The good, the bad, and the ugly test effect: Does biomedical testing in surveys change health care seeking behavior?*

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Abstract

This paper is the first to rigorously analyze unintended effects of biomedical testing in surveys. Random assignment of blood pressure measurements in a 2013 household survey in Tanzania, and a second survey of the same individuals two years later, allows for the identification of this “test effect” on hypertension (high blood pressure) awareness, health care provider consultations for hypertension, and uptake of voluntary health insurance. As these were the baseline and follow-up surveys of a health insurance impact evaluation, the possible bias in the insurance impact estimates caused by the test effect can also be estimated. Since, complying with ethical standards, respondents who were tested were told their test result, the differential effect of a “good” versus a “bad” test result

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can be determined. Evidence is found that a bad test result significantly increases hypertension awareness, as well as the likelihood of health care provider consultations for hypertension. However, there is no evidence of a test effect on health insurance enrollment. Furthermore, no evidence is found of a bias in health insurance impact estimates due to the blood pressure measurement, for any of the outcomes.

**Keywords:** survey methodology, test effect, biomedical test, blood pressure measurement, health insurance, Tanzania.

**JEL:** C83, C93, I12, I13.

### 1. Introduction

As developing countries generally have no population-wide administrative health care data, health economics research requires population representative data to be collected through surveys. These often include self-reported morbidity indicators as measures of health status. However, these subjective health measures suffer from misreporting due to respondents’ lack of knowledge of their true health status (Sen, 2002), respondents’ tendency to report a socially desirable health status (Latkin and Vlahov, 1998; Adams et al., 2005), or because of recall bias (Das et al., 2012). Instead, researchers can opt to collect objective health measures by including biomedical tests in the survey, such as anthropometric measurements, blood pressure measurements, and blood or saliva tests. While this allows more precise knowledge of a respondent’s true health status, biomedical testing in surveys has its own drawbacks. The test may give false positives or false negatives (Banoo et al., 2008), there may be non-response bias due to test refusal (e.g. Reniers and Eaton, 2009; Janssens et al., 2014), and test results can even be faked by interviewers (Janssens et al., 2010).

The current paper is about another—not yet rigorously researched—potential drawback of biomedical testing in surveys, namely its ability to change a respondent’s future health care seeking behavior. Such change in behavior could effectively cause a carefully chosen representative sample to cease being repre-
sentative after the survey. In a panel setting it may bias research outcomes. There may also be a positive side to this change in behavior that should be considered. Namely, if receiving biomedical measurements causes a rise in health insurance demand among the poor, which has proven notoriously difficult in developing countries (Gwatkin et al., 2004; Victora et al., 2004; Gwatkin and Ergo, 2011), large-scale biomedical testing could get us one step closer to the holy grail of health care in developing countries: universal health coverage.

It is well known that being surveyed can change people’s behavior. Knowledge of being observed in the scope of an impact evaluation can cause behavioral change in both the treatment and control group, called the Hawthorne and John Henry effect, respectively (Duflo et al., 2007). The so-called question-behavior effect, which includes self-prophecy and mere-measurement effects, occurs when people are asked questions about future behavior and consequently change their behavior in line with their answers (Sherman, 1980; Feldman and Lynch, 1988; Sprott et al., 2006; Dholakia, 2010). The survey effect occurs when asking questions about a certain subject causes a reminder or salience shock that makes people act more responsibly (Bridge et al., 1977; Zwane et al., 2011; Crossley et al., 2014; Axinn et al., 2015). The type of effect that is most similar to this paper, is testing water quality in the scope of a household survey (Jalan and Somanathan, 2008; Davis et al., 2011; Luoto et al., 2011; Zwane et al., 2011; Hamoudi et al., 2012). Just as disclosing information about one’s water quality in developing countries potentially closes an information gap, giving biomedical test results raises awareness of one’s medical condition, rather than acting as a reminder of something already known. This effect is intrinsically different from the survey effect, the question-behavior effect, the Hawthorne and John Henry effect, and can be called a “test effect”.

This paper is based on data from two household surveys in the Kilimanjaro region in Tanzania. In the first, conducted in January-March of 2013, 80% of households were randomly assigned to receive blood pressure measurements. Complying with ethical standards, the survey medical officer, upon measuring a respondent’s blood pressure, would inform the individual of the result. In case of
a high blood pressure measurement, the respondent was advised to seek medical care. The same households were revisited two years later, in March of 2015. These surveys were collected in the scope of an impact evaluation of a subsidized micro health insurance scheme, and included questions on health status, health care utilization, and health insurance. Half of the sample gained access to the voluntary health insurance program in the fall of 2013, approximately six months after the first, i.e. baseline, survey.

These data allow us to assess the effect of blood pressure measurements in a household survey setting on awareness of one’s hypertension (high blood pressure) status, on doctor visits for hypertension, and on take-up of health insurance. We can furthermore differentiate the effect of a “good” and a “bad” (high) blood pressure measurement on these outcomes, and see how the health insurance intervention adds to these effects. Finally, we can see whether the test effect biases the insurance impact estimates for these outcomes. To the author’s knowledge, this paper is the first that rigorously analyzes unintended effects of biomedical testing in surveys.

The paper will proceed as follows. The next section will provide background information on the research population and the health insurance intervention. Section 3 describes the experiment and the data. Thereafter the model is presented, followed by the econometric analysis in section 5. Finally, section 6 concludes.

2. Background: health insurance intervention

The background of the surveys is an impact evaluation of the so-called KNCU Health Plan, a subsidized health insurance scheme in the Kilimanjaro region of Tanzania, funded by the the Health Insurance Fund, a Dutch NGO. This health insurance was offered to coffee farmers who are active members of the Kilimanjaro Native Cooperative Union (KNCU), and their household members.1 It

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1Based on interviews with local village leaders, approximately two out of five households in the study area are estimated to be such “KNCU households”, ranging from 10% to 89%,
covered outpatient services at the primary level, including hypertension treat-
ment, as well as maternal and child care (both inpatient and outpatient). It was
coupled with upgrading of designated health facilities in the vicinity of the local
population. The insurance was voluntary and available at the household level,
rather than individual level. The annual co-premium was priced on a sliding
scale, ranging from 12,000 Tanzanian Shilling (TZS) for a one person household,
to 45,000 TZS for a 9 to 12 person household.\(^2\)

KNCU is organized into about 90 so-called primary societies (KNCU), which
are spread throughout the Kilimanjaro region. Because the KNCU Health Plan
was gradually expanded by primary society since April 2011, the insurance
intervention and control groups consisted of several primary societies in districts
Hai, Moshi Rural, and Rombo.\(^3\) These were chosen such that they were far
enough apart to prevent spill-overs from the intervention to the control group,
and such that they were similar at baseline on key characteristics such as access
to health facilities, altitude, distance to Moshi town, type of coffee grown, and in
which district they were located.\(^4\) Approximately six months after the baseline
survey the KNCU Health Plan was offered to the treatment group only.\(^5\)

The study population, located in the districts Hai and Moshi Rural,\(^6\) is quite
poor, with daily per capita consumption averaging 2234 TZS or 1.40 USD (3.5
USD at PPP) at baseline.\(^7\) The full KNCU Health Plan premium thus amounts
to almost one week of average per capita consumption. At baseline, 10.8% of
the survey sample had health insurance: 2.1% were insured by the Community

\(^{2}\)Since the full premium was 14,000 TZS per person, this implies a subsidy level of 14% up
to 73%, depending on household size.
\(^{3}\)Five primary societies in the insurance intervention group, and four in the control group.
\(^{4}\)For more information on the insurance intervention and control group choice and similar-
ities at baseline, see AID and AIGHD (2013).
\(^{5}\)It proved not possible to introduce the KNCU Health Plan in the Rombo district, which is
why the insurance intervention and control primary society in this district were subsequently
excluded from the KNCU Health Plan impact evaluation and from the follow-up survey.
\(^{6}\)Rombo district is not part of the study population, since it was not included in the
follow-up survey, see footnote 5.
\(^{7}\)Source: baseline survey. 1 USD \(\approx\) 1,600 TZS in February 2013 (Oanda). 1 USD \(\approx\) 0.4
USD at PPP in Tanzania in 2013 (World Bank).
Health Fund (CHF), and 8.5% by the National Health Insurance Fund (NHIF).\(^8\)

As of May 2015, the KNCU Health Plan fully merged with the CHF in a public-private partnership with local governments of Kilimanjaro districts Siha, Hai, and Moshi Rural, and was re-named *improved* Community Health Fund (iCHF). iCHF is now available to the full populations of these districts, including the insurance control group.

3. Data collection and description

The baseline survey was conducted between 25 January to 6 March 2013 by Economic Development Initiatives (EDI) Ltd., an independent Tanzanian survey firm. Six teams totaling 24 interviewers and seven health officers conducted household interviews and biomedical tests, respectively, in 1,500 households (half of which belonged to the insurance intervention group). All individuals, including those not assigned to receive blood pressure measurements, were asked to give written consent for the biomedical part of the interview. Complying with ethical standards, without this consent biomedical measurements and questions were excluded from the interview.

The household questionnaire was conducted in Swahili,\(^9\) using computers with the specialized survey software Surveybe. It was very extensive, containing sections on education, employment, consumption, household assets, gifts and loans, coffee production, risk and time preferences, self-reported health status, health care expenditures, and health care seeking behavior.

Furthermore 80% of sampled households were randomly assigned for all adult household members to receive blood pressure measurements.\(^\text{10}\) If an individual

\(^8\)CHF is a community based health insurance, available to the full district population, and managed by the district government. Its co-premium is 10,000 TZS per household per year. Insured individuals are entitled to outpatient treatment in public health facilities in the district. However, treatment is not always free in practice. NHIF is the government health insurance, available to government employees, and their family members. It covers all health care in public, and selected private, health facilities.

\(^9\)In rare occasions a local translator was needed to for translation into Chagga, the native language of the region.

\(^\text{10}\)Stratified by sub-village. See appendix A for more sampling details.
had high blood pressure (systolic blood pressure ≥ 140 mmHg or diastolic blood pressure ≥ 90 mmHg) in two out of three measurements, the medical officer would point out to the person that they should visit a health care professional for additional testing and treatment.\textsuperscript{11}

Two years later, in March 2015, EDI Ltd. returned to interview the same households. Because Rombo district was not anymore included in the follow-up survey (see footnote 5), the sample was reduced from 1,500 to 1,000 households. The follow-up survey was less extensive than the baseline survey, but included questions on self-reported health status, health care utilization, health expenditures and detailed health insurance questions (including health insurance status one year before the follow-up survey, in March 2014).\textsuperscript{12}

The 1,000 baseline households had a total of 4,122 household members, out of which 2,530 were adults (BP test: 2,038; No BP test: 492).\textsuperscript{13} Out of all adults 2,159 (85\%) consented for the biomedical part of the survey (BP test: 1,738 = 86\%; No BP test: 421 = 85\%). From all who received the blood pressure measurement (namely all consenting adults, except 43 individuals who did give consent but were not tested), 588 (35\%) had high blood pressure in at least two out of three measurements, i.e. a bad test result.

Out of the 1,000 baseline households 966 were reached at follow-up. The households that could not be interviewed had either moved, were unavailable or had refused an interview. Out of the baseline consenting adults 1,800 (83\%) were still members of the household at follow-up (BP test: 1,444 = 83\%; No BP test: 356 = 85\%) and 1,536 (85\%) consented at follow-up (BP test: 1,243 = 86\%; No BP test: 293 = 82\%).\textsuperscript{14} These 1,536 individuals will be used in the

\textsuperscript{11}Hypertension can be diagnosed only after high blood pressure is measured multiple times over the span of several days. In the scope of the 2013 survey individual blood pressure measurements were taken on the same day, and are thus insufficient for diagnostic purposes.

\textsuperscript{12}Ethical and general research clearance for both survey rounds was received from the Tanzanian National Institute for Medical Research (NIMR) and the Tanzania Commission for Science and Technology (COSTECH), respectively.

\textsuperscript{13}“BP test” are the individuals in households that were randomly assigned to receive blood pressure measurements, and “No BP test” are those in households that were not assigned to receive blood pressure measurements.

\textsuperscript{14}Only 25 out of those had missing test result at baseline.
analyses. Individuals who left the household or did not give consent at follow-up were more often male, younger, healthier, better educated, less often employed, and were more likely to have had financial health shock at baseline, compared to those who were available for the (biomedical part of the) follow-up survey. The baseline characteristics of the individuals who were not available for the (biomedical part of the) follow-up survey were however balanced between the blood pressure test and no test group.\textsuperscript{15}

Table 1: Means of baseline variables, by blood pressure test assignment (adults)

<table>
<thead>
<tr>
<th></th>
<th>BP test Mean (N=1243)</th>
<th>No BP test Mean (N=293)</th>
<th>∆Mean p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Main</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Insurance program treatment group</td>
<td>0.48</td>
<td>0.54</td>
<td>0.186</td>
</tr>
<tr>
<td>Self-reported HT</td>
<td>0.23</td>
<td>0.26</td>
<td>0.189</td>
</tr>
<tr>
<td>BP check - past 12 months</td>
<td>0.34</td>
<td>0.37</td>
<td>0.467</td>
</tr>
<tr>
<td>Consult for HT - past 12 months</td>
<td>0.16</td>
<td>0.19</td>
<td>0.229</td>
</tr>
<tr>
<td>Any health insurance</td>
<td>0.15</td>
<td>0.13</td>
<td>0.367</td>
</tr>
<tr>
<td><strong>Socio-economic characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>54.8</td>
<td>57.7</td>
<td>0.016*</td>
</tr>
<tr>
<td>Female</td>
<td>0.61</td>
<td>0.59</td>
<td>0.476</td>
</tr>
<tr>
<td>Married\textsuperscript{a}</td>
<td>0.69</td>
<td>0.70</td>
<td>0.686</td>
</tr>
<tr>
<td>Employed - past 12 months</td>
<td>0.21</td>
<td>0.17</td>
<td>0.073\textsuperscript{+}</td>
</tr>
<tr>
<td>Educ\textsuperscript{b}; None</td>
<td>0.09</td>
<td>0.13</td>
<td>0.094\textsuperscript{+}</td>
</tr>
<tr>
<td>Educ: Less than primary school</td>
<td>0.31</td>
<td>0.32</td>
<td>0.827</td>
</tr>
<tr>
<td>Educ: Primary school</td>
<td>0.54</td>
<td>0.49</td>
<td>0.163</td>
</tr>
<tr>
<td>Educ: More than primary school</td>
<td>0.06</td>
<td>0.06</td>
<td>0.853</td>
</tr>
<tr>
<td><strong>Self-reported illness/ injury</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chronic illness</td>
<td>0.41</td>
<td>0.46</td>
<td>0.157</td>
</tr>
<tr>
<td>Acute illness / injury - past 12 months</td>
<td>0.50</td>
<td>0.52</td>
<td>0.553</td>
</tr>
<tr>
<td>Hospitalization - past 12 months</td>
<td>0.07</td>
<td>0.08</td>
<td>0.546</td>
</tr>
<tr>
<td><strong>Household characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual consumption\textsuperscript{c} - PC (TZS/1,000)</td>
<td>860</td>
<td>872</td>
<td>0.742</td>
</tr>
<tr>
<td>Financial health shock - past 12 months</td>
<td>0.37</td>
<td>0.39</td>
<td>0.632</td>
</tr>
<tr>
<td>Household size</td>
<td>4.40</td>
<td>4.09</td>
<td>0.073\textsuperscript{+}</td>
</tr>
<tr>
<td>#Young children in HH (age &lt; 5)</td>
<td>0.20</td>
<td>0.12</td>
<td>0.005\textsuperscript{**}</td>
</tr>
<tr>
<td>#Elderly in HH (age ≥ 60)</td>
<td>0.70</td>
<td>0.78</td>
<td>0.199</td>
</tr>
<tr>
<td>#Reproductive age women (15–45) in HH</td>
<td>0.51</td>
<td>0.39</td>
<td>0.042\textsuperscript{*}</td>
</tr>
</tbody>
</table>

Note: The table shows statistics for all adults who gave consent for the biomedical part of both surveys (questions and measurements). Means are weighted and p-values clustered at the household level, in accordance with the sampling method. BP=blood pressure; HT= hypertension; HH= household; PC= per capita; \textsuperscript{a}Includes mono- and polygamous marriage; \textsuperscript{b}Highest completed educational level; \textsuperscript{c}One outlier excluded. \textsuperscript{+} p<0.10, \textsuperscript{*} p<0.05, \textsuperscript{**} p<0.01, \textsuperscript{***} p<0.001.

\textsuperscript{15}Data not shown, but available upon request.
Table 1 compares, for all adults who consented for the biomedical part in both surveys, the baseline means of the outcome variables and other control variables by blood pressure test assignment. Out of the 22 baseline characteristics, three are not balanced at a 5% level, all age related. Individuals in the no blood pressure test group are on average older than those who were assigned to receive blood pressure measurements.

Figure 1 shows the means of the outcomes of interest, over time, disaggregated by test and insurance treatment. From the first two graphs it can be seen that after two years, as is to be expected, the percentage of self-reported hypertension increased (decreased) in both the insurance intervention and control area among those who received a bad (good) test result. Among those who were not assigned to receive blood pressure measurements the percentage of self-reported hypertension decreased in the insurance control area, and remained similar in the insurance intervention area. We see a similar trend when looking at the percentage of individuals who consulted a healthcare provider for hypertension in the past 12 months (second set of graphs), except that this percentage decreased for both the insurance intervention and control area among those not assigned to receive the blood pressure measurements. The third set of graphs shows the percentage of individuals enrolled in any health insurance scheme. As mentioned in section 2, already at baseline almost 11% of the surveyed individuals had health insurance (2% CHF, 9% NHIF). In the insurance treatment area we see a rise in health insurance in 2014 and 2015, irrespective of the blood pressure measurement. Note that the KNCU Health Plan was introduced there in the fall of 2013. There is no indication that individuals with a bad test result are more likely to take health insurance than those with a good test result. In the control group there is a rise of (CHF) health insurance take-up in 2015, especially for the individuals who were not assigned to receive blood pressure measurements at baseline. The reason for this increase is unclear from the data.
Figure 1: Hypertension awareness, health care provider consultations, and health insurance enrollment by test result and insurance intervention area (adults). Note that the “No BP test” individuals are those residing in households not assigned to receive blood pressure tests.
4. Model

For the kth outcome of interest, $Y_k$, the test effect—irrespective of its result—is captured by parameter $\beta_k$ in the following difference-in-differences individual fixed effects model:16

$$y_{kit} = \beta_k (M_i \times T_t) + \gamma_k T_t + \delta_{ki} + \epsilon_{kit}, \quad (1)$$

where $y_{kit}$ is the kth outcome value for individual $i$ at time $t$, which is equal to 0 at baseline (February 2013), and 1 at follow-up (March 2015).17 $M_i$ is a dummy equal to 1 if individual $i$ was assigned to receive blood pressure measurements at baseline,18 and 0 otherwise. The time dummy $T_t$ is 0 at baseline and 1 when $t = 1$, such that parameter $\gamma_k$ captures the common time trend. The individual time invariant characteristics are captured in the fixed effect $\delta_{ki}$, and $\epsilon_{kit}$ is the error term.

To differentiate between the effects of a good and a bad test result we split up $M_i = G_i + B_i$, such that $G_i$ and $B_i$ are dummy variables for a good and bad test result, respectively. The parameters of interest are then $\beta_{kg}$ and $\beta_{kb}$ in the following equation:

$$y_{kit} = \beta_{kg} (G_i \times T_t) + \beta_{kb} (B_i \times T_t) + \gamma_k' T_t + \delta_{ki}' + \epsilon_{kit}'. \quad (2)$$

The outcome of the test has no additional effect above that of the test itself iff $\beta_{kg} = \beta_{kb} = \beta_k$.19

16Equation 1 is a linear probability model, since all outcomes of interest are binary. A non-linear model is in theory preferred, e.g. the “changes-in-changes” model by Athey and Imbens (2006), as suggested by Blundell and Dias (2009). However, as shown by Angrist and Pischke (2009, p. 197-205) and Wooldridge (2002, p. 472), estimated marginal effects and standard errors from a non-linear model are in general similar to those of its linear counterpart.

17Except when we are considering health insurance take-up between 2013 and 2014, in which case $t = 1$ one year after the baseline survey (March 2014).

18This excludes individuals who did not give consent for the biomedical part of the survey, but includes the few who gave consent, but did not receive the test.

19Note that there is no intermediate control group which receives the test, but does not learn its outcome, as in Jalan and Somanathan (2008). This means that we cannot determine the effect of administering the test only (without letting the respondent know its outcome). Because of this we are unable to control for a bad test result in both the treatment and the
Adding to equation 1 interaction terms with dummy $D_i$ denoting the insurance intervention area, i.e. the insurance program intent to treat (ITT), gives:

\begin{equation}
\hat{y}_{kit} = \tilde{\beta}_k(M_i \times T_i) + \tilde{\eta}_k(M_i \times D_i \times T_i) + \tilde{\theta}_k(D_i \times T_i) + \gamma_k T_i + \tilde{\epsilon}_{kit},
\end{equation}

Parameter $\tilde{\theta}_k$ captures the insurance intervention ITT on the outcome. The parameter of interest in equation 3 is $\tilde{\eta}_k$, since it represents the bias from the blood pressure test (disregarding the test result) in the insurance intervention ITT estimate.\textsuperscript{20} Note finally that because the randomization of the testing treatment ($M_i$) was equally divided between the insurance intervention and control area by design, we have that $M_i \perp D_i$.

Adding interaction terms with $D_i$ to equation 2 gives:

\begin{equation}
\hat{y}_{kit} = \tilde{\beta}_{kb}(G_i \times T_i) + \tilde{\beta}_{kb}(B_i \times T_i) + \tilde{\eta}_{kb}(G_i \times D_i \times T_i) + \tilde{\eta}_{kb}(B_i \times D_i \times T_i) + \tilde{\theta}_k(D_i \times T_i) + \gamma_k T_i + \tilde{\epsilon}_{kit},
\end{equation}

where the parameters of interest are $\tilde{\eta}_{kb}$ and $\tilde{\eta}_{kb}$, giving the bias in the insurance intervention ITT estimate from a good and bad test result, respectively.

\textsuperscript{20}This can be seen as follows. Let us define $\Delta y_{ki} := y_{kit} - y_{k10}$. Omitting the subscript $k$ and writing $M_i(D_i)$ instead of $M_i \times T_i(D_i \times T_i)$ for ease of notation, we can write:

\begin{align*}
E(\Delta y_i | M_i, D_i) &= C + E(\Delta \epsilon_i | M_i, D_i) = C + M_i D_i E(\Delta \epsilon_i | M_i = 1, D_i = 1) \\
&+ (1 - M_i) D_i E(\Delta \epsilon_i | M_i = 0, D_i = 1) + M_i (1 - D_i) E(\Delta \epsilon_i | M_i = 1, D_i = 0) \\
&+ (1 - M_i) (1 - D_i) E(\Delta \epsilon_i | M_i = 0, D_i = 0),
\end{align*}

where $C$ is a constant. The term $(E_{10} - E_{00})$ is the ITT of the insurance program in absence of blood pressure measurements; $(E_{10} - E_{00})$ is the ITT of the blood pressure measurements without the availability of the insurance program; and $[(E_{11} - E_{10}) - (E_{01} - E_{00})]$ is the ITT of the insurance program in the presence of blood pressure measurements, minus the ITT in absence of the blood pressure measurements, i.e. the bias in the insurance ITT due to the blood pressure measurements. Note finally that the within estimator is equivalent to the first difference estimator up to a constant.
5. Analysis

Because of the random assignment of households into receiving the blood pressure tests at baseline we can reasonably assume that the time trend in absence of baseline testing between the test and no-test group would be the same. Then, using a two period balanced panel, the above equations can be consistently estimated with the fixed effects estimator (Cameron and Trivedi, 2009). All regressions are done using the command “xtreg, fe” in Stata 11.2 software (StataCorp, 2009). According to the sampling frame, observations are weighted by their sampling probabilities, and errors are clustered at the household level. Only individuals who gave consent for the biomedical part of both surveys are included in the regressions.

Table 2: Results, equation 1 (adults)

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP test × T</td>
<td>0.022</td>
<td>0.014</td>
<td>0.044</td>
<td>0.009</td>
</tr>
<tr>
<td>(0.032)</td>
<td>(0.039)</td>
<td>(0.030)</td>
<td>(0.032)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>T</td>
<td>-0.018</td>
<td>0.029</td>
<td>-0.064*</td>
<td>0.063*</td>
</tr>
<tr>
<td>(0.028)</td>
<td>(0.034)</td>
<td>(0.027)</td>
<td>(0.028)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Observations</td>
<td>3064</td>
<td>3056</td>
<td>3056</td>
<td>3072</td>
</tr>
</tbody>
</table>

Fixed effects regression on balanced two-period panel; weighted and standard errors clustered at the household level, according to the sampling frame. Standard errors in parentheses. BP=blood pressure; HT=hypertension; 12m=12 months; T=time dummy; † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 2 shows the results corresponding to equation 1. There is no evidence of a test effect when we do not differentiate by test result, for all outcomes, at a 10% level. As expected, there is positive time trend in insurance take-up. Namely, there was a significant increase of 6 percentage points (pp) in health insurance enrollment one year after baseline, and 13 pp two years later. There is a significant and unexpected negative time trend of 6 pp in consultations for hypertension in the past 12 months.

Results corresponding to equation 2 are shown in table 3. Here we see evidence of a test effect for self-reported hypertension and consultations for hypertension in the past 12 months. Namely, there is a significant 14 pp increase in self-reported hypertension for those individuals who had a bad test result at
Table 3: Results, equation 2 (adults)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-reported</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP check:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consult for</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Insured HT: 12m</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HT: 12m</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Good BP × T</td>
<td>-0.053</td>
<td>-0.003</td>
<td>0.001</td>
<td>0.016</td>
<td>-0.049</td>
</tr>
<tr>
<td>(0.032)</td>
<td>(0.042)</td>
<td>(0.031)</td>
<td>(0.034)</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>High BP × T</td>
<td>0.140***</td>
<td>0.039</td>
<td>0.113**</td>
<td>-0.009</td>
<td>-0.068</td>
</tr>
<tr>
<td>(0.039)</td>
<td>(0.045)</td>
<td>(0.038)</td>
<td>(0.035)</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>-0.018</td>
<td>0.029</td>
<td>-0.064*</td>
<td>0.063*</td>
<td>0.131***</td>
</tr>
<tr>
<td>(0.028)</td>
<td>(0.034)</td>
<td>(0.027)</td>
<td>(0.028)</td>
<td>(0.039)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3014</td>
<td>3008</td>
<td>3006</td>
<td>3022</td>
<td>3016</td>
</tr>
<tr>
<td>P(β̂kg = β̂kb)</td>
<td>&lt;.001***</td>
<td>0.260</td>
<td>&lt;.001***</td>
<td>0.289</td>
<td>0.420</td>
</tr>
</tbody>
</table>

Fixed effects regression on balanced two-period panel; weighted and standard errors clustered at the household level, according to the sampling frame. Standard errors in parentheses. BP=blood pressure; HT=hypertension; 12m=12 months; T=time dummy; * p < 0.10, ** p < 0.05, *** p < 0.01.

baseline, compared to those who were not tested. There is also a 5 pp decrease in self reported hypertension for those with a good test result. However, this is not significantly different from zero at a 10% level. Having had a bad test result at baseline increases the probability to consult a health care provider for hypertension significantly, by 11 pp. A good test result had no influence on consultations for hypertension. That there is a significant difference between a good and a bad test result for these outcomes is confirmed by the small p-value corresponding to the Wald test of $\beta_{kg} = \beta_{kb}$. There is on the other hand no effect of a bad test result on insurance take up in 2014 and 2015. These effects are not only insignificant, they are even negative. Thus table 3 gives no evidence of adverse selection due to the test.\(^{21}\)

Table 4 shows the estimation results corresponding to equation 3. There is a significant 13 pp impact of the KNCU Health Plan on health insurance enrollment in 2014, and a positive (5 pp), but non-significant impact on health insurance enrollment in 2015. There is however no evidence of biased impact estimates due to the test for all outcomes, when the test result is disregarded, since the parameter “BP test × D × T” (\(\tilde{\eta}_k\)) estimate is never significantly different from zero at a 10% level. As in tables 1 and 2 we see a negative time

\(^{21}\)When running regressions (4) and (5) of table 3 at the household level (replacing the individual bad test result with a dummy for a bad test result in the household, and similarly replacing the individual good test result with a dummy for only good test results in the household) the signs and significance of the parameter estimates remain the same.
Table 4: Results, equation 3 (adults)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP test × T</td>
<td>0.064 ± 0.047</td>
<td>0.025 ± 0.051</td>
<td>0.056 ± 0.043</td>
<td>0.018 ± 0.044</td>
<td>-0.061 ± 0.072</td>
</tr>
<tr>
<td>BP test × D × T</td>
<td>-0.079 ± 0.064</td>
<td>-0.023 ± 0.051</td>
<td>-0.021 ± 0.021</td>
<td>-0.002 ± 0.062</td>
<td>0.022 ± 0.072</td>
</tr>
<tr>
<td>D × T</td>
<td>0.555 ± 0.056</td>
<td>0.001 ± 0.054</td>
<td>0.034 ± 0.055</td>
<td>0.128 ± 0.055</td>
<td>0.047 ± 0.081</td>
</tr>
<tr>
<td>T</td>
<td>-0.048 ± 0.041</td>
<td>0.028 ± 0.038</td>
<td>-0.082 ± 0.039</td>
<td>-0.006 ± 0.039</td>
<td>0.105 ± 0.069</td>
</tr>
</tbody>
</table>

Observations: 3064

Fixed effects regression on balanced two-period panel; weighted and standard errors clustered according to the sampling frame. Standard errors in parentheses.

BP = blood pressure; HT = hypertension; 12m = 12 months; T = time dummy; D = insurance intervention area; † p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 5 shows the estimation results corresponding to equation 4. Just as with the results of equation 2 in table 3, but even more pronounced, we see a significant positive effect of a bad test result on self-reported hypertension (17 pp increase) and health care provider consultations for hypertension (12 pp increase). Also similarly to table 3, there is no effect of a good or bad test result on other outcomes. The insignificant parameter estimates of “Good BP × D × T” (\(\tilde{\eta}_{kg}\)) and “High BP × D × T” (\(\tilde{\eta}_{kb}\)), as well as the insignificant
Wald test of $\tilde{\eta}_{kg} = \tilde{\eta}_{kb}$, for all outcomes, again give no evidence that the test biases the KNCU Health Plan impact estimates. Possibly this is because the KNCU Health Plan is offered at the household level only, thus effectively limiting adverse selection.\textsuperscript{22}

6. Conclusion

This paper is the first to rigorously analyze the effects of blood pressure measurements in a household survey setting on hypertension awareness, consultations for hypertension, and take-up of voluntary health insurance take-up. The test intervention was laid over a health insurance intervention, which allowed to assess whether potential behavioral change due to increased awareness of one’s hypertension status biased health insurance impact estimates.

It was found that a bad test result significantly increased hypertension awareness, as well as health provider consultations for hypertension. However, no test effect was found on health insurance enrollment. Moreover, there was no evidence that blood pressure measurements biased health insurance impact estimates.

References


\textsuperscript{22}Running regressions (4) and (5) of table 5 at a household level, analogously to footnote \textsuperscript{21}, gives results similar to those of table 5.


J Davis, AJ Pickering, K Rogers, S Mamuya, and AB Boehm. The effects of informational interventions on household water management, hygiene behaviors, stored drinking water quality, and hand contamination in peri-urban


StataCorp. Stata statistical software: Release 11. College Station, TX: StataCorp LP, 2009.


Appendix A  Sampling

In November 2012 to January 2013 a census was conducted of all households belonging to active KNCU members of the insurance intervention and control areas in districts Hai, Moshi Rural, and Rombo of the Kilimanjaro region. A random sample of 1,500 households was then selected from the census, stratified by geographic area and insurance intervention.\textsuperscript{23} Namely 500 households were drawn from the Rombo district and 1,000 from the Hai and Moshi Rural districts (the study population in Moshi Rural district is near the border with Hai district), such that half of the sample in each of these areas was drawn from the insurance intervention area, and the other half from the insurance control area. Because of logistical reasons an additional stratification was made at the smallest administrative unit, the sub-village, such that from each sub-village, in each stratum, approximately the same number of households was randomly drawn. Thus, sampling probability weights are necessary in the analyses.

\textsuperscript{23}The census was furthermore used by the KNCU Health Plan administrator as administrative base for the insurance.