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ABSTRACT

Patients rely on medical care providers to act in their best interests because providers understand disease pathology and appropriate treatment much better than patients. Providers, however, not only give advice (diagnose) but also deliver (sell) treatments based on that advice. This creates a moral hazard dilemma where provider financial interests can diverge from patient interests, especially when providers are motivated more by profits than by altruism. We investigate how profit motivated versus altruistic preferences influence medical care decision making in the context of malaria in Kenya. We measured the appropriateness of care using data from an audit study that employed standardized patients (SP) who were trained to present as real patients the identical clinical case scenario to providers. The SPs were confirmed to be malaria negative before and after field work with a very reliable and sensitive blood test at a high-quality laboratory. We measured provider preferences using a lab in the field, real stakes, modified version of the dictator game. We find that more profit-motivated providers report higher rates of false-positive malaria test results than do more altruistic providers. Specifically, purely profit motivated providers report 30 percentage points more positives than providers who are altruistically motivated, and providers likely knew that the positive results that they reported to their patients were false. We also find that more profit motivated providers sold more unnecessary antimalarial drugs than did more altruistic providers. Based on mediation analysis, more profit-oriented providers sold more drugs not only because they knowingly reported more false positives, but also because they promoted drugs sales more conditional on a positive test result. Thus, profit motivated providers seem to have misrepresented test results to sell more unnecessary malaria-related drugs.

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1. Introduction

In his seminal paper, Arrow (1963) recognized that asymmetric information in health care creates a moral hazard dilemma in which provider interests can diverge from patient interests. Patients depend on the judgement of more knowledge medical care professionals to diagnose their medical conditions and to recommend appropriate treatments. Providers, however, not only give advice but also deliver (sell) diagnostic tests and treatments based on that advice. Thus, diagnosticians have a financial incentive to recommend procedures that are profitable regardless of their medical necessity. These "credence" good conditions create an opportunity for providers to exploit patients' trust and recommend more services than patients would otherwise demand under full information.[1] For example, providers often sell profitable but medically unnecessary antibiotics[2] and antimalarial drugs,[3] and conduct more imaging exams than are medically necessary (Afendulis and Kessler 2007; Baker 2010). Provider altruism, however, could protect against these types of these self-dealing abuses as altruistic providers are more likely to make accurate diagnoses and provide more appropriate treatments that are in their patients' best interests (Jack 2005).

We investigate how provider profit-motivated versus altruistic preferences influence medical care decision making. We test whether profit-motivated preferences distort clinical care with data from an audit study that employs standardized patients (SP) to measure the appropriateness of the care delivered using the same clinical case scenario.[4] We trained individuals (SPs) to present an identical standardized illness case scenario as real walk-in clients to providers. By using trained SPs portraying the same illness case to generate the care data, we

[1] Credence goods are products or services where the quality characteristics are not easily observable so that consumers often rely on experts who sell the products or services for advice on what to purchase. Health services are a credence good where providers both give expert diagnostic advice to less knowledgeable patients and then sell them treatment based on that advice. Examples of other credence goods include car and appliance sales, repair services, financial services, and insurance. See for example Wolinsky 1993; Taylor 1995; Chevalier and Ellison 1997; Hubbard 1998; 2002; Dulleck and Kerschbamer 2006; Levitt and Syverson 2008; Chen, Gertler, and Yang 2016; Kerschbamer, Sutter, and Dulleck 2017; Balafoutas and Kerschbamer 2020.

[2] For antibiotic overuse see: Iizuka 2007; Currie, Lin, and Zhang 2011; Currie, Lin, and Meng 2014; Chen, Gertler, and Yang 2016; Fleming-Dutra et al. 2016; Satyanarayana et al. 2016; Daniels et al. 2019; Sulis et al. 2020; J. King et al. 2022.

[3] For antimalarial overuse see; Ansah et al. 2010; J. Cohen, Dupas, and Schaner 2015; J. L. Cohen et al. 2013; O'Meara et al. 2016; J. King et al. 2022.

[4] SPs have been used to measure quality of care extensively. For example see: Peabody et al. 2000; J. Das et al. 2012; Mohanan et al. 2015; J. Das et al. 2016; Kwan et al. 2018; 2019; V. Das et al. 2021; Kwan et al. 2022; Boone et al. 2023; Wagner et al. 2024.

avoid bias from selection on patient illness type and severity that is inherent in care data collected using other common methods such as patient exit interviews, direct clinical observation, or health records (Peabody et al. 2000). We measure provider preferences using a lab in the field real-stakes modified version of the dictator game (Andreoni and Miller 2002; Jakiela 2013; Fisman, Jakiela, and Kariv 2017).

We investigate these issues in the context of malaria in Kenya. Malaria is a well understood illness with clear diagnostic and effective treatment protocol and has a high disease burden. Nearly all deaths and serious illness are preventable through effective and inexpensive medication (World Health Organization 2022). We developed an acute malaria SP case scenario for which local and international clinical practice guidelines recommend that the patient should be given a malaria test and then a frontline anti-malarial drug if the patient tests positive (Kenya Ministry of Public Health and Sanitation 2014).

We then examine whether there is a higher rate of (false) positives and antimalarial drug sales when providers are more profit driven and less altruistic. Any positive test results are ***false positives*** because the SPs were confirmed to be malaria negative immediately before and again after fieldwork using a very reliable and sensitive blood test at a high-quality laboratory. We include SP fixed effects in the empirical models to control for any additional unobserved SP heterogeneity that may be correlated with care decisions, and a rich set of provider background, training, experience, and medical knowledge characteristics to control for provider heterogeneity that also may be correlated with both altruism and medical decisions.

Our data come from a sample of private for-profit primary health care clinics in Kenya, a common organizational form.[5] Malaria is a serious public health concern with over 70% of the population is at risk of infection, and malaria elimination is a priority policy both in Kenya and internationally. Highly specific and sensitive (i.e. low false positive and negative rates) malaria test diagnostics and treatment with effective front-line medication are widely available and affordable (World Health Organization 2015; Feachem et al. 2019). Low-cost diagnostics allow ready screening at the first sign of disease, leading to early detection and treatment for infected individuals (Wu and Zaman 2012; Hillemann et al. 2011).

[5] Over 40% of the 12,000+ primary care facilities in Kenya are for-profit private clinics and 52% of malarial cases are treated there (Ministry of Health, Kenya Master Health Facility List at http://kmhfl.health.go.ke).

We find that more profit-motivated providers report significantly higher rates of positive malaria test results; specifically, purely profit motivated providers report 30 percentage points (pp) more positive test results than providers who completely altruistically motivated. Based on clinical practice guidelines, a positive test result should lead to a recommendation to purchase antimalarial drugs sold by the clinic, which are unnecessary for truly negative individuals. We indeed find that more profit motivated providers unnecessarily sell significantly more antimalarial drugs.[6] Using mediation analysis, we find that the more profit-oriented providers sell more antimalarials not only because they report more false positives, but also because they promote drug sales more conditional on a positive test result.

It is likely that the providers knew that the positive test results that they reported to their patients were in fact negative but chose to falsely tell the patient that the test result was positive anyway. The tests used universally in Kenya are highly reliable and specific (i.e., low false positive rate) as well as easy to administer (Ochola et al 2006, Roth et al 2016). The overall false positive rate in our sample is 35 pp, which is well above the false positive rates of 2.2 to 13 pp found in clinical studies (Lee et al 2014). Thus, more profit motivated providers seem to have chosen to misrepresent test results to sell more unnecessary malaria-related drugs.

This paper adds to our understanding of medical decision making and the extent it results in suboptimal quality of care. A large body of evidence demonstrates low levels of quality of care, even when it is defined as meeting the minimum standard of correct care based in clinical practice guidelines (Barber, Bertozzi, and Gertler 2007; J. Das, Hammer, and Leonard 2008; Currie, Lin, and Zhang 2011; J. Das et al. 2012; Sylvia et al. 2015; Mohanan et al. 2015; Daniels et al. 2017; Kwan et al. 2018; J. Das et al. 2018; Di Giorgio et al. 2020; V. Das et al. 2021; J. King et al. 2022; Wagner et al. 2024). Stricter definitions of quality in the literature can capture the more complex nature of actual care provision. For example, providers may provide correct care to a patient based on their symptoms, but may also prescribe harmful or unnecessary antibiotics in the same patient visit (Kwan et al. 2019; J. J. King et al. 2019; Kwan et al. 2022). Providers may also offer additional unnecessary tests and treatments (Kwan et al. 2018; Satyanarayana et al. 2016; Daniels 2020). Most studies explain these variations through provider absenteeism, low provider training and knowledge, and low drug stock levels; however, substandard levels of care exist even in settings with high provider knowledge and sufficient

[6] We know that the drugs are not needed because they are sold to patients who have false positive test results.

stock (Boone et al. 2023; Wagner et al. 2024). Few studies explicitly examine profit motivation (lack of altruism) as an explanation for low quality of care.

Our work is also related to a literature of health care in the US. A number of studies appeal to provider altruism to explain charity care (Arrow 1963; Nyman 1999; Herring 2005) and non-profit organizations' deviation from profit maximization (See Sloan 2000 for a review). While there is substantial literature trying to measure altruism in health care,[7] there are few studies that analyze the direct influence of altruism and even fewer in LMICs. A notable exception is Li, Dow, and Kariv (2017) who examine the influence of provider altruism on resident specialty choice.

Our findings more generally contribute to the understanding of the role of altruism in economic behavior. Much of the earlier empirical work has focused on measuring altruism (Andreoni and Miller 2002; Jakiela 2013; Fisman, Jakiela, and Kariv 2017), fairness and inequity aversion (Fehr and Schmidt 2010), and social-image concerns (Andreoni and Bernheim 2009). Empirical studies that link real behavior to direct measures of altruism and pro-social preferences are related to performance on pro-social jobs and tasks (Deserranno 2019; Ashraf, Bandiera, and Jack 2014; Barr and Zeitlin 2010), selection of more prosocial jobs or volunteering (Lagarde and Blaauw 2014; Carpenter and Myers 2010), charitable giving (Benz and Meier 2008), return of misdirected letters (Franzen and Pointner 2013), and targeting by politicians for vote-buying (Finan and Schechter 2012).

2. Data

The sample frame consisted of the 3,002 private for-profit health clinics across Kenya that were not faith-based or part of an existing franchise network. We randomly sampled 232 distributed across 34 of Kenya's 47 counties, of which 157 agreed to participate in the study. Data were collected in May 2019 from 289 SP encounters, with 178 clinicians across the 157 clinics. There was a maximum of 2 SP visits to a clinic.

We also administered a provider survey to the 178 providers who participated in the SP encounters. Providers were invited to participate in a dictator game to assess their altruism. The

[7] For a review of the measure of altruism in health care literature see Galizzi et al. (2023).

survey also collected information on clinical knowledge, training, experience, and other background characteristics.[8]

a. Standardized Patient Case Encounters

During encounters with providers, SPs portrayed real patients presenting a standardized, pre-scripted acute adult malaria case. The SPs were confirmed to be malaria-negative based on malaria microscopy tests administered by a reliable, high-quality laboratory immediately before and after the month-long field work period. Field work supervisors also monitored SPs for any potential illness symptoms throughout field work; all were otherwise healthy.

We developed the malaria SP case scenario based on King et al. (2022) using adaptations from several other SP studies (J. Das et al. 2012; Daniels et al. 2017; J. J. King et al. 2021; Kwan et al. 2018; 2019; Sylvia et al. 2015; J. King et al. 2022). We also convened a Technical Advisory Group (TAG) consisting of four Kenyan clinicians with expertise in malaria and case presentation in primary care. Our TAG advised on case development, local guidelines, and outcome measures, as well as participated in SP training. The malaria case was extensively pilot tests in a population like our study's population.

The SPs participated in developing the standardized narrative (e.g., name, age, family situation, living situation, etc.) for the acute malaria case scenario and were trained to provide standardized responses to history and other questions if asked by the provider. The case and field work protocol were piloted by the SPs over a two-week period. The pilot was designed to mirror the plan for SP field work as closely as possible in settings like the clinic sample. The pilot objectives were to test: (1) the case flow and answers prepared for provider questions, (2) data flow, and (3) that providers treat the SPs as they would real patients and did not detect them as actors.

The SP case scenario was a 28-year-old female or male who had recently traveled to a malaria endemic area. She or he presents with fever, headache, and thinks s/he has malaria.

[8] Of the 289 SP encounters, we were able to interview the precise provider of 265 (92%) at the same clinic of the encounters. For the remaining 24 (8%) of SP encounters, we utilized an alternative provider from the same clinic who reported seeing similar patients and included an indicator that the observation was a proxy in the analysis. We repeated all analyses with the matched sample of 265 encounters without proxies. The results, reported in Appendix B Tables B2 through B5, are very close to the results with the full sample.

During each visit, the SP begins with, "Doctor, I think I have malaria." The SP then responds to the providers' questions in a standardized way.[9]

To ensure accurate and comprehensive recall, SPs completed an exit questionnaire administered by a fieldwork supervisor within 3 hours after each visit. The questionnaire collected information regarding the visit, including lab tests ordered and results, and medicines dispensed (sold). For each visit, SPs and their field supervisors attempted to identify all providers seen by the SPs. The list of providers formed the provider survey sampling frame.

b. SP Recruitment and Training

Because the SPs would visit clinics across Kenya, recruitment focused on obtaining a mix of females and males who not only represented the appropriate age for the malaria SP case but also could speak the range of languages in areas of the clinic sample. The most promising SP recruits did not report any potentially undesirable characteristics for this type of fieldwork: (i) discomfort with deception (i.e., pretending to be ill), (ii) fear of being in a health facility, (iii) had previous work history or had close relatives working in medical care, and (iv) was judgmental of medical care providers.

The 3-week SP training was modified from Kwan et al. (2019). Week 1 focused on learning the SP case, adapting the case to different regions across Kenya, and dress code. Week 2 included mock interviews (play scenarios in the classroom between providers and patients), improvisation techniques, risk mitigation strategies, and the post encounter questionnaires. Week 3 included more complex mock interviews and dry runs at health clinics.

Over the course of the three weeks, we implemented a selection process where we invited back the strongest SPs who demonstrated qualities that would be fitting for fieldwork. At the end of training, the most promising candidates were then recruited to conduct the two-week pilot. Based on their performance in the pilot, the best 29 individuals (15 females and 14 males) were hired as SPs for the field work.

2. Measurement

a. Care Outcomes

[9] **Appendix A** contains the detailed SP scenario narrative including scripted responses to likely questions..

We use the data from the SP encounters to construct clinical outcome measures. We based those measures on the 2010 Kenya national clinical guidelines for the diagnosis and treatment of Malaria (Kenya Ministry of Public Health and Sanitation 2010; Kenya President's Malaria Initiative 2018). The guidelines recommend obtaining a confirmatory diagnosis with a parasitological test, either malaria rapid diagnostic test (mRDT) or malaria microscopy, followed by first-line treatment with artemether-lumefantrine (AL).

Our main outcomes, then, are: (i) whether any laboratory malaria test (either mRDT or microscopy) was administered, (ii) whether the patient was **told** the test result was positive for malaria -- a positive test result is a false positive because all SPs were confirmed negative for malaria at the beginning and end of field work, (iii) whether the anti-malarial drug AL was prescribed and sold to the patient, (iv) whether paracetamol for fever was sold, and (v) whether any non-efficacious medicines sold.

b. Provider Altruism

To elicit altruistic preferences, we implemented a real-stakes, modified dictator game (Fisman, Jakiela, and Kariv 2017; Jakiela 2013; Li, Dow, and Kariv 2017). The provider was given a sum of money (endowment) and asked how much he or she would like to give to a patient (client). The client is then given that amount in mobile money, and the provider gets to keep the remaining amount.

The game is run with 4 different patients. The first is a real client randomly selected from the provider's waiting room, who is seeking child health, family planning, or adult health services, and is meant to anchor the game with a specific person. The other 3 are hypothetical clients designed to cover the range of patients who use primary health clinics: (i) a client with a child who is sick with watery diarrhea, (ii) an adult who thinks he has malaria, and (iii) a female who comes in for family planning services.

The game is played several times with each patient varying the multiplier of the amount awarded to the patient. For example, if the multiplier is 3x, then the patient receives 3 times the amount that the provider gives the client. For the real patient the multiplier is varied 5 times: 1x, 2x, 3x, 4x, and 5x. For each of the other patients, there are 3 multipliers: 1x, 3x and 5x. Hence, the game is played a total of 14 times.

One concern is that the amount the provider gives the patient may not necessarily represent true altruistic preferences. The provider may be concerned that the data collector will think they are greedy if they give what they really want, and therefore less altruistic providers tend to give more. We tried to mitigate this concern by having the enumerators turn over the electronic tablets used to collect the responses in the game to the provider to be able to enter their responses in private, and payouts were received over the phone at the end of the interview.

Our primary measure of altruism is each provider's average share of the endowment given to the client or "client budget share" (CBS) over the 14 observations. CBS ranges from zero (i.e., the provider allocated an average of 0% of the endowment to the client and thus decided to keep 100% for self) to one (i.e., the provider allocated an average of 100% to the client and kept 0% for self). We consider the game "real stakes" because the provider is told at the beginning that one of the decisions will be randomly selected to be paid out at the end with mobile money to both provider and the real patient.

An alternative measure of altruism is derived from the structural estimation of each provider's utility function (Fisman, Jakiela, and Kariv 2017; Jakiela 2013; and Li, Dow, and Kariv 2017). Several studies have used the following constant elasticity of substitution (CES) utility function given by:

$$u_s = [\alpha(\pi_s)^\rho + (1 - \alpha)(\pi_o)^\rho]^{\frac{1}{\rho}} \quad , \qquad (1)$$

where π_s is the amount of the endowment kept by the provider; π_o is the amount given the patient; $0 \leq \alpha \leq 1$ is the weight of the payoff to self; and $\rho \leq 1$ is the willingness to trade off payments to self and other in response to price changes. We call individuals $\alpha = 1$ ($\alpha = 0$) perfectly selfish or perfectly or profit-motivated (perfectly altruistic), as they put all weight on the payoff to self (other). [10]

Our preferred measure is CBS for several reasons. First, both CBS and α are estimated using CBS as data. There is no extra or different information being used to estimate α. The difference is that CBS is a simple mean while α comes from a nonlinear least squares procedure involving 2 parameters instead of 1. Measurement error is introduced if the CES functional form

[10] We follow the methods laid out in Li, Dow, and Kariv (2017) to estimate the parameters of the CES utility function.

assumption is incorrect. In addition, α is likely less precisely estimated than CBS because we need to estimate 2 CES parameters to obtain α, as opposed to 1 for CBS with only 14 observations. While α is derived from a more theoretically sound basis, CBS is based on the same underlying information and is likely to have less measurement error due to its relative simplicity.

c. Provider Knowledge and Background Characteristics

To capture provider knowledge, the provider survey respondents completed a vignette module that presented the same malaria case the SPs presented during their encounters. Providers were then asked a series of questions about what they would do during a visit to diagnose and treat the case. We then constructed provider knowledge measures of whether the provider would follow the Kenyan clinical practice guidelines for the diagnosis and treatment of acute malaria (Kenya Ministry of Public Health and Sanitation 2010; Kenya President's Malaria Initiative 2018).

We also collected additional characteristics that represented provider experience and ability, and that could possibly be correlated with both altruism and clinical care decisions. These included provider age and gender, training qualification (e.g., medical doctor, clinical officer, nurse, midwife, lab technologist), whether the provider was temporary staff as opposed to permanent clinical staff at the clinic, years of experience in medical care practice, years of experience at the clinic, and frequency in which the provider sees an acute malaria like the one presented in the vignette module.

3. Identification and Estimation

We estimate the following model specification with robust clustered standard errors at the clinic levels:

$$Y_{ijk} = \beta_0 + \beta_1 * (1 - CBS_j) + \beta_2 * Provider_j + SP_j + \varepsilon_{ijk} \quad , \qquad (2)$$

Where:

Y_{ijk} = Care outcome of encounter i by SP j with provider k

CBS_j = Average Client Budget Share from the dictator game for provider j

$Provider_j$ = Provider j characteristics

ε_{ijk} = error term

In the analysis, in place of altruism we use "Profit Motivation" measured as (1 – CBS), i.e., the share the provider keeps in the dictator game, as opposed to the share the provider chooses to give to the client. We consider both a continuous version of (1 – CBS) and an indicator of whether the provider is among the "Most Profit Motivated" indicated by being in the top quartile of the (1 – CBS) distribution (i.e., CBS is in bottom quartile). The continuous version requires a cardinal interpretation of CBS as linear in altruism, whereas the Most Profit Motivated indicator is based on fewer assumptions and simply asks whether the provider is in the lower tail of the altruism distribution. We also estimate a version using α instead of (1 – CBS) to assess robustness to functional form.

There are two main threats to identifying the causal relationship between care outcomes and provider profit motivation (altruism): (i) patient selection and (ii) provider heterogeneity. In the first case, patients with characteristics that are correlated with better care outcomes, such as severity of illness or a demanding personality, could select providers with different levels of altruism. The use of SPs presenting a standardized case to providers to generate the data controls for selection based on illness type, and the inclusion of SP fixed effects controls for selection based on SP actor personality and any other unobservable characteristics.

In the second case, bias would be introduced if, for example, more altruistic providers were also more skilled in the management of malaria. To control for provider heterogeneity correlated with altruism and care outcomes, we include a set of provider and clinic characteristics. The potential set of controls are described in section 3c above. Rather than just include all the possible control variables, we utilized double-selection lasso linear regression to identify the most appropriate controls (Belloni, Chernozhukov, and Hansen 2014).

4. Results

a. Descriptive Analysis

Table 1 reports descriptive statistics. Among the 289 encounters, SPs saw female providers in over a third of the visits and were attended mainly by clinical officers (40%) and nurses or midwives (46%). Providers were by and large experienced with an average of 17.7 years working as a health care provider and were largely permanent staff at the clinic (86%). Providers

were experienced with malaria as 78% of providers report seeing cases of acute malaria at least monthly.

There is a substantial "know-do gap", a well-documented phenomenon referring to the difference between provider knowledge and provider actions in practice (J. Das et al. 2015; Mohanan et al. 2015). When presented with an acute adult malaria case in a medical vignette, 98% of the providers correctly reported that they would manage the case by ordering a malaria test. Provider practice differed from knowledge as only 81% of the SP encounters resulted in any clinically appropriate laboratory test for malaria. Of those who received a test, 30% of providers told the SP they (falsely) tested positive for malaria.

The (1 – CBS) profit motivation measure ranged from 100% (perfectly "profit-oriented") to 6% (most "altruistic"), with a mean of 51%. The most profit-oriented quartile of providers had a mean (1 – CBS) of 79% and the most altruistic quartile had a mean (1 – CBS) of 25%. The histogram of the distribution of (1 – CBS), profit motivation, is presented in Figure 1.

To visualize how provider knowledge and care outcomes vary across the range of provider profit motivation (1 - CBS), we estimated local polynomial smoothed bivariate regressions of the outcomes against (1 – CBS), overlayed on top of the (1 – CBS) histogram in Figure 1. Knowledge and the probability of ordering a malaria test were both constant across provider profit motivation (1 – CBS), implying a constant know-do gap over the distribution of (1 – CBS). However, the false positive test rate increases with (1 – CBS), i.e., false positives rise with stronger provider profit-motivated preferences. More profit motivated (above median) providers return false positive results in 26.0% of the time; while the less profit motivated (below median), providers returned false positive results 22.4% of the time. The false positive analyses are unconditional, i.e., for the whole sample regardless of whether a test was conducted or not.

b. Effect of Altruism on Care Outcomes

Table 2 reports the estimation results for the probability of ordering a malaria test. The analysis whether the test result was reported to be positive uses the whole sample, regardless of whether a test was conducted. Provider profit motivation, regardless of how it is measured (i.e., (1 – CBS), whether CBS is in the bottom quartile, or α) has no statistically significant impact on ordering a malaria test. Moreover, the estimated effect sizes are small relative to the mean of 81.3%.

Profit motivation, however, has a large and statistically significant effect on whether the provider reports a (false) positive test result regardless how profit motivation is measured (Table 3). The estimated effect sizes are meaningful and consistent with expectations. Unconditional on a malaria test ordered (panel A), purely profit motivated providers report 29.3 pp more false positives than do purely altruistic providers (column 1), and 14.9 pp more at average levels of Profit Motivation (51%). We also examine the extent to which linearity of our altruism measure drives the estimates using an indicator for whether the provider is in the top quartile of the profit motivation (1 – CBS) distribution. Providers who are in the top quartile report 12.5 pp more false positives than do more altruistic providers (column 2). Finally, the results are also robust to using α (column 3) in place of (1 – CBS). In this case, purely profit motivated providers report 22.3 pp more false positives than do providers who are only motivated by altruism.

Panel B in Table 3 reports the results for the sample conditional on having a malaria test. Since provider profit motivation is orthogonal to the probability of having a test, these results do not suffer from selection bias. Purely profit motivated providers report 33.9 pp more false positives than do purely altruistic providers (column 4), and providers who are in the most profit motivated quartile report 16.4 pp more false positives than do more altruistic providers (column 5). Finally, the conditioned results are also robust to using α (column 6) in place of (1 – CBS). In this case, purely profit motivated providers report 23.4 pp more false positives than do providers who are only motivated by altruism.

Profit motivation also has a large and statistically significant effect on sales of the antimalarial drug Artemether Lumefantrine (Table 4, Panel A). The estimated effect sizes are meaningful and consistent with the effect of profit motivation on false positives in Table 3. Purely profit motivated providers sell 23.7 pp more than do purely altruistic providers (column 1), and 14.9 pp more at average levels of Profit Motivation (51%). We find that 25% most profit motivated providers sell significantly more (14.7 pp) of the front-line antimalarial drug AL than do more altruistic providers (column 2). However, more profit motivated providers do not sell any more paracetamol for fever or more of any other (non-efficacious) drugs (panels B and C).

c. Mediation Analysis

There are a couple of possible mechanisms for altruism to affect anti-malarial drug sales. First, more profit motivated providers report a higher false positive rate, leading to higher antimalarial

drug sales to treat the malaria (indirect effect). Conditional on a false positive, more profit motivated providers might also try to sell these drugs at a higher rate than more altruistic providers (direct effect). We assess these potential mechanisms through a mediation analysis that tries to decompose the treatment effects into these direct and indirect pathways (Huber 2020). This analysis is not causal, but rather a descriptive decomposition of the total casual effect into direct and indirect mechanisms.

The full mediation model is:

$$AL_{ijk} = \beta_0 + \beta_1 * (1 - CBS_j) + \beta_2 * Provider_j + SP_j + \varepsilon_{ijk} \quad (3)$$

$$AL_{ijk} = \gamma_0 + \gamma_1 * Positive_i + \gamma_2 * (1 - CBS_j) + \gamma_3 * Provider_j + SP_j + \varepsilon_{ijk} \quad (4)$$

$$Positive_{ijk} = \theta_0 + \theta_1 * (1 - CBS_j) + \theta_2 * Provider_j + SP_j + \varepsilon_{ijk} \quad , \quad (5)$$

where AL_{ijk} is whether the SP was sold the antimalarial drug AL during encounter *i,* and $Positive_{ijk}$ is whether the SP was told to have tested positive for malaria during encounter *i*. The total effect of profit motivation is β_1, the share of the total effect explained by the direct effect of profit motivation is γ_2/β_1, and the indirect effect is $(\gamma_1 * \theta_1)/\beta_1$.

Table 5 presents the results of the mediation analysis using the sample of encounters that were tested for malaria, i.e., conditional on having a malaria test. The estimated total effect, β_1 from equation 3, of Profit Motivation is 0.277 and 0.203 for the Most Profit Motivated, reported in columns (1) and (2), respectively. We estimate the direct and indirect effects using estimates of γ_1, γ_2, and θ_1 from columns (3) and (5) for the continuous (1 – CBS) measure of Profit Motivation, and from (4) and (6) for the indicator for the Most Profit Motivated. We find that about one-third the share of total effect is explained by the direct effect of profit motivation, while 53% is explained by the indirect effect through the influence of profit motivation and reporting a false positive. Using the binary indicator of the 25% Most Profit Motivated, the direct effect explains 60% of the total effect and the indirect effect explains 30%. These results suggest that provider altruistic preferences influence drug sales even conditional on a positive test result.

5. Conclusion

We investigated how provider profit-driven versus altruistic preferences influence medical care decision making using data from an audit study. This study employs standardized

patients (SP) to measure the appropriateness of the care delivered by medical care providers using the same clinical case scenario. SPs presented an identical standardized illness case scenario as real walk-in clients to providers. We measured provider preferences using a real-stakes modified version of the dictator game. We then examined whether there is a higher rate of false positives and antimalarial drug sales when providers are more profit-driven and less altruistic. We investigated these issues in the context of acute malaria, which is a well understood illness with clear diagnostic and effective treatment protocol, has a high disease burden, and nearly all deaths and serious illness are preventable through effective and inexpensive medication.

We find that more profit-oriented providers report higher rates of false positive malaria tests. We also find that more profit-oriented providers sell more drugs than the more altruistic providers, not only because they report more false positives, but also because they promote drugs sales more even conditional on a positive test result.

We know that these positive test results are *false positives* because we confirmed that our SPs were malaria negative before and again after less than the monthlong duration of fieldwork using a very reliable and sensitive blood test at a high-quality laboratory. Moreover, providers likely knew that the positive results that they reported to their patients were false. The tests used universally in Kenya are highly reliable and specific as well as easy to administer. In many cases, the test result was likely negative, but the provider chose to falsely tell the patient that the test result was positive. Thus, more profit motivated providers chose to misrepresent test results to sell more antimalarial drugs that were ultimately unnecessary.

These results suggest that more profit-motivated providers are willing to falsify laboratory test results to make higher profits. Profit motivation seems to interfere with providers acting in the best interests of their patients. Since providers understand disease pathology and appropriate treatment much better than do patients, diagnosticians have a financial incentive to recommend procedures that are profitable regardless of their appropriateness. We show that these financial incentives result in poor quality and costly care when providers are profit motivated as opposed to altruistic. Hence, provider altruism plays a critical role in insuring efficacious and cost-effective medical care.

References

Afendulis, Christopher C, and Daniel P Kessler. 2007. "Tradeoffs from Integrating Diagnosis and Treatment in Markets for Health Care." *American Economic Review* 97 (3): 1013–20.

Andreoni, James, and B Douglas Bernheim. 2009. "Social Image and the 50–50 Norm: A Theoretical and Experimental Analysis of Audience Effects." *Econometrica* 77 (5): 1607–36.

Andreoni, James, and John Miller. 2002. "Giving According to GARP: An Experimental Test of the Consistency of Preferences for Altruism." *Econometrica* 70 (2): 737–53.

Ansah, Evelyn K, Solomon Narh-Bana, Michael Epokor, Samson Akanpigbiam, Alberta Amu Quartey, John Gyapong, and Christopher JM Whitty. 2010. "Rapid Testing for Malaria in Settings Where Microscopy Is Available and Peripheral Clinics Where Only Presumptive Treatment Is Available: A Randomised Controlled Trial in Ghana." *Bmj* 340.

Arrow, Kenneth J. 1963. "Uncertainty and the Welfare Economics of Medical Care." *The American Economic Review* 53 (5): 941–73.

Ashraf, Nava, Oriana Bandiera, and B Kelsey Jack. 2014. "No Margin, No Mission? A Field Experiment on Incentives for Public Service Delivery." *Journal of Public Economics* 120: 1–17.

Baker, Laurence C. 2010. "Acquisition of MRI Equipment by Doctors Drives up Imaging Use and Spending." *Health Affairs* 29 (12): 2252–59.

Balafoutas, Loukas, and Rudolf Kerschbamer. 2020. "Credence Goods in the Literature: What the Past Fifteen Years Have Taught Us about Fraud, Incentives, and the Role of Institutions." *Journal of Behavioral and Experimental Finance* 26: 100285.

Barber, Sarah L, Stefano M Bertozzi, and Paul J Gertler. 2007. "Variations In Prenatal Care Quality For The Rural Poor In Mexico: Indigenous Women Received Fewer Procedures than Other Women in Private Health Facilities; Disparities Were Much Less Prominent in Public Facilities." *Health Affairs* 26 (Suppl2): w310–23.

Barr, Abigail, and Andrew Zeitlin. 2010. "Dictator Games in the Lab and in Nature: External Validity Tested and Investigated in Ugandan Primary Schools."

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2014. "Inference on Treatment Effects after Selection among High-Dimensional Controls." *Review of Economic Studies* 81 (2): 608–50.

Benz, Matthias, and Stephan Meier. 2008. "Do People Behave in Experiments as in the Field?—Evidence from Donations." *Experimental Economics* 11: 268–81.

Boone, Claire E, Paul J Gertler, Grace Makana Barasa, Joshua Gruber, and Ada Kwan. 2023. "Can a Private Sector Engagement Intervention That Prioritizes Pro-Poor Strategies Improve Healthcare Access and Quality? A Randomized Field Experiment in Kenya." *Health Policy and Planning* 38 (9): 1006–16.

Carpenter, Jeffrey, and Caitlin Knowles Myers. 2010. "Why Volunteer? Evidence on the Role of Altruism, Image, and Incentives." *Journal of Public Economics* 94 (11–12): 911–20.

Chen, Brian K., Paul J. Gertler, and Chun-Yuh Yang. 2016. "Physician Ownership of Complementary Medical Services." *Journal of Public Economics* 144 (December): 27–39. https://doi.org/10.1016/j.jpubeco.2016.09.005.

Chevalier, Judith, and Glenn Ellison. 1997. "Risk Taking by Mutual Funds as a Response to Incentives." *Journal of Political Economy* 105 (6): 1167–1200.

Cohen, Jessica, Pascaline Dupas, and Simone Schaner. 2015. "Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial." *American Economic Review* 105 (2): 609–45.

Cohen, Jessica L, Prashant Yadav, Corrina Moucheraud, Sarah Alphs, Peter S Larson, Jean Arkedis, Julius Massaga, and Oliver Sabot. 2013. "Do Price Subsidies on Artemisinin Combination Therapy for Malaria Increase Household Use?: Evidence from a Repeated Cross-Sectional Study in Remote Regions of Tanzania." *PloS One* 8 (7): e70713.

Currie, Janet, Wanchuan Lin, and Juanjuan Meng. 2014. "Addressing Antibiotic Abuse in China: An Experimental Audit Study." *Journal of Development Economics* 110: 39–51.

Currie, Janet, Wanchuan Lin, and Wei Zhang. 2011. "Patient Knowledge and Antibiotic Abuse: Evidence from an Audit Study in China." *Journal of Health Economics* 30 (5): 933–49.

Daniels, Benjamin. 2020. "Primary Care Providers Are, Fundamentally, Risk Managers–And This Is a Challenge for Health Policy." *The Lancet Regional Health–Western Pacific* 3.

Daniels, Benjamin, Amy Dolinger, Guadalupe Bedoya, Khama Rogo, Ana Goicoechea, Jorge Coarasa, Francis Wafula, Njeri Mwaura, Redemptar Kimeu, and Jishnu Das. 2017. "Use of Standardised Patients to Assess Quality of Healthcare in Nairobi, Kenya: A Pilot, Cross-Sectional Study with International Comparisons." *BMJ Global Health* 2 (2): e000333.

Daniels, Benjamin, Ada Kwan, Madhukar Pai, and Jishnu Das. 2019. "Lessons on the Quality of Tuberculosis Diagnosis from Standardized Patients in China, India, Kenya, and South Africa." *Journal of Clinical Tuberculosis and Other Mycobacterial Diseases* 16: 100109.

Das, Jishnu, Jeffrey Hammer, and Kenneth Leonard. 2008. "The Quality of Medical Advice in Low-Income Countries." *Journal of Economic Perspectives* 22 (2): 93–114.

Das, Jishnu, Alaka Holla, Veena Das, Manoj Mohanan, Diana Tabak, and Brian Chan. 2012. "In Urban and Rural India, a Standardized Patient Study Showed Low Levels of Provider Training and Huge Quality Gaps." *Health Affairs* 31 (12): 2774–84.

Das, Jishnu, Alaka Holla, Aakash Mohpal, and Karthik Muralidharan. 2016. "Quality and Accountability in Health Care Delivery: Audit-Study Evidence from Primary Care in India." *American Economic Review* 106 (12): 3765–99.

Das, Jishnu, Ada Kwan, Benjamin Daniels, Srinath Satyanarayana, Ramnath Subbaraman, Sofi Bergkvist, Ranendra K Das, Veena Das, and Madhukar Pai. 2015. "Use of Standardised Patients to Assess Quality of Tuberculosis Care: A Pilot, Cross-Sectional Study." *The Lancet Infectious Diseases* 15 (11): 1305–13.

Das, Jishnu, Liana Woskie, Ruma Rajbhandari, Kamran Abbasi, and Ashish Jha. 2018. "Rethinking Assumptions about Delivery of Healthcare: Implications for Universal Health Coverage." *BMJ* 361: k1716.

Das, Veena, Benjamin Daniels, Ada Kwan, Vaibhav Saria, Ranendra Das, Madhukar Pai, and Jishnu Das. 2021. "Simulated Patients and Their Reality: An Inquiry into Theory and Method." *Social Science & Medicine*, 114571.

Deserranno, Erika. 2019. "Financial Incentives as Signals: Experimental Evidence from the Recruitment of Village Promoters in Uganda." *American Economic Journal: Applied Economics* 11 (1): 277–317.

Di Giorgio, Laura, David K Evans, Magnus Lindelow, Son Nam Nguyen, Jakob Svensson, Waly Wane, and Anna Welander Tärneberg. 2020. "Analysis of Clinical Knowledge, Absenteeism and Availability of Resources for Maternal and Child Health: A Cross-

Sectional Quality of Care Study in 10 African Countries." *BMJ Global Health* 5 (12): e003377.
Dulleck, Uwe, and Rudolf Kerschbamer. 2006. "On Doctors, Mechanics, and Computer Specialists: The Economics of Credence Goods." *Journal of Economic Literature* 44 (1): 5–42. http://www.jstor.org/stable/30032295.
Feachem, Richard GA, Ingrid Chen, Omar Akbari, Amelia Bertozzi-Villa, Samir Bhatt, Fred Binka, Maciej F Boni, et al. 2019. "Malaria Eradication within a Generation: Ambitious, Achievable, and Necessary." *The Lancet* 394 (10203): 1056–1112.
Fehr, Ernst, and Klaus M Schmidt. 2010. "On Inequity Aversion: A Reply to Binmore and Shaked." *Journal of Economic Behavior & Organization* 73 (1): 101–8.
Finan, Frederico, and Laura Schechter. 2012. "Vote-Buying and Reciprocity." *Econometrica* 80 (2): 863–81.
Fisman, Raymond, Pamela Jakiela, and Shachar Kariv. 2017. "Distributional Preferences and Political Behavior." *Journal of Public Economics* 155: 1–10.
Fleming-Dutra, Katherine E, Adam L Hersh, Daniel J Shapiro, Monina Bartoces, Eva A Enns, Thomas M File, Jonathan A Finkelstein, et al. 2016. "Prevalence of Inappropriate Antibiotic Prescriptions among US Ambulatory Care Visits, 2010-2011." *Jama* 315 (17): 1864–73.
Franzen, Axel, and Sonja Pointner. 2013. "The External Validity of Giving in the Dictator Game: A Field Experiment Using the Misdirected Letter Technique." *Experimental Economics* 16: 155–69.
Galizzi, Matteo, Geir Godager, Jing Li, Ismo Linnosmaa, Timo Tammi, and Daniel Wiesen. 2023. "Economics of Healthcare Provider Altruism."
Herring, Bradley. 2005. "The Effect of the Availability of Charity Care to the Uninsured on the Demand for Private Health Insurance." *Journal of Health Economics* 24 (2): 225–52.
Hillemann, Doris, Sabine Rüsch-Gerdes, Catharina Boehme, and Elvira Richter. 2011. "Rapid Molecular Detection of Extrapulmonary Tuberculosis by the Automated GeneXpert MTB/RIF System." *Journal of Clinical Microbiology* 49 (4): 1202–5.
Hubbard, Thomas N. 1998. "An Empirical Examination of Moral Hazard in the Vehicle Inspection Market." *The RAND Journal of Economics*, 406–26.
———. 2002. "How Do Consumers Motivate Experts? Reputational Incentives in an Auto Repair Market." *The Journal of Law and Economics* 45 (2): 437–68.
Huber, Martin. 2020. "Mediation Analysis." *Handbook of Labor, Human Resources and Population Economics*, 1–38.
Iizuka, Toshiaki. 2007. "Experts' Agency Problems: Evidence from the Prescription Drug Market in Japan." *The Rand Journal of Economics* 38 (3): 844–62.
Jack, William. 2005. "Purchasing Health Care Services from Providers with Unknown Altruism." *Journal of Health Economics* 24 (1): 73–93.
Jakiela, Pamela. 2013. "Equity vs. Efficiency vs. Self-Interest: On the Use of Dictator Games to Measure Distributional Preferences." *Experimental Economics* 16 (2): 208–21.
Kenya Ministry of Public Health and Sanitation. 2010. *National Guidelines for Diagnosis, Treatment and Prevention of Malaria in Kenya*. Kenya Ministry of Health.
———. 2014. "National Guidelines for the Diagnosis, Treatment and Prevention of Malaria in Kenya." Kenya Ministry of Public Health and Sanitation Nairobi Kenya.
Kenya President's Malaria Initiative. 2018. *Kenya Malaria Operational Plan FY 2018*. President's Malaria Initiative.

Kerschbamer, Rudolf, Matthias Sutter, and Uwe Dulleck. 2017. “How Social Preferences Shape Incentives in (Experimental) Markets for Credence Goods.” *The Economic Journal* 127 (600): 393–416.

King, Jessica JC, Jishnu Das, Ada Kwan, Benjamin Daniels, Timothy Powell-Jackson, Christina Makungu, and Catherine Goodman. 2019. “How to Do (or Not to Do)… Using the Standardized Patient Method to Measure Clinical Quality of Care in LMIC Health Facilities.” *Health Policy and Planning* 34 (8): 625–34.

King, Jessica JC, Timothy Powell-Jackson, Christina Makungu, Nicole Spieker, Peter Risha, Abdallah Mkopi, and Catherine Goodman. 2021. “Effect of a Multifaceted Intervention to Improve Clinical Quality of Care through Stepwise Certification (SafeCare) in Health-Care Facilities in Tanzania: A Cluster-Randomised Controlled Trial.” *The Lancet Global Health* 9 (9): e1262–72.

King, Jessica, Timothy Powell-Jackson, James Hargreaves, Christina Makungu, and Catherine Goodman. 2022. “Pushy Patients Or Pushy Providers? Effect Of Patient Knowledge On Antibiotic Prescribing In Tanzania: Study Examines the Effect of Patient Knowledge on Antibiotic Prescribing in Tanzania.” *Health Affairs* 41 (6): 911–20.

Kwan, Ada, Claire E Boone, Giorgia Sulis, and Paul J Gertler. 2022. “Do Private Providers Give Patients What They Demand, Even If It Is Inappropriate? A Randomised Study Using Unannounced Standardised Patients in Kenya.” *BMJ Open* 12 (3): e058746.

Kwan, Ada, Benjamin Daniels, Sofi Bergkvist, Veena Das, Madhukar Pai, and Jishnu Das. 2019. “Use of Standardised Patients for Healthcare Quality Research in Low-and Middle-Income Countries.” *BMJ Global Health* 4 (5): e001669.

Kwan, Ada, Benjamin Daniels, Vaibhav Saria, Srinath Satyanarayana, Ramnath Subbaraman, Andrew McDowell, Sofi Bergkvist, et al. 2018. “Variations in the Quality of Tuberculosis Care in Urban India: A Cross-Sectional, Standardized Patient Study in Two Cities.” *PLoS Medicine* 15 (9): e1002653.

Lagarde, Mylene, and Duane Blaauw. 2014. “Pro-Social Preferences and Self-Selection into Jobs: Evidence from South African Nurses.” *Journal of Economic Behavior & Organization* 107: 136–52.

Lee JH, Jang JW, Cho CH, Kim JY, Han ET, Yun SG, Lim CS. 2014. "False-positive results for rapid diagnostic tests for malaria in patients with rheumatoid factor." Journal of Clinical Microbiology. Oct;52(10):3784-7.

Levitt, Steven D, and Chad Syverson. 2008. “Market Distortions When Agents Are Better Informed: The Value of Information in Real Estate Transactions.” *The Review of Economics and Statistics* 90 (4): 599–611.

Li, Jing, William H Dow, and Shachar Kariv. 2017. “Social Preferences of Future Physicians.” *Proceedings of the National Academy of Sciences* 114 (48): E10291–300.

Mohanan, Manoj, Marcos Vera-Hernández, Veena Das, Soledad Giardili, Jeremy D Goldhaber-Fiebert, Tracy L Rabin, Sunil S Raj, Jeremy I Schwartz, and Aparna Seth. 2015. “The Know-Do Gap in Quality of Health Care for Childhood Diarrhea and Pneumonia in Rural India.” *JAMA Pediatrics* 169 (4): 349–57.

Nyman, John A. 1999. “The Value of Health Insurance: The Access Motive.” *Journal of Health Economics* 18 (2): 141–52.

Ochola, L B, P Vounatsou, T Smith, M L H Mabaso, C R J C Newton 2006. “The reliability of diagnostic techniques in the diagnosis and management of malaria in the absence of a gold standard.” Lancet Infect Dieases 2006; 6:582–88

O'Meara, Wendy Prudhomme, Manoj Mohanan, Jeremiah Laktabai, Adriane Lesser, Alyssa Platt, Elisa Maffioli, Elizabeth L Turner, and Diana Menya. 2016. "Assessing the Independent and Combined Effects of Subsidies for Antimalarials and Rapid Diagnostic Testing on Fever Management Decisions in the Retail Sector: Results from a Factorial Randomised Trial in Western Kenya." *BMJ Global Health* 1 (2).

Peabody, John W, Jeff Luck, Peter Glassman, Timothy R Dresselhaus, and Martin Lee. 2000. "Comparison of Vignettes, Standardized Patients, and Chart Abstraction: A Prospective Validation Study of 3 Methods for Measuring Quality." *Jama* 283 (13): 1715–22.

Roth, Johanna M., Daniël A. Korevaar, Mariska M. G. Leeflang & Pètra F. Mens (2016) "Molecular malaria diagnostics: A systematic review and meta-analysis," Critical Reviews in Clinical Laboratory Sciences, 53:2, 87-105

Satyanarayana, Srinath, Ada Kwan, Benjamin Daniels, Ramnath Subbaraman, Andrew McDowell, Sofi Bergkvist, Ranendra K Das, Veena Das, Jishnu Das, and Madhukar Pai. 2016. "Use of Standardised Patients to Assess Antibiotic Dispensing for Tuberculosis by Pharmacies in Urban India: A Cross-Sectional Study." *The Lancet Infectious Diseases* 16 (11): 1261–68.

Sloan, Frank A. 2000. "Not-for-Profit Ownership and Hospital Behavior." *Handbook of Health Economics* 1: 1141–74.

Sulis, Giorgia, Benjamin Daniels, Ada Kwan, Sumanth Gandra, Amrita Daftary, Jishnu Das, and Madhukar Pai. 2020. "Antibiotic Overuse in the Primary Health Care Setting: A Secondary Data Analysis of Standardised Patient Studies from India, China and Kenya." *BMJ Global Health* 5 (9): e003393.

Sylvia, Sean, Yaojiang Shi, Hao Xue, Xin Tian, Huan Wang, Qingmei Liu, Alexis Medina, and Scott Rozelle. 2015. "Survey Using Incognito Standardized Patients Shows Poor Quality Care in China's Rural Clinics." *Health Policy and Planning* 30 (3): 322–33.

Taylor, Curtis R. 1995. "The Economics of Breakdowns, Checkups, and Cures." *Journal of Political Economy* 103 (1): 53–74.

Wagner, Zachary, Manoj Mohanan, Rushil Zutshi, Arnab Mukherji, and Neeraj Sood. "What drives poor quality of care for child diarrhea? Experimental evidence from India." *Science* 383, no. 6683 (2024): eadj9986.

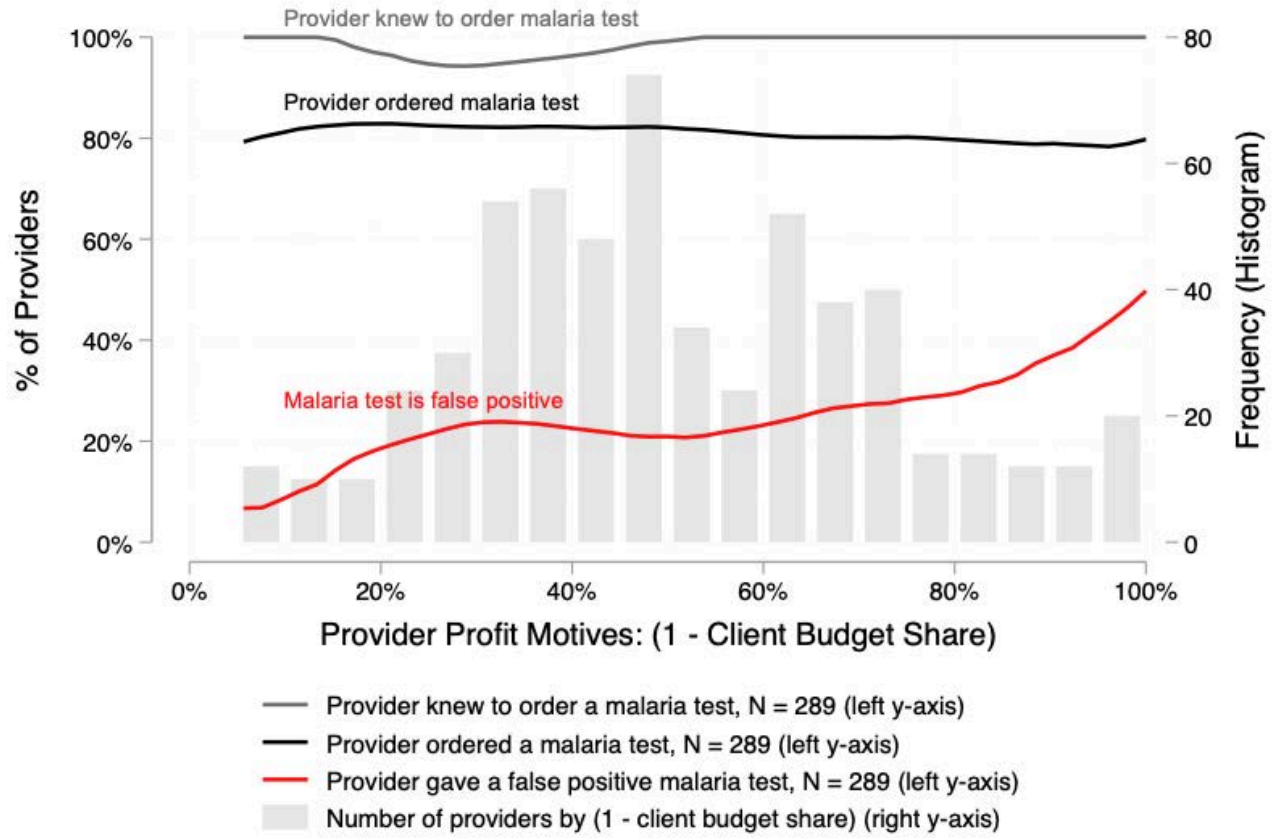
Wolinsky, Asher. 1993. "Competition in a Market for Informed Experts' Services." *The RAND Journal of Economics*, 380–98.

World Health Organization. 2015. *Global Technical Strategy for Malaria 2016-2030*. World Health Organization.

———. 2022. *World Malaria Report 2022*. World Health Organization.

Wu, Grace, and Muhammad H Zaman. 2012. "Low-Cost Tools for Diagnosing and Monitoring HIV Infection in Low-Resource Settings." *Bulletin of the World Health Organization* 90: 914–20.

Figure 1. Percent of providers who knew to order a malaria test, ordered a malaria test, and gave false-positive test results by provider profit motivated preferences.



Note: Local polynomial smooth plots (left x-axis) correspond to the percent of providers who knew to order any malaria test as measured by vignette survey (grey line), percent of the same sample of providers who ordered any malaria test as measured by standardized patients (SPs; black line), and percent of the same sample of providers who gave a false positive malaria test result (red line) across provider profit motivation as measured as 1 minus client budget share or CBS (average across 14 decisions) as measured by a real-stakes, modified dictator game. Histogram (right x-axis) depicts frequency of providers along (1 – CBS).

Table 1: Descriptive statistics (N=289)

	Mean	SD
Provider characteristics		
Provider is female	0.38	--
Provider age		
Under 30 years	0.16	--
30-50 years	0.58	--
Above 50 years	0.26	--
Provider qualification		
Medical doctor	0.03	--
Clinical officer	0.40	--
Nurse or Midwife	0.46	--
Other	0.11	--
Provider is permanent clinical staff	0.86	--
Years worked at clinic	9.13	8.25
Years worked in health care	17.72	14.38
Provider knowledge of ordering malaria test	0.98	--
How often provider sees an acute malaria case		
Almost Every Day	0.31	--
Almost Every Week	0.23	--
Once a Month	0.24	--
Less than once a month	0.21	--
Unknown	0.01	--
Provider profit motivation: Average (1 – CBS)	0.51	0.21
Provider profit motivation: Average α	0.67	0.25
Case management outcomes		
Malaria test was ordered	0.81	--
Malaria test reported positive (unconditional)	0.24	--
Malaria test reported positive (conditional)	0.30	--
Sold antimalarial drug Artemether-Lumefantrine	0.30	--
Sold paracetamol for fever	0.25	--
Sold any other (non-efficacious) medicine	0.74	--

Note: Other provider qualifications reported include: lab technician (11), nurse's aide (2), receptionist/administrative (2), other (9), and unknown (7). All values are N = 289 except where provider knowledge of ordering malaria test (N=286) and malaria test reported positive conditional on any test (N=235). Malaria test refers to rapid diagnostic test or microscopy (no providers ordered both).

Table 2. Any Malaria Test (=1)

	(1)	(2)	(3)
Profit Motivation (1 - CBS)			
Coefficient	0.026		
Std. Error	(0.118)		
p-value	[0.828]		
Most Profit Motivated (=1 if CBS ≤ 25th percentile)			
Coefficient		-0.016	
Std. Error		(0.057)	
p-value		[0.779]	
Profit Motivation (α)			
Coefficient			-0.013
Std. Error			(0.110)
p-value			[0.906]
Observations	285	285	282
Mean dependent variable		0.813	
SP fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equation (2). Each entry reports the estimated coefficient on altruism, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.

Table 3. (False) Positive Malaria Test Result (=1)

	Panel A			Panel B		
	Unconditional			Conditional on Malaria Test		
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Motivation (1 - CBS)						
Coefficient	0.293			0.339		
Std. Error	(0.133)			(0.162)		
p-value	[0.027]			[0.037]		
Most Profit Motivated (=1 if CBS ≤ 25th percentile)						
Coefficient		0.125			0.164	
Std. Error		(0.070)			(0.080)	
p-value		[0.074]			[0.041]	
Profit Motivation (α)						
Coefficient			0.223			0.234
Std. Error			(0.111)			(0.141)
p-value			[0.045]			[0.097]
Observations	285	285	285	231	231	
Mean dependent variable		0.242			0.298	
SP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equation (2). Each entry reports the estimated coefficient on altruism, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.

Table 4. Drug Sales

	Panel A		Panel B		Panel C	
	Sold antimalarial drug Artemether Lumefantrine (=1)		Sold paracetamol for fever (=1)		Sold any other (non-efficacious) medicines (=1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Motivation (1 - CBS)						
Coefficient	0.237		0.136		-0.001	
Std. Error	(0.143)		(0.123)		(0.128)	
p-value	[0.098]		[0.270]		[0.994]	
Most Profit Motivated (=1 if CBS ≤ 25th percentile)						
Coefficient		0.147		0.078		-0.050
Std. Error		(0.073)		(0.064)		(0.065)
p-value		[0.045]		[0.220]		[0.442]
Observations	285	285	285	285	285	285
Mean dependent variable	0.301		0.249		0.744	
SP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equation (2). Each entry reports the estimated coefficient on altruism, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.

Table 5: Mediation Analysis

(conditional on having a malaria test)

	Panel A				Panel B	
	Sold antimalarial drug Artemether Lumefantrine (=1)				Positive Malaria test Result	
	Equation (3)		*Equation (4)*		*Equation (5)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Motivation (1 - CBS)						
Coefficient	0.277		0.100		0.339	
Std. Error	(0.162)		(0.140)		(0.162)	
p-value	[0.087]		[0.478]		[0.037]	
Most Profit Motivated (=1 if CBS ≤ 25th percentile)						
Coefficient		0.203		0.122		0.164
Std. Error		(0.079)		(0.068)		(0.080)
p-value		[0.011]		[0.072]		[0.041]
Malaria test positive (=1)						
Coefficient			0.496	0.486		
Std. Error			(0.069)	(0.068)		
p-value			[0.000]	[0.000]		
Observations	231	231	231	231	231	231
Mean dependent variable	0.285				0.298	
SP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equations 3, 4 and 5 conditional on having a malaria test. Each entry reports the estimated coefficient, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.

Appendix A

Standardized Case: Malaria

JOHN (Male Living in Nearest Town)

John is 28 years old and has been working at a bakery in nearest town e.g. Nairobi as a cashier for the last 4 years. He has been living in [Nairobi or Nearest Town] for the last 5 years. Two weeks ago, he traveled up country (Either Kisumu, Kakamega, Busia, Siaya, Bungoma, Migori, Homabay, Kilifi, Mombasa or Kwale) to see his friend since he was on leave.

During his stay upcountry (Either Kisumu, Kakamega, Busia, Siaya, Bungoma, Migori, Homabay, Kilifi, Mombasa or Kwale), he did not use a treated mosquito net, because it was so dusty. A few days ago, John started having headaches and a high fever. He hasn't had much of an appetite lately.

Yesterday John woke up with a headache and was feeling cold, despite how it was sunny outside. He was also feeling fatigued, had joint pains. John suspects it is because of the trip he recently made up-country, and it reminds him of another time he had malaria. He decided to call his employer to take a day off so that he can visit a doctor. He arrived at this decision, since he vomited after having breakfast and he had vomited the previous night. A few times during the last night he experienced a bit fever and chills.

John comes from a family of 4: two brothers and one sister whereby he is the second born. He is currently living with the younger brother who he is supporting in a one-bedroom house in (nearest town the SP is working from). No one else from his family seems to be showing symptoms like his. Two years ago, his sister had a headache and was treated at a local clinic and she got well. Today, he visits a doctor to see if his condition can be helped.

JOAN (Female Living in Nearest Town)

Joan is 28 years old and is currently looking for a job. She was working as a waitress, but the hotel closed three months ago. She has been living in [Nearest Town, e.g. Nairobi] for the last 4 years. She recently moved in with her boyfriend. [*If outside Kisumu:* One month ago, she traveled to Kisumu for a vacation with her boyfriend and was there for a week.] Joan has only one sister, and she is the last born in the family. She grew up in Machakos and moved to (nearest town e.g. Nairobi) 4 years ago when she got a job as a waitress in a big restaurant. Occasionally, Joan supports her single mother who owns a grocery shop.

[If outside Kisumu: Since she came back] In the past couple days, Joan has been feeling a little tired and has had back pains, which she suspected is from the long hours they traveled on the road.

Today, Joan woke up nauseated and vomited two times, and she did not have appetite for breakfast. She had joint pains all over and was shivering as well. She decided to see a doctor at a nearby clinic.

Opening statement:

<u>Doctor, I think I have malaria.</u>

History questions asked by the provider and their answers:

1. Q: What are your symptoms?
   A: I have a fever and headache.

2. Q: Which symptom started first?
   A: They started at the same time

3. Q: How long have you had these symptoms for?
   A: For three days.

4. Q: Is the fever constant or does it come and go?
   A: It comes and goes.

5. Q: Does the fever go up and down?
   A: Yes.

6. Q: When you have a fever is it very high?
   A: Sometimes high, sometimes low.

7. Q: Have you been able to eat and drink?
   A: Yes, I ate a small breakfast and drank some water.

8. Q: Have you had any vomiting or diarrhoea?
   A: Yes, just vomiting

9. Q: Have you taken any medicines?
   A for John/Joan: No

10. Q: Have you taken a malaria test?
    A: No

11. Q: When was the last time you had malaria?
    A: About one year ago.

12. Q: Have you travelled recently?
    A: Yes, I've been to (Either Kisumu, Kakamega, Busia, Siaya, Bungoma, Migori, Homabay, Kilifi, Mombasa or Kwale)

13. Q: Have you had difficulty breathing?
    A: No

14. Q: Have you had any wheezing?
    A: No.

15. Q: Have you had any muscle or joint pain?
    A: Yes, my muscles and joints ache.

16. Q: Do you have chest pain?
    A: No.

17. Q: Do you have a cough?
    A: No

18. Q: Have you had a cold, sneezing, sore throat or stuffiness in the last few days?
    A: No.

19. Q: Have you had any fainting or convulsions?
    A: No.

20. Q: Do you feel dizzy?
    A: Yes

21. Q: Are you allergic to any medicines?
    A: No.

22. Q: Do you have any other problems?
    A: No.

23. Q: [For female case] When was your last period?
    A: *About four days ago.*

24. Q: [For female case] Are you/could you be pregnant?
    A: *No*

25. Do you feel pain while swallowing?
    A: No

26. Where is the location of the headache?
    A: Front upper part of the head.

27. What is the severity/intensity of the headache?
    A: Moderate.

Appendix B. Estimation results excluding the 24 encounters with replacement providers

Table B2. Any Malaria Test (=1)

	(1)	(2)	(3)
Profit Motivation (1 - CBS)			
Coefficient	-0.022		
Std. Error	(0.130)		
p-value	[0.864]		
Most Profit Motivated (=1 if CBS ≤ 25th percentile)			
Coefficient		-0.045	
Std. Error		(0.062)	
p-value		[0.469]	
Profit Motivation (α)			
Coefficient			-0.058
Std. Error			(0.117)
p-value			[0.623]
Observations	262	262	259
Mean dependent variable		0.804	
SP fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equation (2). Each entry reports the estimated coefficient on altruism, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.

Table B3. (False) Positive Malaria Test Result (=1)

	Panel A. Unconditional			Panel B. Conditional on Malaria Test		
	(4)	(4)	(5)	(6)	(5)	(6)
Profit Motivation (1 - CBS)						
Coefficient	0.315			0.357		
Std. Error	(0.137)			(0.170)		
p-value	[0.022]			[0.036]		
Most Profit Motivated (=1 if CBS ≤ 25th percentile)						
Coefficient		0.123			0.170	
Std. Error		(0.075)			(0.089)	
p-value		[0.101]			[0.057]	
Profit Motivation (α)						
Coefficient			0.222			0.233
Std. Error			(0.123)			(0.154)
p-value			[0.072]			[0.131]
Observations	262	262	259	210	210	210
Mean dependent variable		0.234			0.272	
SP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equation (2). Each entry reports the estimated coefficient on altruism, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.

Table B4. Drug Sales

	Panel A. Sold antimalarial drug Artemether Lumefantrine (=1)		Panel B. Sold paracetamol for fever (=1)		Panel C. Sold any other (non-efficacious) medicines (=1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Motivation (1 - CBS)						
Coefficient	0.223		0.115		0.030	
Std. Error	(0.144)		(0.137)		(0.139)	
p-value	[0.120]		[0.400]		[0.831]	
Most Profit Motivated (=1 if CBS ≤ 25th percentile)						
Coefficient		0.146		0.078		-0.043
Std. Error		(0.075)		(0.070)		(0.071)
p-value		[0.051]		[0.264]		[0.549]
Observations	262	262	262	262	262	262
Mean dependent variable	0.287		0.249		0.751	
SP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equation (2). Each entry reports the estimated coefficient on altruism, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.

Table B5: Mediation Analysis

(conditional on having a malaria test)

	Panel A. Sold antimalarial drug Artemether Lumefantrine (=1)				Panel B. Positive Malaria test Result	
	Equation (3)		*Equation (4)*		*Equation (5)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Profit Motivation (1 - CBS)						
Coefficient	0.250		0.080		0.357	
Std. Error	(0.166)		(0.149)		(0.170)	
p-value	[0.131]		[0.592]		[0.036]	
Most Profit Motivated (=1 if CBS ≤ 25th percentile)						
Coefficient		0.198		0.119		0.170
Std. Error		(0.085)		(0.078)		(0.089)
p-value		[0.020]		[0.126]		[0.057]
Malaria test positive (=1)						
Coefficient			0.452	0.442		
Std. Error			(0.074)	(0.073)		
p-value			[0.000]	[0.000]		
Observations	210	210	210	210	210	210
Mean dependent variable		0.272			0.272	
SP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports the results of the estimation of equations 3, 4 and 5 are conditional on having a malaria test. Each entry reports the estimated coefficient, robust standard errors clustered at the clinic level in parentheses, and the two-sided p-value in brackets. All models include SP fixed effects and controls selected by double-selection lasso linear regression. The list of potential controls is provided in Table 1.