar underlying blood pressure. As discussed below, our results are robust to decreasing and increasing the number of matches to 3 and 5, respectively. We will also show that the effects are also very similar when reducing the distance in mean systolic blood pressure between treated and untreated individuals to 8 and 5. When allowing the distance to be maximum 8, we restrict our sample to individuals with at least 142 of mean systolic blood pressure. When the maximum distance is set to 5, our sample consists of individuals with at least 148 of mean systolic blood pressure.

Table 5: Matching/nearest neighbor estimates—Effect of receiving a referral letter on change in blood pressure, diagnosis and use of medication

	Change in systolic blood pressure 2013–17	Change in diastolic blood pressure 2013–17	Prob. of being hypertensive (2017)	Diagnosis (2017)	Medication (2017)
			No controls		
ATET	-8.484	-2.817	-.196	.277***	.117**
P-value	.321	.365	.171	.000	.023
Obs.	207	207	207	207	207
Average distance	1.21	1.21	1.21	1.21	1.21
			With controls		
ATET	-9.810*	-2.270	-.122	.225***	.132**
P-value	.078	.354	.217	.005	.010
Obs.	204	204	204	204	204
Average distance	.984	.984	.984	.984	.984
			With controls + SD		
ATET	-12.63**	-6.394**	-.374***	.207**	.136***
P-value	.024	.010	.000	.011	.009
Obs.	204	204	204	204	204
Average distance	1.59	1.59	1.59	1.59	1.59

Note: The table shows Average Treatment Effects on Treated (ATET) estimates of receiving a referral card in 2013 on blood pressure related outcomes using a matching estimator. Change in systolic blood pressure is the difference between the average of the three systolic blood pressure measures in 2017 and in 2013. Change in diastolic blood pressure is the difference between the average of the three diastolic blood pressure measures in 2017 and in 2013. We define someone as being hypertensive if the mean systolic or diastolic blood pressure measurements was greater or equal to 140 and 90, respectively. Diagnosis is a dummy equal to 1 if the respondent has been diagnosed by a medical professional in the last two years (2017 survey). Medication is a dummy equal to 1 if the respondent is currently taking medication for blood pressure (2017 survey). We restrict the number of matches to be at least 4 and match respondents based on their mean systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. “Distance” represent the mean of the average distances between each observation and their matches. “With controls” includes a sex dummy, age and region dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

with hypertension is about 27.7 percentage points when the matching is based only on the mean of the three measurements and 21-22 percentage points when we add our set of control variables in the matching score. It is worth noting that the ATET on both changes in systolic/diastolic blood pressure and on the probabilities of being hypertensive and diagnosed in 2017 are very similar to our RDD results. This would indicate that the effects of receiving a referral letter are rather constant along the range of blood pressure between 140 and 160 mmHg.

In contrast to the RDD results, our matching analysis suggests a statistically significant and positive effect on the probability of taking medication. The last column of Table 5 shows that individuals who received a referral letter were about 11.7 percentage points (p-value = 0.02) more likely to be taking medication than others in our specification without controls and 13.2 percentage points (p-value = 0.01) when we match individuals based on our set of control variables. The effects are very similar once the standard deviation of the three measurements are also included in the matching function (13.6 percentage points, p-value = 0.01). These effects are about twice larger than those reported in our RDD setting. One possible explanation could stem from the fact that the RDD specification uncovers the treatment effect right at the 160 cutoff while the effects of our matching specification presented in Table 5 uncovers the average treatment effect on treated for individuals with different *true* levels of blood pressure. Therefore, it is not surprising that our results can potentially be qualitatively similar but differ in magnitude and statistical power across our two different econometric strategies.

To assess the quality of our matching, we computed the average distance in the mean systolic blood pressure between treated individuals and their nearest neighbors that are used in the estimation. A short average distance between these two groups would indicate that they are similar in terms of mean systolic blood pressure and therefore comparable. In our benchmark analysis without any controls, the average distance in systolic blood pressure between treated and untreated individual is about 1.21 mmHg, suggesting that our treated individuals are indeed matched with comparable individuals in terms of mean systolic blood pressure.

Table A.7 in the Appendix shows that our results are similar when increasing or decreasing the number of minimum matches to 5 and 3, respectively, instead of 4. Restricting the distance between the mean blood pressure to be at maximum 8 and 5 units instead of 10 results results in similar average treatment effects on the treated as well (Tables A.8 and A.9 in the Appendix). Moreover, we investigate whether our results hold when assuming that the "true" systolic blood pressure is proxied by the median of the three blood pressure measurements instead of the mean. Because the mean is correlated with the maximum value whereas the median is not, matching treated and untreated individuals based on their median systolic blood pressure could better reflect the actual effect of getting a referral letter by comparing individuals that are more similar in terms of their "true blood" pressure. Table A.10 in the Appendix shows that are results are once again very similar.

Conclusion is identical when we consider the last two systolic blood pressure measurements instead of the three we have at hand. As the first blood pressure measurement could be more prone to measurement error and less reflect the "true" underlying blood pressure of individuals, due to stress, anxiety and so on, taking into account only the last two measurements could potentially better represent individual's "true" blood pressure. We show in Table A.11 of the Appendix that our results are very robust to that restriction as well. [26]

b) Health behaviors and knowledge: As it was the case in our RDD analysis, we investigate the pathways through which the referral letters could have had an effect on change in blood pressure. Tables 6 present the corresponding matching estimates of the ATET of getting a referral letter on the various pathways discussed above. Again, our matching analysis suggests no statistically significant changes in high blood pressure-related knowledge. Our results do suggest however a change in health behaviors. More specifically, while receiving a referral card did not have any effect on the probability of adding extra salt to one's plate and on consuming sweet drinks in a given day, our results indicate that individuals who received a referral letter consume more teaspons of sugar in their tea or coffee per day than others (about 1 teaspoon depending on the specification). They were also more likely to decrease their physical activity between 2013 and 2017, as evidenced in the last column of Table 6.[27] These results are in line with those obtained in our RDD specification, although they are precisely estimated in our matching analysis whereas they were not in our RDD strategy.

These results are surprising because they go against the usual "Western" recommendations to treat high blood pressure. While usual recommendations in developed countries advocate a decrease in salt and sugar consumption, in conjunction with increase in physical activity, individuals who received a referral letter do not seem to follow these guidelines in this context. While it is not possible to find a precise reason for this behavior, possible explanations are: 1) presence of a substitution effect of medication, where individuals rely on medical treatment rather than behavior changes to control their blood pressure; 2) given the very poor context characterized by dietary restrictions, individuals cannot "afford" to change their diets; 3) given the high intensity agricultural labor context, individuals are physically active on a daily basis and there is little "room" to make further improvements.

[26]Table A.12 in the Appendix presents the ATE instead the ATET. The quality of the matches is not as good in the ATE as in the ATET because ATE requires all individuals who have not received a referral letter to be matched with individuals who did received a referral letter. As shown in 3, those who received a referral letter are not uniformly distributed in the range of the mean systolic blood pressure considered in our matching strategy. This means that a large share of the individuals who did not receive a referral letter is matched with individuals who have on on average higher mean systolic blood pressure. The effects presented in Table A.12 are however in line with those presented in our benchmark specification.

[27]Table A.13 shows that the decrease in physical activity is in fact due to a drop in vigorous physical activity. It is also worth nothing that the drop in physical activity does not seem to be accompanied by an increase in body mass, either measured in terms of BMI or waist-to-hip ratio.

Table 6: Matching/nearest neighbor estimates—–Effect of receiving a referral letter on hypertension knowledge and diet

	Knowledge			*Health Behaviors*			
	Know about HBP	Know symptoms	Know about treatment	Extra salt to plate	Consume sweet drinks	# teaspoons sugar used in tea/coffee per day	Change in weekly MET score
				No controls			
ATET	.115	.072	.056	-.018	.099	.765	-44.1
P-value	.473	.663	.714	.885	.514	.120	.100
Obs.	207	207	207	207	207	207	204
Distance	1.21	1.21	1.21	1.21	1.21	1.21	1.23
				With controls			
ATET	-.077	-.115	.009	-.213*	.067	1.30***	-77.9**
P-value	.260	.273	.920	.051	.423	.001	.005
Obs.	204	204	204	204	204	204	202
Average distance	.984	.984	.984	.984	.984	.984	.995
				With controls+SD			
ATET	-.071	-.126	.097	-.094	-.029	.923**	-137***
P-value	.303	.193	.291	.358	.733	.010	.000
Obs.	204	204	204	204	204	204	202
Average distance	1.59	1.59	1.59	1.59	1.59	1.59	1.59

Notes: The table shows Average Treatment Effects on Treated (ATET) estimates of receiving a referral card in 2013 on knowledge about hypertension and diet in 2017 using a matching estimator. The knowledge measures are dummies based on whether they know what high blood pressure is, whether they are able to name at least one of its symptoms and whether they know that having high blood pressure required life-long treatment. Extra salt to plate and consumption of sweet drinks are dummies. We restrict the number of matches to be at least 4 and match respondents based on their mean systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies. "MET" stands for metabolic equivalent of task and it is a maeasure of physical activity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Matching/nearest neighbor estimates——Effect of receiving a referral letter on overall subjective health

	Change in standardized SF12 physical score 2013–17	Change in standardized SF12 mental score 2013–17	Change in 5-year survival expectation 2013–17
		No controls	
ATET	.729**	.588*	-.326**
P-value	.046	.072	.026
Obs.	201	201	190
Distance	1.239	1.239	1.308
		With controls	
ATET	.070	.200	-.039
P-value	.757	.476	.656
Obs.	201	201	190
Average distance	1.000	1.000	1.031
		With controls + SD	
ATET	-.013	.111	.033
P-value	.954	.690	.688
Obs.	201	201	190
Average distance	1.603	1.603	1.641

Note: The table shows Average Treatment Effects on Treated (ATET) estimates of receiving a referral card in 2013 on health in 2017 using a matching estimator. SF12 subjective physical and mental health scores are constructed using twelve questions about general health status, mobility and ability to perform daily activities as well as emotional health. 5-year survival expectation is the subjective probability of survival in 5 years elicited using a methodology developed by Delavande and Kohler (2009). We restrict the number of matches to be at least 4 and match respondents based on their mean systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

c) Overall subjective health: Table 7 shows the effects of receiving a referral letter on subjective physical and mental health SF12 scores and 5-year survival expectation. Results on these three outcome variables are not consistent across the different specifications and it is therefore hard to draw any hard evidence on the effects of the referral card on subjective health based on the matching specification. Finally, the second panel of Table A.6 shows that receiving a referral letter did not have any statistically significant effect on the probability of dying between 2013 and 2017, nor has it had any impact on attrition. This confirms the RDD results presented before that our analysis is not biased due to sample selection.

Table 8: Summary of the causal effects found in this study

	Blood pressure	Hyper-tension	Diagnosis	Medi-cation	Know-ledge	Risky health behav-iors	Subjective health
RDD	$\Downarrow$	$\Downarrow$	$\Uparrow$	–	–	–	$\uparrow$
Matching	$\Downarrow$	$\Downarrow$	$\Uparrow$	$\Uparrow$	–	$\uparrow$	–

Note: Upwards (downwards) double arrows show the presence of positive (negative) and statistically significant effects at conventional levels (p-value=0.05). Upwards (downwards) arrows show the presence of positive (negative) and statistically significant effects at conventional levels on some dimensions of the characteristics considered. Dashes represent lack of statistically significant effects or not consistent/ambiguous effects across specifications.

6 Conclusions

This study is the first to provide estimates of the *long-term causal effects* on health outcomes of a population-based NCD-focused health screening in a SSA low-income population. Filling this knowledge gap is critical because of NCD screening interventions have been heralded as a critical component of possible responses to the emerging NCDs epidemic in LMICs (Geldsetzer *et al.* 2019; Islam *et al.* 2014; WHO 2013a). Specifically, we analyze the effects of a referral letter given to at-risk individuals in Malawi who were measured with high blood pressure and therefore face a heightened likelihood of CVDs. Comparing individuals whose blood pressure was just above the cutoff that determines whether a referral letter is given to those just below that cutoff, we are able to identify the causal effects of at-risk individuals receiving a referral letter. Outcomes of interest are measured four years after the screening, and include hypertension as well as health behavior and subjective health indicators.

A summary of the main results is presented in Table 8. Our analysis shows that screening was effective in reducing both systolic and diastolic blood pressure among at-risk individuals. Our findings indicate that individuals who received a referral letter in 2013 were also less likely to be hypertensive in the follow-up survey four years later in 2017. We also show that at-risk individuals were more likely to be diagnosed as hypertensive by a medical professional as a result of getting the referral letter, and we find evidence that they were also more likely to be taking medication for blood pressure at the time of the interview. Our key findings are robust to various sample selections and econometric methods, which reinforces both the internal and external validity of our findings, the latter being particularly relevant to policy makers.

Our study also shows that individuals do not seem to modify other health behaviors that could reduce blood pressure such as lowering their consumption of salt and sugar. Although this might initially be surprising, it is consistent with several aspects of the local LIC context. For example, individuals, including persons at elevated risk of CVDs, may have very limited options in adjusting their health behaviors along these margins. Hypertension is also driven by distinctive risk factors (e.g., obesity and Western diets continue to be rare; see Kohler *et al.* 2018b), therefore rendering conventional behavioral responses less effective. In addition, behavioral guidelines for the treatment of hypertension are developed mostly on research from high- and middle-income countries, and are often not adopted to the realities of LIC contexts.

If anything, we observe a behavioral response that is the opposite to what one would expect given the current "Western" recommendations in terms of high blood pressure management. Our findings suggest that at-risk individuals who receive a referral letter tend to consume more sugar and are less physically active. While the precise reasons for these behavioral changes related to diet and physical activity are difficult to determine, several possible explanations exist. For instance, this could be due to a substitution effect, with individuals relying on medical treatment rather than behavior changes to control their blood pressure. Alternatively, given an overall unbalanced and calorie-restricted diet, individuals may also be very limited in their options to make any changes in their food consumption, and recommendations to reduce specific food consumption may even be perceived counterfactual. Due to the high intensity of agricultural labor, being physically active is also part of individuals' daily routine with only limited abilities for further improvement. Interestingly, and consistent with our finding that at-risk individuals are less active after receiving a referral latter, 80% of respondents reported that their blood pressure is informative about their ability to work (which is generally not the case).

The long-term effects of receiving a referral letter pertain not only to hypertension per se, but have spillover effects on other health dimensions. Specifically, we find some evidence that at-risk individuals who received a referral letter perceived their mental health more favorably than others. The effects are statistically significant only in the RDD specification, but we can at least rule out any negative effects of learning about having high blood pressure on subjective health. We were also not able to clearly identify which factors above and beyond the increase in the use of hypertension medications can explain this pattern.

Overall, our findings are important in that they document the effectiveness of a simple and inexpensive population-based health screening that resulted in sustained increases in health-seeking behaviors for NCDs among at-risk individuals in a rural LIC context. Similar to related findings about preventive versus curative health care seeking among the poor (Banerjee and Duflo 2011), our study thus shows that individuals seem to be willing to spend time and effort to treat NCDs (in our case, through hypertension medication), but they are less willing to modify their habits and day-to-day routines as risk-reduction strategies to prevent or delay the onset of such NCDs. Given the lack of conventional risk factors for hypertension in SSA LICs, the behavioral responses to high blood pressure are not fully clear from a public health/biomedical perspective. On the one hand, recommendations from the Western context, like losing weight or increasing physical activity, are not necessarily the appropriate recommendations in LICs. Other recommendations like reduction in salt consumption may be hard to follow, as salt use is probably deeply ingrained in the local food culture and may also play important roles in the preservation of food. On the other hand, the possibilities of at-risk individuals to respond to the referral card with health care seeking are often limited because access to care is difficult and costly, and service providers are often ill-prepared to manage or treat NCDs. Yet, as our findings illustrate, diagnosis and treatment through medication seems to be the primary pathway through which at-risk individuals managed to reduce their hypertension risk subsequent to receiving a referral letter. Our results suggest that individuals do not find information about their high blood pressure level distressing in the sense that we do not observe any negative effects on self-rated mental health and depressive symptoms in at-risk individuals who were given a referral letter. This is an important finding because a potential downside of population-based screenings are concerns about possible negative mental health implications of alerting individuals about underlying disease risk factors when they may have limited options to prevent or treat the respective diseases.

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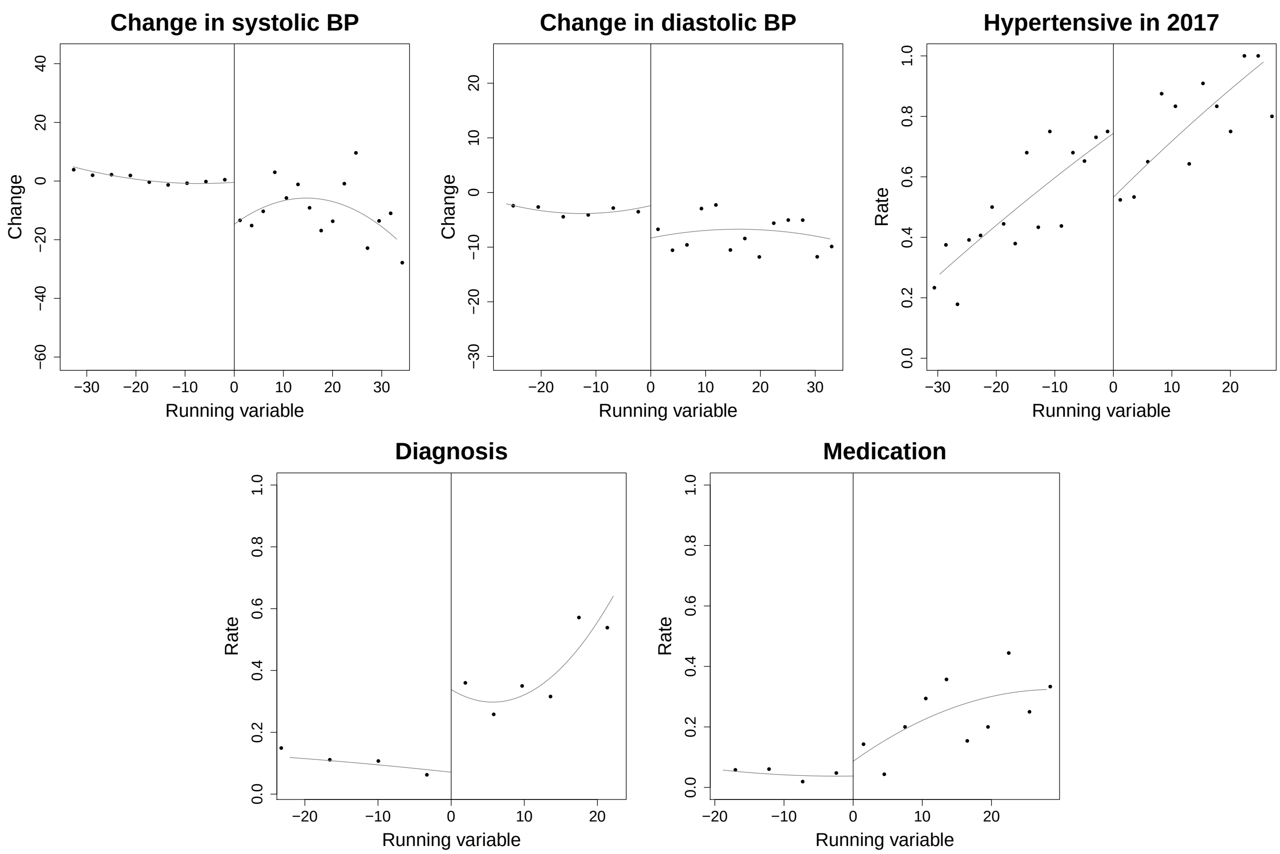
A Online Appendix: Additional results

Figure A.1: Effects of getting a referral letter on changes in systolic blood pressure (top left), changes in diastolic blood pressure (top middle), the probability of being hypertensive in 2017 (top right), hypertension diagnosis (bottom left) and hypertension medication (bottom right) at the cutoff.



Note: The graphs show average blood pressure outcomes conditional on the maximum systolic blood pressure in 2013. Individuals right of the vertical line received the referral card in 2013. The outcome in the top-left graph is the average change in systolic blood pressure from 2013 to 2017. The outcome in the top-middle graph is the average change in diastolic blood pressure from 2013 to 2017. In the top-right graph, we define someone as being hypertensive if the mean systolic or diastolic blood pressure measurements was greater or equal to 140 and 90, respectively. The outcome in the bottom-left graph is whether individuals got diagnosed by a medical professional in the last two years (2017 survey). The outcome in the bottom-right graph is whether individuals are currently taking medication (2017 survey). Optimal bandwidths on both sides of the cutoffs are derived using 2nd order local-polynomial and triangular kernels. Bins are derived optimally using variance evenly-spaced method using spacing estimators (Calonico *et al.* 2014a,b, 2015, 2017). Each dot represents the means of the respective outcome in a given bin.

Table A.1: Results of the RDD specification using 2nd order local polynomials

Specifications	Effects	Std. errors	P-values	OB-	OB+	N-	N+
A. Change in systolic blood pressure							
Quadratic	-14.05^{**}	6.918	0.042	31.40	32.79	427	153
Quadratic with controls	-15.06^{**}	7.015	0.032	26.95	34.31	343	154
B. Change in diastolic blood pressure							
Quadratic	-5.951^{*}	3.447	0.084	27.82	31.82	364	150
Quadratic with controls	-4.701	3.539	0.184	21.55	31.44	275	148
C. Probability of being hypertensive in 2017							
Quadratic	-0.195	0.143	0.173	28.02	25.88	373	127
Quadratic with controls	-0.217	0.139	0.118	30.87	25.05	405	126
D. Diagnosis							
Quadratic	0.257^{**}	0.129	0.047	22.27	21.88	294	117
Quadratic with controls	0.221^{*}	0.123	0.073	20.95	24.00	256	125
E. Medication							
Quadratic	0.045	0.090	0.618	18.83	27.51	218	136
Quadratic with controls	0.038	0.086	0.655	18.60	29.10	214	142

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All these specifications use triangular weights. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. The change in systolic and diastolic blood pressure is $mean(x_1, x_2, x_3)^{2017} - mean(x_1, x_2, x_3)^{2013}$ with $x = \{systolic, diastolic\}$. We use a Mean Square Error (MSE) optimal bandwidth selector.

Table A.2: Results of the RDD specification using rectangular weights

Specification	Effects	Std. errors	P-values	OB-	OB+	N-	N+
A. Change in systolic blood pressure							
Linear	-14.79^{**}	5.878	0.012	21.07	13.37	280	87
Linear with controls	-15.09^{**}	6.026	0.012	18.04	14.38	214	90
B. Change in diastolic blood pressure							
Linear	-7.055^{**}	3.119	0.024	16.57	12.03	192	83
Linear with controls	-7.892^{**}	3.083	0.011	13.80	13.23	148	86
C. Probability of being hypertensive in 2017							
Linear	-0.190^{*}	0.110	0.085	18.82	16.79	218	102
Linear with controls	-0.221^{**}	0.109	0.042	18.95	17.29	214	103
D. Diagnosis							
Linear	0.256^{**}	0.112	0.022	13.61	10.79	151	69
Linear with controls	0.185^{*}	0.108	0.088	11.58	11.89	118	76
E. Medication							
Linear	0.061	0.076	0.425	18.22	10.71	218	69
Linear with controls	0.012	0.072	0.870	18.18	11.07	214	76

Note: The table shows estimates of the effect of receiving a referral card in 2013 on blood pressure related outcomes using a regression disconinuity design. Change in systolic blood pressure is the difference between the average of the three systolic blood pressure measures in 2017 and in 2013. Change in diastolic blood pressure is the difference between the average of the three diastolic blood pressure measures in 2017 and in 2013. We define someone as being hypertensive if the mean systolic or diastolic blood pressure measurements was greater or equal to 140 and 90, respectively. Diagnosis is a dummy equal to 1 if the respondent has been diagnosed by a medical professional in the last two years (2017 survey). Medication is a dummy equal to 1 if the respondent is currently taking medication for blood pressure (2017 survey). These specifications use rectangular weights instead of triangular ones. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. The change in systolic and diastolic blood pressure is $mean(x_1, x_2, x_3)^{2017} - mean(x_1, x_2, x_3)^{2013}$ with $x = \{systolic, diastolic\}$. We use a Mean Square Error (MSE) optimal bandwidth selector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Results of the RDD specification using identical optimal bandwidths for all four main outcomes

Specifications	Effects	Std. errors	P-values	OB-	OB+	N-	N+
			A. Change in systolic blood pressure				
Linear	-12.88^{**}	5.947	0.030	23.57	18.43	312	108
Linear with controls	-14.28^{**}	5.952	0.016	21.30	18.72	275	107
			B. Change in diastolic blood pressure				
Linear	-5.439^{*}	2.867	0.058	23.57	18.43	312	108
Linear with controls	-6.029^{**}	2.811	0.032	21.30	18.72	275	107
			C. Probability of being hypertensive in 2017				
Linear	-0.197^{*}	0.111	0.076	23.57	18.43	312	108
Linear with controls	-0.228^{**}	0.112	0.042	21.30	18.76	275	107
			D. Diagnosis				
Linear	0.225^{**}	0.094	0.017	23.57	18.43	312	109
Linear with controls	0.192^{**}	0.091	0.035	21.30	18.72	275	108
			E. Medication				
Linear	0.063	0.066	0.339	23.57	18.43	312	109
Linear with controls	0.042	0.064	0.515	21.30	18.72	275	108

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. These specifications use same optimal bandwidths for the four main outcome variables. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. The change in systolic and diastolic blood pressure is $mean(x_1, x_2, x_3)^{2017} - mean(x_1, x_2, x_3)^{2013}$ with $x = \{systolic, diastolic\}$. We use a Mean Square Error (MSE) optimal bandwidth selector.

Table A.4: Results of the RDD specification restricting the bandwidth to be the same bandwidths on both sides of the cutoffs

Specifications	Effects	Std. errors	P-values	OB-	OB+	N-	N+
A. Change in systolic blood pressure							
Linear	-13.04^{**}	6.162	0.034	18.85	18.85	218	108
Linear with controls	-14.24^{**}	6.039	0.018	19.04	19.04	229	108
B. Change in diastolic blood pressure							
Linear	-5.697^{*}	2.937	0.052	19.31	19.31	233	109
Linear with controls	-5.777^{**}	2.717	0.034	21.35	21.35	275	115
C. Probability of being hypertensive in 2017							
Linear	-0.192^{*}	0.106	0.070	23.22	23.22	312	122
Linear with controls	-0.219^{**}	0.105	0.037	23.18	23.18	307	121
D. Diagnosis							
Linear	0.236^{**}	0.112	0.036	13.44	13.44	151	87
Linear with controls	0.201^{*}	0.105	0.056	14.32	14.32	160	90
E. Medication							
Linear	0.047	0.077	0.543	14.30	14.30	163	91
Linear with controls	0.036	0.075	0.629	14.05	14.05	160	90

Note: The table shows estimates of the effect of receiving a referral card in 2013 on blood pressure related outcomes using a regression disconinuity design. Change in systolic blood pressure is the difference between the average of the three systolic blood pressure measures in 2017 and in 2013. Change in diastolic blood pressure is the difference between the average of the three diastolic blood pressure measures in 2017 and in 2013. We define someone as being hypertensive if the mean systolic or diastolic blood pressure measurements was greater or equal to 140 and 90, respectively. Diagnosis is a dummy equal to 1 if the respondent has been diagnosed by a medical professional in the last two years (2017 survey). Medication is a dummy equal to 1 if the respondent is currently taking medication for blood pressure (2017 survey). All these specifications use triangular weights. $OB-$ and $OB+$ represent the bandwidths below and above the cutoffs, respectively, and are restricted to be identical. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. The change in systolic and diastolic blood pressure is $mean(x_1, x_2, x_3)^{2017} - mean(x_1, x_2, x_3)^{2013}$ with $x = \{systolic, diastolic\}$. We use a Mean Square Error (MSE) optimal bandwidth selector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Results of the RDD specification on the change in physical activity and weight

Specification	Effects	Std. errors	P-values	OB-	OB+	N-	N+
			A. Change weekly hours of moderate activity				
Linear	-1.803	4.265	0.672	24.52	23.39	323	123
Linear with controls	-1.947	4.331	0.653	23.33	22.74	306	120
			B. Change weekly hours of vigorous activity				
Linear	-7.931	4.900	0.106	11.16	14.52	119	90
Linear with controls	-8.973^{*}	4.907	0.067	10.91	14.75	102	89
			C. Change in weight				
Linear	0.143	1.529	0.925	19.95	13.36	223	85
Linear with controls	-0.048	1.530	0.975	19.79	13.94	223	85
			D. Change in BMI				
Linear	-0.401	0.588	0.495	18.52	14.22	209	88
Linear with controls	-0.519	0.619	0.402	17.69	13.66	197	84
			E. Waist to hip ratio (2017)				
Linear	-0.017	0.016	0.298	19.17	19.39	226	108
Linear with controls	-0.025	0.016	0.123	19.87	19.56	224	107

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All these specification use triangular weights. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. The change in systolic and diastolic blood pressure is $mean(x_1, x_2, x_3)^{2017} - mean(x_1, x_2, x_3)^{2013}$ with $x = \{systolic, diastolic\}$. We use a Mean Square Error (MSE) optimal bandwidth selector.

Table A.6: Causal effects on mortality and attrition

1. Regression Discontinuity Design							
	Effects	Std. errors	P-values	OB-	OB+	N-	N+
A. Mortality							
Linear	0.019	0.082	0.814	18.37	14.92	252	106
Linear with controls	0.057	0.078	0.466	21.09	14.59	318	106
B. Attrition							
Linear	0.000	0.045	0.996	31.67	17.30	445	106
Linear with controls	0.010	0.044	0.817	29.77	16.71	414	104

2. Matching Strategy				
	ATET	P-value	Obs.	Average distance
A. Mortality				
No controls	.013	.936	242	.871
With controls	-.033	.593	242	.916
With controls + SD	-.009	.883	242	1.538
B. Attrition				
No controls	.010	.666	218	.920
With controls	.015	.710	218	.959
With controls + SD	-.039	.334	218	1.575

Note: The table shows the effect of the referral card given in 2013 on mortality and attrition in 2017. Specifications in the RDD use triangular weights. $OB-$ and $OB+$ represent the optimal bandwidths below and above the cutoffs, respectively. $N-$ and $N+$ represent the number of observations included in the optimal bandwidths below and above the cutoffs, respectively. We use a Mean Square Error (MSE) optimal bandwidth selector. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Results of the matching estimations on the main outcomes variables with different restrictions on the number of minimum matches

	Change in systolic blood pressure	Change in diastolic blood pressure	Prob. of being hypertensive (2017)	Diagnosis	Medication
			A. At least 3 matches		
			No controls		
ATET	-3.867	-1.316	-.113	.272***	.112**
P-value	.685	.690	.313	.000	.032
Obs.	207	207	207	207	207
Distance	.933	.933	.933	.933	.933
			With controls		
ATET	-9.471*	-1.628	-.078	.292***	.135***
P-value	.089	.500	.439	.000	.009
Obs.	204	204	204	204	204
Average distance	.904	.904	.904	.904	.904
			With controls + SD		
ATET	-6.418	-2.750	-.290***	.257***	.162***
P-value	.271	.272	.002	.002	.003
Obs.	204	204	204	204	204
Average distance	1.503	1.503	1.503	1.503	1.503
			B. At least 5 matches		
			No controls		
ATET	-8.164	-2.622	-.204	.289***	.123**
P-value	.293	.375	.178	.000	.0150
Obs.	207	207	207	207	207
Distance	1.228	1.228	1.228	1.228	1.228
			With controls		
ATET	-10.39*	-2.416	-.126	.223***	.128**
P-value	.051	.304	.197	.005	.018
Obs.	204	204	204	204	204
Average distance	1.057	1.057	1.057	1.057	1.057
			With controls + SD		
ATET	-12.18**	-4.995**	-.226**	.235***	.171***
P-value	.028	.040	.021	.004	.002
Obs.	204	204	204	204	204
Average distance	1.665	1.665	1.665	1.665	1.665

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The results represent the Average Treatment Effects on Treated (ATET) of getting a referral card on the various outcomes listed in the columns. We restrict the number of matches to be at least 3 (Panel A) and 5 (Panel B) and match respondents based on their mean systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies.

Table A.8: Results of the matching estimations on the main outcomes variables, restricting possible matches to be within a distance of 8 maximum

	Change in systolic blood pressure	Change in diastolic blood pressure	Prob. of being hypertensive (2017)	Diagnosis	Medication
			No controls		
ATET	-8.484	-2.817	-.196	.277***	.117**
P-value	.321	.365	.171	.000	.023
Obs.	181	181	181	181	181
Distance	1.21	1.21	1.21	1.21	1.21
			With controls		
ATET	-9.046	-1.769	-.100	.215***	.118**
P-value	.101	.463	.309	.008	.026
Obs.	178	178	178	178	178
Average distance	1.055	1.055	1.055	1.055	1.055
			With controls + SD		
ATET	-7.386	-2.029	-.266***	.199**	.093*
P-value	.206	.404	.006	.015	.077
Obs.	178	178	178	178	178
Average distance	1.659	1.659	1.659	1.659	1.659

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The results represent the Average Treatment Effects on Treated (ATET) of getting a referral card on the various outcomes listed in the columns. We restrict the number of matches to be at least 4 and match respondents based on their mean systolic blood pressure in 2013, limiting the distance for possible matches to be at most 8. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies.

Table A.9: Results of the matching estimations on the main outcomes variables, restricting possible matches to be within a distance of 5 maximum

	Change in systolic blood pressure	Change in diastolic blood pressure	Prob. of being hypertensive (2017)	Diagnosis	Medication
			No controls		
ATET	-9.440	-2.960	-.216	.253***	.079*
P-value	.299	.367	.156	.001	.089
Obs.	106	106	106	106	106
Distance	1.275	1.275	1.275	1.275	1.275
			With controls		
ATET	-6.068	-.024	-.049	.260***	.115**
P-value	.301	.992	.648	.003	.0250
Obs.	105	105	105	105	105
Average distance	1.38	1.38	1.38	1.38	1.38
			With controls + SD		
ATET	-10.66*	-2.107	-.313***	.234***	.120**
P-value	.057	.401	.001	.0090	.023
Obs.	105	105	105	105	105
Average distance	1.978	1.978	1.978	1.978	1.978

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The results represent the Average Treatment Effects on Treated (ATET) of getting a referral card on the various outcomes listed in the columns. We restrict the number of matches to be at least 4 and match respondents based on their mean systolic blood pressure in 2013, limiting the distance for possible matches to be at most 5. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies.

Table A.10: Results of the matching estimations on the main outcomes variables, matching observations based on their median systolic blood pressure value instead of mean

	Change in systolic blood pressure	Change in diastolic blood pressure	Prob. of being hypertensive (2017)	Diagnosis	Medication
			No controls		
ATET	-6.109	-3.058	-.121	.289***	.119**
P-value	.325	.223	.161	.000	.027
Obs.	256	256	256	257	257
Distance	.726	.726	.726	.773	.773
			With controls		
ATET	-9.530*	-3.590	-.087	.209**	.095*
P-value	.087	.119	.343	.011	.096
Obs.	253	253	253	254	254
Average distance	.797	.797	.796	.796	.796
			With controls + SD		
ATET	-8.729	-6.783***	-.163*	.195**	.102*
P-value	.125	.003	.078	.016	.077
Obs.	253	253	253	254	254
Average distance	1.34	1.34	1.34	1.34	1.34

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The results represent the Average Treatment Effects on Treated (ATET) of getting a referral card on the various outcomes listed in the columns. We restrict the number of matches to be at least 4 and match respondents based on their median systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies.

Table A.11: Results of the matching estimations on the main outcome variables, using the last two measurements only

	Change in systolic blood pressure	Change in diastolic blood pressure	Prob. of being hypertensive (2017)	Diagnosis	Medication
			No controls		
ATET	-8.681	-2.590	-.180	.278***	.107**
P-value	.131	.273	.101	.000	.027
Obs.	232	232	232	232	232
Distance	.800	.800	.800	.800	.800
			With controls		
ATET	-9.586*	-1.471	-.171*	.244***	.086*
P-value	.083	.540	.076	.001	.093
Obs.	228	228	228	228	228
Average distance	.909	.909	.909	.909	.909
			With controls + SD		
ATET	-11.13**	-2.460	-.148	.224***	.084
P-value	.033	.268	.128	.006	.135
Obs.	228	228	228	228	228
Average distance	1.338	1.338	1.338	1.338	1.338

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The results represent the Average Treatment Effects on Treated (ATET) of getting a referral card on the various outcomes listed in the columns. We restrict the number of matches to be at least 4 and match respondents based on their median systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies. Here, we are taking into account only the last two measurements to compute the mean systolic blood pressure.

Table A.12: Results of the matching estimations representing the Average Treatment Effects (ATE)

	Change in systolic blood pressure	Change in diastolic blood pressure	Prob. of being hypertensive (2017)	Diagnosis	Medication
			No controls		
ATE	-2.798	-1.901	-.024	.454***	.249*
P-value	.751	.671	.883	.003	.071
Obs.	207	207	207	207	207
Distance	1.21	1.21	1.21	1.21	1.21
			With controls		
ATE	-3.637	-2.652	-.001	.351***	.205***
P-value	.484	.278	.989	.000	.002
Obs.	204	204	204	204	204
Average distance	.984	.984	.984	.984	.984
			With controls + SD		
ATE	-18.94***	-5.890***	.014	.372***	-.005
P-value	.000	.007	.885	.000	.9354
Obs.	204	204	204	204	204
Average distance	1.59	1.59	1.59	1.59	1.59

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The results represent the Average Treatment Effects (ATE) of getting a referral card on the various outcomes listed in the columns. We restrict the number of matches to be at least 4 and match respondents based on their mean systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies.

Table A.13: Results of the matching estimations on the change in physical activity and weight

	Change weekly hours of moderate activity	Change weekly hours of vigorous activity	Change in weight	Change in BMI	Waist to hip ratio (2017)
			No controls		
ATET	3.790	-7.585**	-2.305	-1.073	-.033
P-value	.370	.023	.464	.264	.160
Obs.	206	204	200	200	202
Distance	1.21	1.234	1.211	1.211	1.204
			With controls		
ATET	4.354	-12.42***	-.061	-.048	-.034
P-value	.261	.001	.953	.926	.108
Obs.	204	202	200	200	201
Average distance	.984	.995	1.003	1.003	.998
			With controls + SD		
ATET	-22.54***	-5.302	-1.446	-.134	.015
P-value	.000	.109	.139	.765	.348
Obs.	204	202	200	200	201
Average distance	1.59	1.594	1.613	1.613	1.612

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The results represent the Average Treatment Effects on Treated (ATET) of getting a referral card on the various outcomes listed in the columns. We restrict the number of matches to be at least 4 and match respondents based on their median systolic blood pressure in 2013, limiting the distance for possible matches to be at most 10. "Distance" represent the mean of the average distances between each observation and their matches. "With controls" includes a sex dummy, age and region dummies.

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To whom it may concern:

____was measured with high blood pressure by the Malawi Longitudinal Study of Families and Health, a joint study by the University of Pennsylvania (USA) and the College of Medicine (Malawi) using automatic blood pressure monitor. He/she surpassed 160 mm/Hg systolic and/or 110 mm/Hg diastolic blood pressure by our measurement. We therefore refer him/her to you for further assessment.

Thank you,

Interviewer's last name:___________________________

Signature:_____________________________________