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# Health Workers' Behavior, Patient Reporting and Reputational Concerns: Lab-in-the-Field Experimental Evidence from Kenya

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# ABSTRACT

## Health Workers' Behavior, Patient Reporting and Reputational Concerns: Lab-in-the-Field Experimental Evidence from Kenya*

We use a lab-in-the-field experiment to examine the effectiveness of accountability systems that rely on patient reporting in Kenyan health clinics. We recruit patients and health care providers from public and private health clinics to play a series of modified Trust Games. In the game, patients can send money to providers, who are then able to reciprocate. Patients can then file complaints if they are unhappy with the provider's level of reciprocity. We examine patient and provider behavior in a system where complaints lead to non-monetary consequences in the form of disclosing the complaints to professional peers, a system where complaints lead to monetary penalties, and a system where there are no direct consequences on providers, such as standard complaint boxes (our "control"). We focus on provider reciprocity and patient reporting (or complaining) as our primary behavioral measures in the game. Combining the experimental variation in provider consequences with non-experimental variation in provider and client characteristics such as sector of work, and the existence of personal relationships between clients and providers, we find that: 1) disclosing patients' complaints to providers' professional peers increases providers' pro-social behavior toward patients as much as imposing monetary penalties based on patients' complaints; 2) when complaints lead to tangible consequences (either monetary or non-monetary) for providers, patients are less willing to file such complaints, mainly due to the existence of personal relationships with providers. Overall, our findings support the implementation of citizen reporting systems that leverage peer pressure and reputational concerns.

**JEL Classification:** C90, I15, M59

**Keywords:** health services, bottom-up accountability, patient reporting, peer shaming

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## 1. Introduction

Accountability is often cited as a necessary factor to ensure the efficient provision of public services in developing countries (World Bank, 2004). Low levels of accountability in the health sector are associated with low levels of effort by healthcare providers, which result in high absence rates that range from 20 to 40 percent on a given day (Chaudhury et al., 2006 and World Bank SDI, 2013), limited patient interactions (Das et al., 2016), and low quality of service relative to providers' demonstrated ability (Leonard et al., 2007 and Das and Hammer, 2014). As low levels of effort can contribute to the poor health outcomes found in developing countries (see for example Goldstein, Zivin, Habyarimana, Pop-Eleches and Thirumurthy, 2013), there is growing interest in the potential of citizen monitoring schemes to improve the quality of public service delivery in developing countries (World Bank, 2004). Since the cost of monitoring service providers may be significantly cheaper for citizens than for government agents, well-designed bottom-up monitoring schemes could improve service delivery by enhancing accountability. As citizen monitoring schemes typically rely on informal or non-monetary sanctions, they may be easier to implement than other alternatives, such as top-down accountability systems, which could be especially difficult to administer in developing countries due to weak state or bureaucratic capacities.

A large body of evidence from experiments in the laboratory (e.g., Andreoni and Petrie, 2004; Ariely et al., 2009; Carpenter and Myer, 2010; Erikson et al., 2009; Gill et al. 2017; Linardi and McConnel, 2011; Karlan and McConnel, 2014; Xiao and Houser, 2011) and the field (e.g., Ashraf et al., 2014; Azmat and Iriberri, 2010; Brock et al., 2016; Gerber et al. 2008; Della Vigna et al., 2012) shows that informal mechanisms such as social observability, and public disclosure of performance rankings, can promote pro-social behavior even in the absence of formal incentives. Building on this literature, we conduct a lab-in-the-field experiment in Nairobi, Kenya, involving actual patients and their health providers, where patients can file reports (or complaints) in response to provider behavior in the game. By experimentally varying the consequences of these reports on providers, we can examine the effectiveness, relative to a control group, of reporting systems that lead to either informal (or social) sanctions or monetary penalties on both provider and patient behavior in the laboratory. Moreover, by recruiting actual patients and providers into our study, we are able to explore the relationship between behavior in the game and actual participant characteristics such as employment sector (i.e. private or public sector), provider absenteeism, and patient-provider familiarity.

We employ a modified Trust Game (Berg, Dickhaut and McCabe, 1995, and Serra et. al 2012), which we call the *Reporting Game.* In this game, each participating patient is randomly paired with a provider.

Patients are given an initial endowment, which they can use to send money to their matched provider, and any money sent to providers is tripled. Upon receiving the tripled funds, providers then decide how much money they should send back to the patient. Patients are then given the chance to "file complaints" against their matched provider, if they are not satisfied with the money they receive back. We use Trust Games in our study as they offer some parallels to the patient- provider interactions in real life. As clinical interactions are characterized by information asymmetries, uncertainty (for example, if the provider will be absent), and uneven distribution of powers, they require patients to place their trust in providers. Providers can then reciprocate a patient's trust by providing high-quality service. In the context of our Reporting Game, we thus focus on measures of trust and reciprocity between patients and providers. Specifically, we use the amount of money that providers send back to patients (scaled by the initial transfer amount) as our primary measure of health-worker pro-social behaviour (or reciprocity) toward patients. In addition, we use the patient's decision to file a complaint as a function of the amount returned by the provider as our main measure of the patient's willingness to use a participatory reporting system. Correlations between public sector workers' behaviour in the game and their likelihood of absence from work during unannounced visits suggest that our lab measures capture aspects of real life behaviour of participants.

We examine patient and provider behavior in the game under three types of randomly-assigned patient reporting systems: the Peer Disclosure treatment, the Monetary Penalty treatment, and the Complaint box treatment. Given the policy interest in accountability systems that rely on non-monetary sanctions, our primary treatment of interest is the Peer Disclosure treatment, which leverages providers' reputational concerns by disclosing the number of complaints received about a provider to his or her professional peers (a non-monetary or social sanction). The Complaint Box treatment, in which complaints do not lead to any penalties on providers, serves as our control condition, and is arguably the most relevant benchmark since complaint boxes are the status quo system given their ubiquity in public facilities, such as government health clinics. Further, as the lab-experimental literature has shown that monetary penalties can introduce high powered incentives,[1] the monetary penalty treatment provides a useful benchmark to assess the effectiveness of the Peer Disclosure system, even though monetary punishment systems are unlikely to be implemented in real life.[2] We further explore the impact of the possibility for provider retribution to alter

[1] There is a vast literature on individuals' willingness to impose monetary penalties on others in a lab setting; see for instance Fehr and Gächter (2002), Andreoni, Harbaugh and Vesterlund (2003), Andreoni and Petrie (2004), Fehr and Fischbacher (2004), Xiao and Houser (2005).

[2] Although a reporting system leading to monetary penalties is unlikely to be implemented in the field, it can provide some suggestive insights into the efficacy of a system where customers can punish a provider by switching to another provider, such as under a voucher scheme. In our experiment the size of the monetary penalty was approximately 10 to 60 percent of providers' daily wage depending on rank and seniority.

both provider and patient responses by conducting a Peer Disclosure treatment where providers can impose monetary penalties on the patients who complained against them. Finally, in light of the growing literature showing that public providers and private providers have different traits and motivations (Cowley and Smith, 2014; Serra, Serneels and Barr, 2011; and Brock, Lange and Leonard, 2016), we also examine the potential for differential responses to our specific accountability schemes across these types of health providers.

An important feature of the experiment is that, due to the transparency of each player's actions in the Trust Game, patients are able to clearly evaluate and identify the provider behavior that they deem deserving of a complaint. This is crucial, as it allows us to clearly measure patients' *willingness* to file complaints when reporting systems are available.[3] Moreover, as providers are also aware their actions in the game are easily evaluated, we can clearly measure their responsiveness to the different treatments we implement in the game. As information asymmetries hinder patients' ability to evaluate the quality of clinical care received from providers in real-life interactions, our findings are more relevant for provider misbehaviors that are easily observed by clients, such as absence from work, and requests for bribes or other illegal payments, which are widespread in the health sector in developing countries such as Kenya (Chaudhury et al., 2006, Transparency International, 2011). Although our experiment does not feature a repeated game, which may better simulate repeated real-life clinical interactions, we can instead exploit non-experimental variation in the real-life patient-provider relationships to better understand how such relationships may hinder or enhance the efficacy of the accountability systems we examine.[4] As a result, we are able to contribute to the small existing literature that examines the relationship between anonymity and individuals' willingness to punish others (see for example Balafoutas and Nikiforakis, 2012).

Our study is related to the small but growing literature that employs lab-in-the-field experiments to generate direct measures of health providers' motivations, and responsiveness to different incentive systems in developing countries. Brock et al. (2016) conducted lab-in-the-field experiments with health professionals in Tanzania and found that those who were more generous in the context of a dictator game performed better at work. Serra et al. (2011) found that intrinsically motivated young providers in Ethiopia were more likely to be working in non-profit facilities, mainly located in rural areas, and earn lower wages. Barr, Lindelow and Serneels (2009) tested the effectiveness of monitoring institutions, transparency, and monetary incentives on health providers' performance in a lab-in-the-field experiment conducted with a

[3] There is little data on the rates of citizens' voluntary participation in monitoring systems. Exceptions are Grossman et al. (2016), who estimate participation rates ranging from 3.4 to 6.4% in Uganda; Aker et al. (2015), who find participation rates ranging from 15% to 24% in Mozambique; and Olken (2007), who finds participation rates of approximately 30% in Indonesia.
[4] Due to all the activities, each lab session took at least four hours. Thus, the limited availability of health workers prevented us from implementing repeated games.

sample of Ethiopian nursing students. Contrary to these studies, in which providers are the only decision-makers in the experiment,[5] our experiment examines the strategic interactions between providers and actual patients under different incentive systems.

Our findings show that, relative to a simple Complaint Box, the Peer Disclosure system increases provider reciprocity in the game by over 30 percentage points, or approximately 30 percent. When provider retaliation is allowed, the effectiveness of the Peer Disclosure reporting system, with respect to provider reciprocity, is reduced to between 22 and 25 percentage points relative to the Complaint Box (approximately 21 to 24 percent). However, the coefficients are not statistically different from each other. In addition, we find that Peer Disclosure system is as effective as the Monetary Penalty system. We also find that public sector health workers are more generous toward patients, and more responsive to the Peer Disclosure mechanism than their private sector counterparts, whose reciprocity is only responsive to the Monetary Penalty system. This is consistent with a growing empirical literature (Banuri and Keefer, 2015; Serra et al., 2012; Delfgauuw et al., 2013; Gregg et al., 2011; Kolstad and Lindkvist, 2012) that finds significant differences between public and private sector employees with respect to their pro-social motivations, and their responsiveness to monetary and non-monetary incentives. Our results also show that public sector workers who are more pro-social (or reciprocal) in a standard Trust Game, which preceded the reporting game, are less likely to be absent from work during unannounced visits, which suggests that our lab measures capture aspects of real life behaviour. In addition, we find that less pro-social health workers, as measured in a standard Trust Game, are more responsive to the threat of both peer shaming and monetary sanctions. Given the correlation between provider absence and Trust Game reciprocity, this suggests that non-monetary sanctions based on peer reputational concerns could motivate health worker performance in real life.

With respect to the complaining decisions, on the intensive margin, patients submit more complaints under all systems that attach tangible consequences to the complaints, relative to the Complaint Box baseline. On the extensive margin, the propensity of patients to file unfavourable reports is between 7 to 10 percentage points lower when complaints lead to tangible monetary or non-monetary consequences for providers. Compared to the Complaint Box average, this translates to a 25 to 33 percent reduction in patient complaining. A more in-depth look at patients' complaining decisions shows that the decline in the propensity to report providers is driven by personal acquaintance with providers. Patients who do not recognize any of the providers participating in the experiment are equally likely to complain under the different reporting systems. However, patients who recognize one or more providers at registration are less

[5] Patients are either passive participants, as in a standard dictator game, or they are not part of the experiment.

willing to complain when complaints lead to tangible consequences for providers. This might be due to fear of outside-the-lab retribution – even though play in the game is anonymous – or guilt for causing problems to an acquaintance.

Our study provides important insights and guidance regarding the design of better accountability systems, as it assesses some of the central assumptions and hypotheses behind these systems, such as the willingness of citizens to actively use them and the responsiveness of provider effort to patient feedback in a controlled environment. Given the significant fraction of GDP devoted to personnel in the public health-care sector, improving provider effort and quality of service can have significant implications on public finance management.[6] Our findings show that reporting systems that trigger social sanctions through the disclosure of providers' negative feedback to their professional peers have the potential to significantly and positively affect providers' performance. However, existing social connections between service providers and service recipients are an important factor in the take up of reporting schemes. This suggests that systems that rely on face-to-face monitoring, and possible confrontation between providers and recipients are less likely to be actively utilized by citizens than systems that allow for anonymous reporting. As many developing countries are actively considering accountability systems that rely on social sanctions, these design insights could be especially relevant in the current policy climate.[7]

## 2. Research Methodology and Procedures

As part of the study, we conducted: 1) a survey of public and private health facilities in Nairobi; 2) a survey of patients exiting these facilities; 3) a survey of health providers from the same facilities; 4) lab-in-the field experiments with a subset of health providers and surveyed patients. In this section we start by describing the Kenyan context (Section 2.1) and explaining the study sampling and survey procedures (Section 2.2). We then provide details about our lab-in-the-field experiments, outline our hypotheses (Section 2.3), and explain how the experimental workshops were implemented (section 2.4). We conclude this section by describing our estimation strategy (Section 2.5).

### 2.1 Context

Health expenditures in Kenya grew from 4.5 percent of GDP in 2000 to 5.7 percent in 2014, where the majority of the increased spending was driven by public health expenditures (World Bank WDI, 2017). At

[6] See Das, Holla, Mohpal, Muralidharan (2015) for a discussion on the fiscal costs of teacher absence in India.
[7] For example Tanzania's Big Results Now program relies on the dissemination of public sector performance rankings to district officials, summarized in three color bands (Red, orange, and green), in an effort to improve service delivery.

the same time, key measures of health have improved. The under-5 mortality rate decreased from 100 per 1000 births in 2000 to 53.5 per 1000 births in 2014 (World Bank WDI, 2017,). Moreover, over the same time span, life expectancy in the country has increased from 51.7 years at birth to 66 years at birth (World Bank WDI, 2017).

There are three types of health facilities in Kenya: dispensaries (or clinics), health centers and hospitals. Dispensaries and health centers are the primary health care facilities in most communities. Dispensaries offer basic curative and preventative services and are staffed by nurses and community health workers. In contrast, health centers offer more advanced curative and preventative services, and are staffed by registered clinical officers, nurses and lab technicians. Hospitals provide more specialized curative services and referral services for patients who cannot be treated at dispensaries or health centers. They are staffed by a wide array of medical personnel including surgeons and specialist doctors. Across the country, there are a total over 5,200 dispensaries, 720 health centers, and 450 hospitals, with the private sector accounting for 40 to 55 percent of these facilities (Kenya SPA report, 2011).

The health system in Kenya is plagued with inefficiencies that impede service delivery. Health worker absence is common and more problematic in public health facilities. According to the World Bank's Service Delivery Indicators (SDI), in 2012, almost 30 percent of public health workers were absent on a given day, compared to just over 20 percent of private health workers (World Bank SDI, 2013). These absence rates were higher than teacher absence rates, which averaged approximately 16 percent, suggesting that accountability may be weaker in the health sector (World Bank SDI, 2013). In addition to lower absence rates, private facilities had better infrastructure and equipment, with 85 percent of private facilities having the minimum infrastructure required to be effective, compared to just under 50 percent of public facilities. Adherence to clinical guidelines, based on hypothetical case studies, was also slightly higher in private facilities (48 percent) compared to public facilities (43 percent) (World Bank SDI, 2013). Private facilities also had greater drug availability (80 percent) compared to public facilities (63 percent) (World Bank SDI, 2013). This is consistent with qualitative reports that documented the acute shortages of drugs in public health facilities in Kenya, and highlighted the common practice of providers denying patients drugs in order to resell them on the private market (Transparency International, 2011).

Our survey data, collected from 93 randomly selected public and private health frontline facilities (i.e., health centers and dispensaries) in Nairobi County, show similar patterns of service delivery (Table 1). Public facilities in our sample were generally larger, had higher case-loads and were more likely to have laboratories, beds and surgical facilities compared to private health facilities. However, relative to private health facilities, public facilities were less likely to have a complaint box or a published list of prices, which suggests a lower level of transparency and accountability. Patient satisfaction with providers and the overall quality of care was also lower in public facilities. This may be driven by factors such as longer waiting times in public facilities, even when scaled by patient case-loads. However, public facilities were significantly less expensive than private facilities as a result of government policies aimed at reducing user fees. The differences in costs, waiting times and patient satisfaction may partly explain why richer and more educated patients visited private facilities.

**2.2 Survey design and sampling**

We used the Master Facility List from the Ministry of Health's eHealth website[8] to create an initial list of facilities, which we then pared down to include only public, private, and NGO dispensaries and health centers in Nairobi County. We chose to focus on dispensaries and health centers as these are the primary service providers for most Kenyans. These facilities were further screened for their representativeness, therefore we excluded any facilities that overwhelmingly served only a subset of the population (e.g., mothers), only offered limited services (e.g., immunizations and voluntary HIV counseling and testing) or had staff that was out of the ordinary (e.g., mostly medical students). This final list of facilities was then randomized to include an even number of public and private facilities in the study. These facilities were then grouped by geographic proximity to make clusters of three facilities. Each cluster was then randomly assigned a treatment group, as further explained in Section 2.4.

We conducted facility surveys and exit interviews with randomly selected patients in 93 public and private dispensaries and health centers. Our field teams spent about a week surveying each facility and its patients. The facility surveys collected information on infrastructure, management, the staff roster, and staff absence. We conducted 1,784 patient exit interviews. These surveys collected information on health habits, current health, satisfaction with the care they received on the day of the interview and in the past, and socio-demographic information. The staff rosters and patient exit interviews served as our "sampling frames", which were used to randomly invite individuals to what we called community workshops (the lab-sessions and additional survey data collection) on the Saturday of the week in which we conducted the exit survey and facility survey. The participating health providers were surveyed after participating in the experiments. Finally, a week after the workshop, we conducted second unannounced visits to the surveyed facilities to record absence of health workers. The structure and timing of the data collection are displayed graphically in Figure A1 in Appendix.

We aimed to have five health workers and ten patients participate in each workshop. We invited individuals

[8] See http://ehealth.or.ke/

to our workshop following a randomly ordered call list from each cluster of three facilities. When possible given the geographical clustering, we selected two public facilities and one private facility to participate in the workshop. We intentionally over recruited individuals to ensure that we had a sufficient number of participants at each session. We selected the first two providers who arrived from each of the two public facilities in the cluster and the first provider to arrive from the private facility. We selected patients in a similar manner, choosing the first four patients who arrived from the first public facility and three patients each from the second public facility and the private facility. If this participant composition was not possible due to insufficient attendance, we used a simpler "first-come first admitted" process. We canceled workshops if less than six patients and three providers attended.[9] We paid participants a fee of 300 Kenya shillings (KES) if they were a patient, and 500 KES if they were a healthcare worker. In addition to this fee, patients and providers could earn up to 2400 KES by playing the games during the workshops.[10]

### 2.3 The lab-in-the-field experiment

Each patient is given an endowment $E_P$ and each provider is given an endowment $E_H$. Patients can send some of their endowment to the matched provider. If a patient sends an amount X, the provider gets three times that, 3X. The provider then decides whether to return any of the received amount to the patient, and how much. The amount sent back, Y, is therefore such that $0 \leq Y \leq 3X$. The patient can then file a complaint against the provider at a fixed cost c, which results in the provider receiving a number of cards with frowning faces on them. Once the patient has paid the fixed cost of complaining, they can express their level of frustration by sending up to five frowning face cards to the provider. F denotes the number of cards that a patient sends, and we limit the number of cards that can be sent to five, so $F \in [0,1,2,3,4,5]$.

Patients first decide how much money they wish to send to the matched health provider and they then decide whether or not to complain about the amount they received back. Patient payoffs are therefore equal to:

$$P_p = \begin{cases} E_p - X + Y, & \text{if the patient does not complain} \\ E_p - X + Y - C(F), & \text{if the patient complains} \end{cases}$$

Health provider payoffs are equal to:

[9] Only one workshop was cancelled due to low attendance.

[10] At the time of the study, the average hourly wage of a nurse in Kenya ranged from 83KES to 656 KES, depending on rank and seniority. Based on per capita GNI, the average hourly wage of a Kenyan was 33 KES.

$$P_H = \begin{cases} E_H + 3X - Y, & \text{if the patient does not complain} \\ E_H + 3X - Y - K(F), & \text{if the patient complains} \end{cases}$$

We conducted four treatments in which we varied K(F), i.e., the cost generated by the complaints on the provider.

1. The *Complaint Box (CB*) treatment simulates a simple reporting system relying on patients' complaints that are privately read by providers. In this treatment, the provider receives an envelope containing the frowning faces (up to five) sent to him or her by the matched patient. No tangible costs to providers are associated with the complaints, therefore in this setting K(F) is equal to zero and the provider's payoffs if the patient complains are identical to the no complaint case;
2. The *Peer Disclosure (PD)* treatment simulates a system relying on complaints that have no monetary consequences for providers but that are publicly disclosed to all the providers participating in the workshop, hence possibly leading to peer shaming. This was achieved by delivering the envelope containing the frowning face cards to the provider, as before, and by displaying the cards received by each provider on the blackboard in the room where all providers were seated. On the board each provider was identified by his or her player number. As under the CB treatment, there are no monetary consequences attached to complaints, therefore K(F) = 0;
3. The *Peer Disclosure with Retaliation (PD-R)* simulates a reporting system that is identical to PD but with the possibility for the provider to retaliate by imposing a monetary penalty on the patient who filed a report. This was achieved by allowing providers, after seeing the information displayed on the board, to retaliate on the matched patient by imposing a monetary penalty R. The penalty was costless for the provider and was levied at the payment stage. This modifies the patient's payoffs to: $E_P - X + Y - C(F) - R$, if the patient complains and the provider retaliates;
4. The *Monetary Penalty (MP)* treatment simulates a system relying on patients' complaints that generate monetary penalties on providers. As in CB, the "frowning face cards" sent by patients are privately seen by providers, but a monetary penalty k for each received card is then levied at the payment stage. This implies that K(F) is now equal to k times F and provider payoffs in case of complaint are equal to: $E_H + 3X - Y - kF$.

Before conducting the Reporting Game described above, we also conducted a standard Trust Game (TG) with the participants. This "Baseline Trust Game" had identical payoffs and initial decision stages as the Reporting Game, but did not include the patient complaining stage. This game was included to allow the participants to get familiar with the mechanics of a Trust Game before they played the more complex reporting game. It also provides us with a baseline measure of providers' reciprocity in the absence of any patient reporting mechanisms.

### 2.3.1 Testable Predictions

Theoretically, if individuals are purely money-maximizers we should expect to see no complaints, and no differences in providers' behaviors across treatments in our reporting game, since filing a complaint is costly (i.e., $C(F) = c > 0$). In other words, in all treatments we should observe $F=0$, $X=0$, and $Y=0$, and all reporting systems should prove ineffective. However, a large number of experimental studies (e.g., Calabuig et al., 2013; Fehr and Gächter, 2002; Fehr and Fischbacher, 2004; Masclet et al., 2003; Xiao and Houser, 2005) have shown that individuals are willing to incur monetary costs to impose monetary or non-monetary penalties to others, and that the possibility of receiving punishment, either formal or informal, significantly affects individual decision-making. It is easy to augment health provider's payoff by including a non-monetary cost, $I(F)$, generated by the receipt of negative feedback by patients, in the form of disapproval cards. In the Monetary Penalty treatment, $K(P)$ would then become equal to $kF + I(F)$, with $I(F) \geq 0$ and increasing in F. In the other treatments, $K(F)$ would be simply equal to $I(F)$. Our hypotheses follow.

**Hypothesis 1:** The Peer Disclosure treatment will induce providers to return more money to patients compared to the Complaint Box treatment.

The Peer Disclosure treatment combines non-monetary penalties (as in CB) with a social comparison and peer shaming mechanism. We are unaware of other empirical studies – based on observational or experimental data – testing the effectiveness of accountability systems that rely on individuals' reputational concerns through the disclosure of received complaints to professional peers. However, many laboratory and field experiments have shown that individuals' behavior responds positively to the possibility of social observability and judgment (e.g., Andreoni and Bernheim, 2009; Andreoni and Petrie, 2004; Ariely et al., 2009; Brock et al 2016; Gerber et al., 2008; Linardi and McConnell, 2011; Xiao and Houser, 2011). Our Peer Disclosure treatment is also related to a number of studies that examine the effect of public disclosure of performance ranking on job productivity and education outcomes (e.g., Ashraf et al., 2014; Azmat and Iriberri, 2010; Blanes i Vidal and Nossol, 2010; Delfgaauw et al., 2013; Eriksson et al., 2009; Gill et al., 2015). The extent to which providers care about peer judgment could be easily reflected in the provider's payoff function by assuming that the non-monetary cost generated by complaints is also a positive function of the visibility of such complaints to peers, i.e., I = I(F, v) where v is equal to zero in CP and MP, since complaints are read in private by providers, but it is equal to 1 in the PD treatment, where complaints are shown to other providers. This implies that patients' complaints generate a higher non-monetary cost in PD as compared to CB.

**Hypothesis 2:** The Peer Disclosure with Retaliation treatment will induce providers to return lower amounts of money to patients as compared to the Peer Disclosure treatment.

The comparison between Peer Disclosure and Peer Disclosure with retaliation is straightforward. Since the possibility of retaliation increases patients' costs of complaining, this should lower providers' expectation of receiving a complaint for any given amount Y that they transfer back to patients. As a result, the amount sent back to patients in the PD-R treatment should be lower than under PD.

**Hypothesis 3:** The Monetary Penalty treatment will induce providers to return more money to patients compared to the Complaint Box treatment.

Hypothesis 3 follows from the fact that in the Monetary Penalty treatment, the cost of receiving patient complaints is equal to kF + I(F), with I(F) $\geq$ 0, and increases in F. It is therefore larger than the corresponding cost I(F) suffered by providers in the Complaint Box treatment, for any positive F.

While the comparison of provider behaviors in the MP and CB treatments is straightforward, we cannot formulate a clear hypothesis with respect to the comparison of the PD and MP treatments. While there is evidence that monetary penalties are more effective than informal punishment in lab settings,[11] the existing literature has not addressed the empirical question of whether the possibility of receiving monetary penalties (as in our MP treatment) is more or less effective than the possibility of receiving peer shaming (as in our PD treatment). Since, in our framework, the cost generated by complaints to the provider is equal to kF + I(F) under MP versus I(F, v) under PD, the PD treatment would be more effective than the MP treatment if

[11] Masclet et al. (2003) in the context of a repeated public goods game find non-monetary penalties to be initially as effective as monetary penalties, yet less effective in later periods. Only a handful of lab experimental studies employ games that introduce monetary punishment in the context of a Trust Game that resembles our reporting game. For instance, Fehr and Rockenbach (2003) and Houser et al. (2008) conduct treatments where the first-mover has to specify a desired back transfer when sending money to the second-mover and could impose a fine if receiving less than the stated desired amount. Rigdon (2009) allows the first mover to also reward the second-mover, while manipulating the size of rewards and penalties. Calabuig et al. (2013)'s design is similar to ours as it eliminates the stated desired back transfer but still employs a third stage of the game where the first-mover can punish second-mover if the amount returned is deemed unsatisfactory. We are unaware of any Trust Games investigating the effectiveness of second-movers' "complaints" while manipulating the monetary or non-monetary consequences of such complaints.

and only if I(F, v) > kF + I(F), i.e., the smaller the monetary penalty k and the higher the provider's sensitivity to peer judgment, $\frac{\partial I(F,v)}{\partial v}$.

**Hypothesis 4**: Public providers will be more reciprocal than private providers. In addition, public and private sector providers will respond differently to the treatments relying on monetary versus non-monetary incentives.

A growing number of studies such as Brock et al, (2015), Kolstad and Lindkvist (2012), and Serra, Serneels and Barr (2011) have found significant differences in pro-social (or intrinsic) motivation between public and private sector workers. In line with these studies, we expect that private and public providers will differ in their baseline level of reciprocity toward patients. We measure this baseline level by conducting a standard Trust Game (the Baseline Trust Game) before the more complex Reporting Game. In line with the existing literature, in the Trust Game, absent the threat of patient complaints, we expect that relative to private providers, public providers will send back more money to patients. This would suggest that public workers are more pro-social than private workers. In addition, public and private providers may differ in their responsiveness to the PD and MP treatments, as they rely on non-monetary and monetary incentives, respectively. This may be due to differential reputational concerns (for the PD and PD-R treatments), and/or differential marginal utility of money (for the Monetary Penalty treatment).

Our predictions with respect to patients' willingness to file reports against providers are less clear. Laboratory experiments that allow for costly punishment have provided evidence of widespread willingness to punish others as a result of social preferences or the desire to enforce social norms. For simplicity, we can assume that although filing a complaint is costly, i.e., C(F) = c > 0, individuals may gain a non-monetary benefit from expressing disapproval toward a health professional that returned less than what the patient considers an appropriate or fair amount. The existing literature suggests that a patient would complain when the non-monetary benefit outweighs the cost C(F). Moreover, if the non-monetary benefit of complaining depends positively on the severity of the provider's punishment, we should expect patients to be more willing to complain under Monetary Penalties and Peer Disclosure than the Complaint Box. However, our experimental environment differs from a typical lab setting in several ways. First, in our reporting game anonymity is partially lifted. Providers and patients see each other before being sent to different rooms to play the game. If they know and recognize each other,[12] their interaction in the lab-in-the-field setting is in

[12] This is not always the case, as the providers that were sampled (and who participated) from a given facility might not be the ones patients interacted with the day of the exit interview. Since our study included a post-experiment survey component that registered personal relationships among participants, we are able to control for such relationships in the empirical analysis.

fact conditioned by the beliefs, norms and expectations that guide the longer-term relationships existing between patients and providers in the field. This implies that fear of outside-the-lab retaliation may lower reporting in our experiment compared to standard lab settings.[13] Moreover, in our experiment, the potential "punisher" is not a "peer" of the individual being punished; on the contrary, the parties involved in the game are likely to be separated by a large social status gap. This might, in turn, further reduce the likelihood of patient reporting.

Formally, the above discussion implies that patients may suffer a non-monetary cost when complaining against a provider. These costs are likely increasing in the number of disapproval cards sent (F), as well as the actual cost incurred by the provider in the event of a complaint (K). Since the Monetary Penalty and the Peer Disclosure treatments both increase K, it is possible that patients' willingness to file complaints will be lower in these treatments than in the Complaint Box treatment, due to an increase in patients' non-monetary cost of complaining. Given that our MP and PD treatments are likely to increase both the non-monetary benefit and the total cost of filing a complaint, relative to the CB treatment, we cannot formulate a clear hypothesis on citizens' willingness to complain under these two treatments.

### 2.4 Implementation

We conducted a total of 24 community workshops in local schools, involving 216 patients, and 103 health providers, mostly nurses and clinical officers. Each workshop started with registration, where we verified that participants were either a provider or a patient recruited from a given facility. Participants were each given a colored badge (green for providers, and orange for patients), and a assigned a number (1 to 5 for providers, and 1 to 10 for patients). Patients and providers were then seated in separate rooms. For the duration of the workshop we referred to each participant by his or her color and identification number. At the end of the experimental session, before the payment stage, we implemented network questionnaires with both patients and providers, in order to register the personal and professional relationships between study participants. Finally, we surveyed the health providers to collect demographic data and information about individual job experiences.

Each experimental subject participated only in one of the four treatments, i.e., we employed a between-subject design. We conducted at least five sessions of each of our four different treatments of the Reporting Game, as shown in Table 2. For each workshop, we managed to recruit between three to five providers, and between seven to ten patients. Table 2 shows the distribution of participants across our

[13] See Balafoutas and Nikiforakis (2012) for an example of field punishment, or lack thereof, in Athens subway stations.

different treatment conditions. Facilities were grouped by geographic proximity into clusters of 3 facilities, and each cluster was invited to a workshop (or session). Each cluster (or session) was then randomly assigned a treatment of the Reporting Game. Therefore, the assignment of patients and providers to any given treatment was determined by the random allocation of their health facility to that treatment. We attempted to have one private facility and two public health facilities in each sampling cluster. When this was not possible, we had three public health facilities per cluster and workshop. As a result, the percentage of private health providers in each treatment ranges between 20 and 30 percent.

We set patient and provider endowments, $E_P$ and $E_H$, each equal to 1000 KES. Patients could send multiples of 200 KES to the matched provider, for a maximum of 800, i.e., $X \in [0, 200, 400, 600, 800]$. Participants knew that whatever was sent by a patient would be tripled by us before being given to the provider. Providers had to decide how much they wanted to return to the patient (in multiples of 200). We set the cost of filing a complaint, c, to 50 KES. In the Monetary Penalty treatment, each complaint card, F, led to a penalty of 100 KES for the provider, i.e., k = 100. In the Peer Disclosure with Retaliation treatment, we set the retaliatory penalty, R, equal to 150 KES.

In order to ensure that patients had a good understanding of the rules of the game, we first read the instructions of the game aloud and then conducted one-to-one interviews with each patient – recall that patients and providers were seated in different rooms. During the one-to-one interviews, we repeated the game instructions, asked comprehension questions, and then registered patients' decisions. Given providers' higher level of education, we did not conduct private interviews with them. Instead, we let them make their decisions in private. Moreover, for providers we employed the strategy elicitation method, i.e., we had providers fill out a form stating how much they would like to send back in the case of each possible amount sent to them by the matched patient, before seeing the actual amount sent. The use of the strategy elicitation method ensured perfect comparability across providers as it ensured that each of them responded to the same set of possible scenarios. Had their responses been directly elicited, the actual scenario faced by each provider would have varied depending on the amount sent by the matched patient.[14]

We also used the strategy elicitation method to register the complaints of each patient. For each possible amount returned by the provider, the matched patient had to state whether he or she would like to complain, and how many frowning face cards to send to the provider. For instance, if a patient sent over 200 KES, the

[14] Whether and to what extent the strategy elicitation affects observed behavior is the subject of an ongoing debate. While the evidence is mixed and the complexity of the experiment seems to be a crucial factor (Brandts and Charness, 2000), a recent survey of the experimental literature (Brandts and Charness, 2011) found no cases of treatment effects generated when using the strategy method and not observed when employing the direct-response method.

provider would receive three times that amount, i.e., 600, and the patient would then have to state whether or not he or she would like to spend 50 KES to complain if the amount returned by the provider was 0, 200, 400 or 600. These four decisions to complain were registered during one-to-one interviews in which field officers went through the previously read aloud instructions, used multiple scripted examples, and tested the patients' understanding with specific comprehension questions before eliciting their complaint choices.

As discussed previously, we first conducted a standard Trust Game (Baseline Trust Game) and then conducted the Reporting Game. This helped promote participant understanding of the games as we anticipated that explaining all the stages of the Reporting Game would be very difficult without having first ensured that subjects were familiar with the two stages of a standard Trust Game.[15] Participants were not informed about the outcomes of each game until the payment stage at the very end of the workshop, and they were paid the earnings from only one randomly selected game.[16]

### 2.5 Empirical Strategy

As treatments are randomly assigned at the session level, we can estimate the treatment effects of the interventions using OLS specifications to examine both client and provider behavior in our experiment. Since all participants in the same session face the same accountability system, we cannot include individual- or session-level fixed effects as they would absorb the treatment assignment. For providers, we focus on the amount of money they send back to patients as our primary outcome measure and use the following OLS specification to estimate the treatment effects:

$$y_{ik}^{r} = \beta_0 + T_i'\beta_1 + X_i'\beta_2 + v_i{}'\beta_3 + \varepsilon_{ik} \qquad (1)$$

where $y^r$ is the ratio of the amount provider *i* returned (or sent back) to the matched client and the amount the client had sent, $k \in [\,200, 400, 600, 800]$. Since *k* was tripled between being transferred to the provider, $y^r$ is a number between 0 and 3, with 0 indicating that the provider kept the tripled amount for himself/herself and 3 indicating that he or she sent the full tripled amount back to the patient. In the next sections, we refer to this outcome variable as the returned-received ratio (R/R). T is the vector of binary treatment indicators, X is the vector of controls such as demographic variables, and the Complaint Box intervention serves as the reference (or omitted) group. We estimate our regressions using the full set of decisions elicited through the strategy method (see section 2.4). Therefore, each provider has four observations in the data documenting how much money they would return to the client for each possible

[15] Note that in each game subjects from one room (for instance, patients) were matched with a different subject from the other room. Participants were made aware of this feature of the experimental design.

[16] The random selection of the payoff-relevant game happened in front of the participants at the end of the workshop, before the payment stage.

amount they could receive from the client (i.e., 200,400, 600 or 800 KES). We include a set of binary variables ($v_i$) to control for each of the initial amounts possibly sent by the client. As participants in a session may face similar shocks, we cluster our standard errors at the session level to account for this possibility. Since there are fewer than 30 clusters, we follow Cameron, Gelbach and Miller (2008, 2015) and use wild-cluster bootstrapping to account for the relatively small number of clusters and report the p-values of the bootstrapping exercise, as well as (regular) clustered standard errors in our results. We also explore the heterogeneity in treatment effects by interacting our treatment variables in equation (1) by a binary variable indicating if the provider is from the public or private sector. We further examine the heterogeneity in treatment effects by provider baseline reciprocity in the standard Trust Game.

For patients, we explore their initial sending behavior and their subsequent complaining decisions using OLS specifications. We examine clients' initial sending behavior using the following specification:

$$y_j^s = \delta_0 + T_j'\delta_1 + X_j'\delta_2 + e_j \tag{2}$$

Where $y^s$ is the amount sent to providers by clients or a binary variable indicating that the client sent the provider a positive amount, T is the vector of treatments indicators, and X is the vectors of controls such as demographic variables.

As patients' complaining decisions were elicited by the strategy method (see section 2.4), each patient has several observations depending on the amount they initially sent. For instance, if a patient sent 200 KES to the matched provider, the patient had to state whether she would like to send up to five cards displaying a frowning face to the provider in each of the following cases: 1) if she received 0 back; 2) if she received 200 back; 3) if she received 400 back; 4) if she received 600 back. If a patient sent 400 KES to the provider, the complaining decision would apply to seven possible scenarios, each corresponding to the provider returning a different amount, in multiples of 200, up to 1200 KES. We use the same methodology in registering complaining decisions when the patient sends 600 and 800 KES to the provider. We use the following OLS specification to examine the patient complaining decisions:

$$C_{jm} = \gamma_0 + T_j'\gamma_1 + X_j'\gamma_2 + \theta_j + u_{jm} \tag{3}$$

Where C is a binary variable indicating whether patient $j$ filed a complaint if the provider sent back $m$ KES ($m$ is discrete). T and X are defined as above and $\theta_j$ is a set of binary variables that control for each possible amount of money returned by the provider. As the set of possible values that providers can return to clients is determined by the initial sending amount, $\theta_j$ also includes controls for the initial amount sent by the client. Specifically, we control for the amount the patient sent to the provider in $\theta_j$, and since there are numerous possibilities for provider return amounts, we include controls for broad ranges of return amounts, including four binary variables indicating the amount returned by the provider equaling zero, lower than the amount sent, equal to the amount sent, or greater than the amount sent.[17] We explore heterogeneity in treatment effects by client wealth and client personal knowledge of at least one provider participating in the workshop. To do this, we interact the treatment variables in equation 3 with binary variables that indicate whether the client knows a participating health worker, and whether the client is above average wealth (based on a constructed index of assets).

Since the decision to file a complaint is conditional on sending a positive amount to the matched provider, our analysis of patients' propensities to complain applies only to the 164 "trusting" patients (out of 216) who decided to send a positive amount to the matched provider. We test for balance in patient sending behavior across the treatments in order to clearly interpret the results in equation 3. Finally, we also examine the number of complaint cards sent by clients as an additional outcome (conditional on filing a complaint).[18]

## 3. A first Look at the Data

### 3.1 Patients and Workshop Participants

We surveyed a total of 1,784 patients from public and private facilities. We randomly invited a subset of surveyed patients to participate in the community workshop. A total of 216 patients participated in the workshops. Although we aimed to have ten patients and five providers per workshop, fewer than ten patients participated in 37% of our workshops, and less than five providers participated in 50% of our workshops. Even though we randomly extended invitations to participants, workshop participants may differ from non-participants. In Table 3 we compare the demographic characteristics of our full sample of 1,784 surveyed patients, and the subsample of 216 patients who participated in the community workshops.[19] Our experimental participants do not seem to significantly differ from our full sample of patients in terms of age, education, wealth, marital status and number of children. The only significant difference between the two samples lies in their gender compositions, with a larger percentage of males participating in the experiment than the percentage of males surveyed while exiting the health facility.

[17] In all specifications, the excluded dummy corresponds to the amount returned being greater than the amount sent.
[18] There are about 220 instances (out of 980) where clients file a complaint.
[19] Since we were unable to survey health professionals at their place of work, we could only survey the health professionals that participated in the experiment. Therefore, for health professionals we cannot formally assess the representativeness of our experimental sample.

Table 4 examines the balance in patient characteristics across the different treatments. The results show that the treatments are balanced in terms of age, marital status, wealth, and employment status. However, there are some significant differences in gender and education between the peer disclosure treatments (PD and PD-R) and the Complaint Box (CB) and Monetary Penalty (MP) treatments. Given these imbalances, we include covariates as controls in our regressions to account for observable differences across treatments.

### 3.2 Providers

In each eligible surveyed facility, we randomly selected a subsample of health providers to invite to the community workshop. A total of 103 health providers participated in the experiments. Table 5 provides an overview of their characteristics, and a comparison across their sector of employment.[20] As part of the survey, we registered the health providers' work schedules for the following week, and we used these schedules to conduct unannounced visits to their facilities in order to record their presence at work. This information is reported in the last row of Table 5.

About 77% of the sampled health professionals work in the public sector. However, with the exception of age and gender, we do not see significant demographic differences between public and private providers. Public health providers are older and more likely to be women. Moreover, they report a higher number of days absent from work in the previous month, although the difference is not statistically significant ($p$=0.210). Our unannounced visits during the week following the community workshop found more than 40% of sampled health professionals absent from work. We do not find any statistically significant differences in absence rates between public and private sector employees.

Table 6 shows the balance in provider characteristics across treatments. The provider sector of employment, absence, and proportion of clinical officers are all balanced across treatments. Although there are minor imbalances in provider gender and age between the peer disclosure and peer disclosure with retaliation treatments, the overall balance in characteristics suggests that the randomization was successful.

### 3.3 Trust Game Behavior, Choice of Sector and Absence from Work

We designed our game to specifically reproduce some salient features of the relationship between patients and health providers in a controlled setting. However, the well-known downside of using a lab-type experiment is that the findings may not generalize to the context of specific interest. To ameliorate this concern, we examine how provider behavior in the lab is correlated with their actual real-life behavior at work. Specifically, we examine the relationship between provider behavior in the Baseline Trust Game that

[20] We pool together the public sector and the non-profit sector, since only 7% of our experimental participants worked in the non-profit sector.

preceded the reporting game, and i) the sector of employment (private or public), and ii) absence from work during unannounced visits to the health facility of primary employment. This analysis can provide some suggestive evidence that the behavioral insights from the games may be applicable in real life situations. For example, Serra et al., (2012) find that the behavior of medical and nursing students in a modified Trust Game, similar to the one employed here, correlates with the same subjects' actual choice of sector and job location three years after graduation.

Our data show that public sector providers are generally more generous than private providers (as measured by their behavior in the Trust Game). On average providers from public sector facilities return about 144% compared to 100% returned on average by private providers ($p$=0.019). The distributions of provider behavior can be seen in in Figure 1 where the majority of public sector providers return at least as much as patients had sent them; i.e., the average returned-received ratio (R/R) is greater than or equal to 1 for 78% of public sector employees. On the other hand, almost half of the private sector providers return less than what was sent to them; i.e., the returned-received ratio (R/R) is less than 1 for nearly 50% of private providers. It is also noticeable that most public sector providers return on average more than half of the tripled amount sent by matched patients. Estimates from regression analysis[21] confirm that public sector providers return to patients a higher percentage of the amount they receive from patients. These findings are in line with a growing theoretical (Prendergast, 2007; Besley and Ghatak, 2005; Francois (2000) and empirical literature (Banuri and Keefer, 2015; Delfgauuw, J., & Dur, R., 2008; Gregg et al., 2011; Kolstad and Lindkvist, 2012) suggesting that private and public sector employees have different motivations and objective functions, which may lead them to respond differently to the same set of incentives.

Table 7 reports the correlation between provider reciprocity in the Baseline Trust Game and absence from work recorded during an unannounced visit to the provider's facility the week following his or her participation in the community workshop.[22] We focus on various measures of (average) reciprocity, namely the average return-received ratio, the proportion of providers who return at least as much as they are sent on average (average R/R>=1), those who return at least half of the pie on average (average R/R>=1/5) and the proportion of providers who, for each amount sent by a patient, return at least that amount (R/R>=1 always). Across all measures, health workers who are more reciprocal tend to be less absent during our unannounced visits, especially if working in the public sector. Although most of the correlations are not statistically significant, possibly due to the small sample size, we do see a significant negative correlation

[21] Regression tables are not included in the paper but they are available from the authors upon request.
[22] During the workshop we recorded each provider's work schedule for the following week and visited the facility at a time where the provider had stated he or she would be at work. We were able to re-visit the workplace of 94 of the 103 health providers.

between the most demanding measure of reciprocity – always returning at least as much as what was sent, no matter the size of the amount sent – and absence among public providers. The findings that providers who return more money to patients in the game are more likely to be working in the public sector and tend to exert more effort in real life provide some validation to the use of our game to mimic the (service) relationship between patients and providers.

## 4. Treatment Effects

### 4.1 Responsiveness of Providers to Different Reporting Systems

Figure 2.a. compares providers' returned amounts for any possible amount (200, 400, 600, 800) sent by the matched patient. In Figure 2.b., we also compare the distribution of provider behavior across the treatments using three broad categories of generosity: 1) providers that on average give back less than what was sent to them; 2) providers that on average give back at least as much as what was sent by the patient, but less than half of the total (tripled) pie; 3) providers that on average give back more than half of the total pie. Overall, these graphs suggest that both the PD and the MP reporting systems improved provider behavior in the game.

In Table 8 we report the OLS estimates from equation (1) where we exploit the richness of the data generated by the strategy elicitation method. As discussed previously, the strategy method elicits four observations from each provider, one for each corresponding amount (200, 400, 600, 800) possibly received from the matched patient. In columns 1 and 2, we use the Returned-Received (R/R) ratio corresponding to each amount sent by patients as our dependent variable. In columns 3 and 4 we estimate linear probability models where the dependent variable is a dummy equal to 1 if the average returned-received ratio is greater than or equal to 1 – meaning that providers returned at least as much as what the patients sent them – and 0 otherwise. In columns 5 and 6 the dependent variable is a dummy equal to 1 if the provider's average R/R is greater than 1, meaning that the provider returned more than what was sent to him or her. In all specifications, we control for the provider's R/R in the Baseline Trust Game which preceded the Reporting Game, as this measures a provider's baseline reciprocity toward patients in the absence of any accountability system. We also control for the amount of money sent by patients in all our specifications, and the excluded treatment dummy is the Complaint Box (CB) reporting system. We report both parsimonious regression specifications, and specifications with a larger set of controls including a dummy for the sector of employment being private or public, the number of patients that each provider said he or she personally knew, a dummy registering whether the provider knew at least one other provider in the workshop, job title (nurse, clinical officer, etc.), and demographics characteristics, such as gender.

Overall, the estimates show that the Peer Disclosure reporting system significantly increased the amount returned to patients and reduced the likelihood that providers sent back an amount that is lower than what was sent by a patient. Focusing on our preferred specifications in Columns 2, 4, and 6, the coefficients imply that relative to the Complaint Box treatment, the PD and MP systems increased the provider return ratio by 42 percentage points and 33 percent points respectively. This translates to a 40 percent increase for the PD treatment and a 32 percent increase for the MP treatment, relative to the Complaint Box mean. The possibility of provider retaliation reduced the effectiveness (or coefficient size) of the PD system. Relative to the Complaint Box, the PD-R system led to a 26 percentage point increase (or roughly a 25 percent increase relative to the mean) in flows back to the patient. However, formal statistical tests show that we cannot reject the equality of all three treatment coefficients (PD, MP, and PD-R). These results are consistent with our main predictions about the effects of the PD and MP treatments (Hypothesis 1 and 2) outlined in section 2.3.

The regression results in Table 8 also show that private providers returned less money to patients than their public sector counterparts. Given this pattern, and the additional public-private differences discussed Section 3.3, we test for differential responses to our treatments by public or private sector of employment in Table 9. This serves as a test of the predictions outlined in Hypothesis 4 in Section 2.3. Focusing on the interactions between the treatments and the private sector binary indicator, we find that the coefficients are consistently negative, and significant for the interaction between PD and the private sector indicator. In addition, the total private effect treatment effects (treatment + treatment x private) are qualitatively close to zero, and formal statistical tests show they are indistinguishable from zero. Overall, the results suggest that public providers are much more responsive to the accountability interventions relying on social sanctions than their private sector counterparts. These results are consistent with the growing literature showing differential motivations of public and private providers, with the former being more likely to respond to reputational concerns, and the latter more likely to be extrinsically (i.e., financially) motivated.

In Table 10, we explore the treatment effect heterogeneity by providers' reciprocity (R/R) in the Baseline Trust Game which was played before the reporting game. The results show that the interactions between the treatments and providers' baseline reciprocity are consistently negative and generally statistically significant across all three specifications in Table 10. This shows that more(less) generous providers responded less (more) to the treatments. Since more generous public providers tend to have lower rates of absenteeism, this suggests that the treatments may promote more pro-social behavior among low-performing (or unmotivated) workers who tend to be absent from work.[23][24]

### 4.2 Patients' Willingness to Complain

Recall that in the Reporting Game, patients had two decisions to make. First, they had to decide how much money they wanted to send to a randomly matched provider in the other room. Then, using the strategy method they had to decide whether or not to complain for every possible amount they could receive back. If they complained, they could send the provider up to five cards displaying a frowning face, but incurred a fixed cost of 50 KES. Given the ambiguous theoretical predictions of the treatments on complaining behavior outlined in Section 2.3, we examine patient complaining behavior using equations (2) and (3) in section 2.5. The results are show in Tables 11 to 14. In Tables 12 to 14 we show both parsimonious specifications and specifications with a larger set of controls including the patient's age, gender, wealth, education, recognition of a health worker, satisfaction with care they received during exit survey, and the prestige or social status ranking they attach to the medical profession.

On average, patients sent about 254 KES to their matched providers.[25] In Table 11, and Columns 1 and 2 of Table 12, we find that the MP and the PD_R treatments increased both the proportion of patients that sent positive amounts to providers (Table 11), and the propensity to send positive amounts (Table 12). The results also show that the only individual characteristics that significantly predict patients' decisions to send a positive amount to a provider are individual wealth and patients' perceptions of the social status of the healthcare profession (coefficients not shown in table). The latter was measured in the exit survey through a set of vignettes displaying different professions and eliciting patients' opinions about how respected each profession was. For each patient, we registered whether they ranked the profession of "doctor" as a "top" profession.[26] Wealthier individuals and individuals who hold the health profession in high regard are more likely to send a positive, and a larger amount to the matched provider in the game.

Since the decision to file a complaint can only be made if the client sends a positive amount to the matched provider, our analysis of patients' propensities to complain is only relevant for the 164 "trusting" patients

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[23] The coefficients on the interactions between our treatments and actual absenteeism were negative but imprecisely estimated as the absenteeism data was collected on a smaller set of providers due to logistical constraints.

[24] We also explored heterogeneity by the number of other health workers known as this would vary the cost of the PD and PD-R treatments. We did not find any significant interactions of our treatments with knowledge of other workers.

[25] In the Trust Game that preceded the Reporting Game, the average amount sent to providers is 279 KES with no statistically significant difference across treatments.

[26] We employed vignettes for 11 professions and asked patients to "*indicate 1 for the job for whom you have the highest respect, 2 for the job for whom you have the second highest respect, and so on, until 11 (1 to 11).*" We categorize a patient as having high regards for the health profession if he or she ranked the profession of doctor as a 1 or a 2.

who decided to send a positive amount to the matched provider. Figure 3 and the bottom four rows of Table 11 show the percentages of patients sending each possible positive amount (200, 400, 600 or 800) to their matched providers under each reporting system. In columns 3 and 4 of Table 12, we examine the amounts sent to providers by the patients who sent a positive amount. The data show that the amounts sent by patients and the percentages corresponding to each amount are balanced across treatments in the "trusting" sample. Therefore, we can more confidently examine the effects of the treatments on complaining behavior in this sample.

In Table 13, we assess patients' willingness to file complaints under the four different treatment conditions using the specification outlined in equation (3). We exploit our use of the strategy elicitation method to register patients' binary complaining decisions for each amount of money they could receive back from the matched provider, out of what they had sent. In columns 1 and 2 we report estimates from linear probability regressions where the dependent variable is a dummy equal to 1 if the patient complained. The results generally show that the treatments decreased the probability of complaining (or reporting) by 7.4 to 10.3 percentage points. Relative to the Complaint Box, this represents a 25-33% decrease in the probability of complaining (depending on the treatment). The results further show that, as expected, the probability of complaining declines with the amount returned by the matched provider.

In columns 3 and 4 of Table 13 we examine the intensity of the complaining decision by looking at the number of frowning face cards that a patient was willing to send to a provider for any possible amount returned by the provider. Recall that a patient could send up to five cards displaying a frowning face after paying a lump sum cost of 50 KES. The OLS regressions on the number of cards sent in Column 4 show that conditional on complaining, patients in the PD treatment sent almost one more frowning face card, and patients in the MP treatments sent almost four-fifths more cards compared to CB. Relative to the Complaint Box mean, this represents a 33 to 44 percent increase in cards sent, respectively. In contrast, the point estimates of the PD-R treatment are smaller and almost half that of the PD treatment. Although, formal statistical tests on our preferred specifications in Columns 2 and 4 show that we cannot reject the equality of all treatments. Overall, the results show that more clients are reticent to complain when their reports lead to actual consequences for providers. However, conditional on filing reports, the interventions lead to greater intensity of complaints (measured by the number of cards sent). As expected, the potential for retribution by providers mutes the intensity of complaints.

In Table 14, we examine the heterogeneous responses to the treatments by wealth and social connections to the health worker. The results in columns 1 and 2 of Table 14 show that wealthier individuals respond differently to the treatments. Focusing on the coefficients of the interaction between wealth and the treatments, we find that wealthier patients (relative to poorer patients) are more likely to complain if reports lead to monetary penalties (MP) than if it leads to no consequences for the providers. However, we do not see any significant interactions with wealth for the PD or PD_R interventions. We further examine the effects of personal knowledge of the provider on the patients' complaining decisions. Focusing on the interaction terms in Columns 3 and 4 of Table 14 we find that patients who recognized one or more health workers participating in the workshop were significantly less likely to complain under the MP treatment, compared to their fully anonymous (or unconnected) peers. The coefficients on the interactions of provider connection (or recognition) with the PD and PD_R treatments are also both negative but they are not statistically significant.

Our findings show that willingness to file complaints about provider behavior depends on a number of factors. Our estimates suggest that the efficacy of the reporting system can actually *reduce* the probability of reporting. As the consequences of receiving a single unfavorable report increase in severity for providers', the probability of an individual patient filing a report actually decreases (the extensive margin). However, conditional on filing a report, the severity of consequences does increase the intensity of reporting (the intensive margin). Consistent with our previous findings, we find that all the three treatment coefficients on patient complaining behavior are statistically indistinguishable. The heterogeneity results are especially noteworthy, as they suggest that social relationships are important, where patients may be reluctant to file reports that have consequences for providers to whom they are socially connected. This may be due to a fear of retribution outside the lab or unwillingness to take action against an acquaintance, both of which seem to be particularly salient under the MP treatment. Our results suggest that social connections are an important factor in the take up of reporting schemes. This implies that anonymity may be an important feature in the design of citizen reporting systems.

## 5. Conclusions

Participatory accountability and monitoring systems relying on social sanctions have been advocated as a possible solution to bad governance and poor service delivery, especially in countries with limited state capacity. The existing literature provides limited guidance on how to best design participatory monitoring schemes in order to maximize both provider responsiveness and citizen use. Using a lab-in-the-field experiment conducted on a sample of actual health providers and patients randomly sampled from public and private health facilities in Nairobi, we examined the effectiveness of citizen reporting schemes which are coupled with either monetary or social non-monetary penalties for underperformance by health-workers.

Overall, we found that systems that attach (any) tangible consequences to citizen reports increase providers' performance, as measured by the amount of money sent back to patients in a modified Trust Game. In particular, our data show that the threat of social sanctions (in the form of peer shaming) is highly effective in increasing provider performance in the game. In addition, our study generated important insights on patients' willingness to file unfavorable reports against providers when facing what they perceive as sub-par behavior. Although our results show that patients complain less when reports lead to tangible negative consequences for providers, the decrease in reporting is modest. The reductions in the willingness to complain are driven by the existence of personal relationships between patient and providers, where these relationships seem especially salient in reporting systems leading to monetary punishment.

Given the low levels of accountability in public health care systems around the developing world, and the high costs and inefficiencies that come with top-down monitoring and enforcement, our findings suggest that citizen monitoring systems that leverage peer pressure and reputational concerns may be a cost-effective approach to improving service delivery. One possible caveat of our study is that in the experiment patients are able to clearly evaluate provider performance and identify provider misbehavior whereas this may be challenging in the field, especially in contexts of low education. While this is certainly true, there exist forms of misbehavior that are prevalent among service providers in the developing world that can be easily recognized by patients, such as absence from work and bribe requests. Such misbehavior could thus be addressed with the accountability systems examined in this paper. Our findings also suggest that improving the anonymity of the reporting system, as suggested by Chassang and Padro i Miguel (2012), is important, as it could significantly increase citizen participation rates. Such a reporting system may require the reporting to be outsourced and managed by a trustworthy third party, potentially in partnership with the government.

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# Tables

## Table 1

## Characteristics of the Health Facilities

| | Public | | | Private | | | Total | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean or percentage | Min | Max | Mean or percentage | Min | Max | Mean of percentage | Min | Max |
| # full time staff | 13.3 (9.42) | 0 | 33 | 3.7 (2.54) | 0 | 13 | 8.7 (8.49) | 0 | 33 |
| # doctors | 0.1 (0.35) | 0 | 2 | 0.15 (0.36) | 0 | 1 | 0.1 (0.35) | 0 | 2 |
| # clinical officers | 1.9 (1.39) | 0 | 5 | 1.3 (1.04) | 0 | 5 | 1.6 (1.27) | 0 | 5 |
| # nurses | 11.3 (8.20) | 1 | 30 | 2.0 (1.39) | 0 | 8 | 6.9 (7.59) | 0 | 30 |
| # part-time staff | 0.6 (2.08) | 0 | 12 | 1.3 (1.96) | 0 | 8 | 0.9 (2.04) | 0 | 12 |
| # patients per day | 189.8 (161.29) | 6 | 800 | 16.8 (13.35) | 1 | 60 | 104.4 (143.77) | 1 | 800 |
| With a lab | 26% | 0 | 1 | 12% | 0 | 1 | 19% | 0 | 1 |
| With a room for surgeries | 81% | 0 | 1 | 72% | 0 | 1 | 77% | 0 | 1 |
| With overnight space for patients | 81% | 0 | 1 | 42% | 0 | 1 | 63% | 0 | 1 |
| With visible complaint box | 44% | 0 | 1 | 69% | 0 | 1 | 56% | 0 | 1 |
| With exposed list of prices | 40% | 0 | 1 | 90% | 0 | 1 | 84% | 0 | 1 |
| **From Exit Surveys:** | | | | | | | | | |
| Waiting time | 88.9 (44.4) | 6.6 | 183.5 | 19.4 (23.79) | 0 | 105 | 58.3 (50.44) | 0 | 183.5 |
| Cost of visit | 47.3 (77.21) | 0 | 300 | 184.0 (149.36) | 0 | 550 | 120.4 (138.36) | 0 | 550 |
| Avg. satisfaction with health worker | 4.38 (0.34) | 3.65 | 4.97 | 4.75 (0.26) | 4.12 | 5 | 4.54 (0.35) | 3.65 | 5 |
| Avg. Satisfaction with care | 4.25 (0.35) | 3.47 | 4.96 | 4.65 (0.49) | 3 | 5 | 4.43 | 3 | 5 |
| Patients' years of schooling | 9.8 (0.93) | 7.7 | 12.2 | 11.3 (1.47) | 7.7 | 14 | 10.5 (1.39) | 7.67 | 14.0 |
| Patient wealth (asset index) | -0.3 (0.39) | -1.1 | 0.5 | 0.6 (0.62) | -0.9 | 1.7 | 0.1 (0.67) | -1.1 | 1.7 |

Note: Facility characteristics, in the upper panel of the table, were registered through facility-level survey. The variables in the bottom panel are generated by surveying patients when exiting the facilities. The asset index that we use as a proxy for patients' wealth was constructed by conducting factor analysis over six household assets: ownership of a TV, a refrigerator, a car, a bank account, good source of fuel, good materials used for house outer walls.

**Table 2**

**Treatments and Sessions**

| | Sessions | Health Professionals | Patients |
|---|---|---|---|
| **Treatment** | | | |
| Complaint Box (CB) | 5 | 24 | 50 |
| Peer Disclosure (PD) | 7 | 26 | 58 |
| Peer Disclosure with Retaliation (PD-R) | 6 | 27 | 56 |
| Monetary Penalties (MP) | 6 | 26 | 52 |
| **Total** | 24 | 103 | 216 |

Note: Each participant (health professional or patient) participated only in one treatment.

## Table 3
### Patient Characteristics: Full Sample vs. Experimental Sample

| | Full Sample | Experimental Participants | P-value |
|---|---|---|---|
| Age | 30.44 (0.24) | 31.14 (0.99) | 0.34 |
| Male | 18% | 23% | 0.08* |
| Yrs. of Education | 10.30 (3.23) | 10.38 (3.44) | 0.69 |
| Wealth (Asset index) | 0.01 (0.02) | -0.06 (0.07) | 0.32 |
| Married | 84% | 80% | 0.14 |
| works for a wage | 24% | 22% | 0.52 |

Note: Standard deviation in parentheses. P-values are generated from two-sided tests of equality of means across samples.

## Table 4
### Patients' Balancing Tests

| | Age | Female (%) | Years of Schooling | Asset Index | Single (%) | Works for a wage (%) |
|---|---|---|---|---|---|---|
| **Complaint Box (CB)** | 30.490 | 0.920 | 9.100 | -0.130 | 0.120 | 0.220 |
| **Peer Disclosure (PD)** | 30.240 | 0.700 | 11.680 | 0.070 | 0.250 | 0.280 |
| **Peer Disclosure with Retaliation (PD-R)** | 31.060 | 0.680 | 11.060 | 0.005 | 0.230 | 0.210 |
| **Monetary Penalty (MP)** | 30.100 | 0.810 | 9.400 | -0.240 | 0.190 | 0.170 |
| P-value (CB=PD) | 0.862 | 0.005*** | 0.003*** | 0.296 | 0.106 | 0.508 |
| P-value (CB=PD-R) | 0.699 | 0.003*** | 0.005*** | 0.477 | 0.169 | 0.835 |
| P-value (CB=MP) | 0.816 | 0.126 | 0.692 | 0.572 | 0.352 | 0.473 |
| P-value (MP=PD) | 0.935 | 0.190 | 0.00*** | 0.134 | 0.508 | 0.166 |
| P-value (PD=PD_R) | 0.595 | 0.126 | 0.0265 | 0.745 | 0.813 | 0.373 |

Note: We report p-values from two-sided t-tests for continuous variables and Chi-square tests for dichotomous variables. Standard deviations in parentheses.

## Table 5
### Characteristics of Health Providers

| | Full Sample | Public Facility | Private Facility | p-value |
|---|---|---|---|---|
| *Mean or percentage* | N=103 | N=77 | N=26 | |
| Work in Health Center (vs Dispensary) | 86% | 84% | 92% | 0.310 |
| Clinical Officer (vs. Nurse) | 25% | 23% | 31% | 0.453 |
| Female | 61% | 66% | 46% | 0.069* |
| Age | 36 (10.03) | 39 (9.78) | 28 (5.43) | 0.000*** |
| Joined health profession to “help the poor” | 24% | 26% | 19% | 0.488 |
| % absent at least 1 day in previous month *(self-reported)* | 28% | 30% | 20% | 0.320 |
| % absent during second visit to the facility | 44% | 45% | 40% | 0.670 |

Note: We report p-values from two-sided t-tests for continuous variables and Chi-square tests for dichotomous variables. Standard deviations in parentheses.

## Table 6
### Health Providers’ Balancing Tests

| | Age | Female (%) | Clinical Officer (%) | Private sector (%) | Absent during second visit (%) |
|---|---|---|---|---|---|
| **Complaint Box (CB)** | 38.875 | 0.583 | 0.250 | 0.25 | 0.421 |
| **Peer Disclosure (PD)** | 33.269 | 0.461 | 0.308 | 0.308 | 0.458 |
| **Peer Disclosure with Retaliation (PD-R)** | 37.889 | 0.778 | 0.259 | 0.185 | 0.370 |
| **Monetary Penalty (MP)** | 35.538 | 0.615 | 0.192 | 0.269 | 0.500 |
| P-value (CB=PD) | 0.053* | 0.389 | 0.650 | 0.650 | 0.807 |
| P-value (CB=PD-R) | 0.759 | 0.135 | 0.940 | 0.574 | 0.729 |
| P-value (CB=MP) | 0.292 | 0.817 | 0.623 | 0.877 | 0.606 |
| P-value (MP=PD) | 0.337 | 0.266 | 0.337 | 0.760 | 0.773 |
| P-value (PD=PD_R) | 0.066* | 0.018** | 0.696 | 0.300 | 0.524 |

Note: We report p-values from two-sided t-tests for continuous variables and Chi-square tests for dichotomous variables. Standard deviations in parentheses.

**Table 7**

**Behavior in the Baseline Trust Game and Absence from Work**

| | **Avg. R/R** | | **% providers with avg. R/R>=1** | | **% providers with avg. R/R>=1.5** | | **% providers with R/R>=1 always** | |
|---|---|---|---|---|---|---|---|---|
| | Public Only | Full sample | Public Only | Full sample | Public Only | Full Sample | Public Only | Full Sample |
| **Present at second visit** | 1.50 (0.81) | 1.35 (0.81) | 84% | 72% | 58% | 49% | 61%** | 59% |
| **Absent at second visit** | 1.41 (0.76) | 1.32 (0.79) | 74% | 73% | 45% | 39% | 38% | 41% |

Note: Standard deviation in parenthesis. Asterisks indicate a significance difference between providers that were absent from work and those that were found at work. *** p<0.01, ** p<0.05, * p<0.1. R/R is the Returned/Received ratio, which measures the proportion of money providers send back to clients relative to the amount initially sent by clients. This can range from 0 to 3.

**Table 8**
**Providers' responsiveness to different reporting systems (Strategy)**

| | Returned/ Received Ratio (R/R) | | Returned/ Received Ratio (R/R) >= 1 | | Returned/ Received Ratio (R/R) >1 | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Peer Disclosure (PD) | 0.390*** | 0.421** | 0.164** | 0.144* | 0.187* | 0.157 |
| | (0.137) | (0.169) | (0.074) | (0.084) | (0.102) | (0.105) |
| | [0.048] | [0.056] | [0.082] | [0.178] | [0.164] | [0.226] |
| PD with Retaliation (PD-R) | 0.220*** | 0.256** | 0.090 | 0.129** | 0.083 | 0.107 |
| | (0.073) | (0.105) | (0.053) | (0.059) | (0.057) | (0.067) |
| | [0.018] | [0.068] | [0.176] | [0.122] | [0.182] | [0.174] |
| Monetary Penalty (MP) | 0.291** | 0.326** | 0.128 | 0.178** | 0.075 | 0.118 |
| | (0.116) | (0.123) | (0.078) | (0.071) | (0.084) | (0.091) |
| | [0.058] | [0.036] | [0.158] | [0.050] | [0.386] | [0.318] |
| Private | ` | -0.307** | | -0.095 | | -0.209* |
| | | (0.141) | | (0.085) | | (0.103) |
| | | 0.074 | | [0.36] | | [0.102] |
| Constant | 0.364*** | 0.424 | 0.409*** | 0.345** | 0.044 | 0.112 |
| | (0.090) | (0.317) | (0.068) | (0.144) | (0.046) | (0.227) |
| | [0.000] | [0.274] | [0.000] | [0.058] | [0.366] | [0.644] |
| Basic Controls | Y | Y | Y | Y | Y | Y |
| Additional Controls | N | Y | N | Y | N | Y |
| Observations | 412 | 412 | 412 | 412 | 412 | 412 |
| R-Squared | 0.479 | 0.510 | 0.288 | 0.324 | 0.294 | 0.334 |
| Mean of Control Group (CB) | 1.039 | 1.039 | 0.625 | 0.625 | 0.448 | 0.448 |
| P-Values for Test of Equality of Coefficients | | | | | | |
| PD=MP | 0.582 | 0.630 | 0.658 | 0.685 | 0.382 | 0.747 |
| PD=PD-R | 0.223 | 0.295 | 0.197 | 0.792 | 0.311 | 0.608 |
| PD-R=MP | 0.596 | 0.630 | 0.547 | 0.428 | 0.926 | 0.911 |

Notes: Clustered standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Wild bootstrap p-values reported in square brackets. The Complaint Box (CB) treatment is the omitted category. Returned/Received ratio measures the proportion of money providers send back to clients relative to the amount initially sent by clients. This can range from 0 to 3. Columns 1 and 2 use the continuous variable, while Columns 3 to 6 use binary variables. Basic Controls include dummies for the amount received from clients and the percent returned in the Baseline Trust Game. Additional controls include age, gender, private sector, health worker job title (a clinical officer vs nurse), how many patients the provider knows, and a dummy for knowing at least one other health provider.

**Table 9**
**Treatment Effects by Sector of Employment**

| | Returned/ Received Ratio (R/R) | Returned/ Received Ratio (R/R) >= 1 | Returned/ Received Ratio (R/R) >1 |
|---|---|---|---|
| | (1) | (2) | (3) |
| Peer Disclosure (PD) | 0.617*** | 0.225** | 0.300*** |
| | (0.173) | (0.088) | (0.094) |
| | [0.002] | [0.048] | [0.020] |
| PD with Retaliation (PD-R) | 0.309** | 0.168** | 0.115 |
| | (0.139) | (0.070) | (0.090) |
| | [0.070] | [0.048] | [0.272] |
| Monetary Penalty (MP) | 0.403*** | 0.231*** | 0.130 |
| | (0.107) | (0.057) | (0.095) |
| | [0.014] | [0.000] | [0.298] |
| private | -0.000 | 0.074 | -0.068 |
| | ` | (0.105) | (0.088) |
| | [1.000] | [0.492] | [0.458] |
| Private x PD | -0.632*** | -0.260* | -0.465*** |
| | (0.185) | (0.133) | (0.101) |
| | [0.004] | [0.092] | [0.006] |
| Private x PD-R | -0.128 | -0.140 | 0.060 |
| | (0.415) | (0.227) | (0.269) |
| | [0.746] | [0.652] | [0.728] |
| Private x MP | -0.314 | -0.219 | -0.043 |
| | (0.219) | (0.209) | (0.109) |
| | [0.254] | [0.420] | [0.688] |
| Constant | 0.334 | 0.301** | 0.061 |
| | (0.299) | (0.126) | (0.221) |
| | [0.344] | [0.034] | [0.820] |
| Basic Controls | Y | Y | Y |
| Additional Controls | Y | Y | Y |
| Observations | 412 | 412 | 412 |
| R-squared | 0.526 | 0.333 | 0.368 |
| Mean of Control Group (CB) | 1.039 | 0.625 | 0.448 |
| P-Values for Test of Equality of Coefficients | | | |
| PD=MP | 0.292 | 0.942 | 0.140 |
| PD=PD-R | 0.114 | 0.456 | 0.0881 |
| PD-R=MP | 0.589 | 0.317 | 0.902 |
| P-Values for Test of Sum of Coefficients | | | |
| PD+ Private* PD=0 | 0.925 | 0.750 | 0.0907 |
| PD-R+ Private* PD-R=0 | 0.571 | 0.880 | 0.405 |
| MP+ Private* MP=0 | 0.710 | 0.952 | 0.458 |

Notes: Clustered standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Wild bootstrap p-values reported in square brackets. The Complaint Box (CB) treatment is the omitted category Returned/Received ratio measures the proportion of money providers send back to clients relative to the amount initially sent by clients. This can range from 0 to 3. Columns 1 and 2 use the continuous variable, while Columns 3 to 6 use binary variables. Basic Controls include dummies for the amount received from clients and the percent returned in the Baseline Trust Game. Additional controls include age, gender, private sector, health worker job title (a clinical officer vs nurse), how many patients the provider knows, and a dummy for knowing at least one other health provider.

**Table 10**
**Heterogeneity by Provider Reciprocity in the Baseline Trust Game**

| | Returned/ Received Ratio (R/R) | Returned/ Received Ratio (R/R) >= 1 | Returned/ Received Ratio (R/R) >1 |
|---|---|---|---|
| | (1) | (2) | (3) |
| Peer Disclosure (PD) | 0.812* | 0.371* | 0.413 |
| | (0.449) | (0.214) | (0.243) |
| | 0.168 | 0.222 | 0.272 |
| PD with Retaliation (PD-R) | 0.270 | 0.341*** | 0.319** |
| | (0.298) | (0.068) | (0.126) |
| | 0.564 | 0.002 | 0.064 |
| Monetary Penalty (MP) | 0.614*** | 0.395*** | 0.266* |
| | (0.130) | (0.116) | (0.136) |
| | 0.000 | 0.006 | 0.156 |
| Private | -0.313** | -0.103 | -0.210* |
| | ` | (0.086) | (0.105) |
| | 0.058 | 0.344 | 0.088 |
| Baseline Reciprocity | 0.880*** | 0.382*** | 0.454*** |
| | (0.103) | (0.063) | (0.082) |
| | 0.000 | 0.000 | 0.000 |
| PD X Baseline Reciprocity | -0.352 | -0.205* | -0.224* |
| | (0.239) | (0.109) | (0.129) |
| | 0.234 | 0.218 | 0.250 |
| PD-R X Baseline Reciprocity | -0.096 | -0.193*** | -0.194** |
| | (0.172) | (0.038) | (0.080) |
| | 0.670 | 0.002 | 0.080 |
| MP X Baseline Reciprocity | -0.269*** | -0.197*** | -0.136 |
| | (0.086) | (0.064) | (0.095) |
| | 0.022 | 0.018 | 0.286 |
| Constant | 0.264 | 0.189 | -0.034 |
| | (0.251) | (0.124) | (0.195) |
| | 0.398 | 0.202 | 0.850 |
| Additional Controls | Y | Y | Y |
| Observations | 412 | 412 | 412 |
| R-squared | 0.587 | 0.370 | 0.385 |
| Mean of Control Group (CB) | 1.039 | 0.625 | 0.448 |
| P-Values for Test of Equality of Coefficients | | | |
| PD=MP | 0.664 | 0.919 | 0.586 |
| PD=PD-R | 0.299 | 0.890 | 0.726 |
| PD-R=MP | 0.273 | 0.677 | 0.758 |
| P-Values for Test of Sum of Coefficients | | | |
| PD+ PD*Baseline Reciprocity = 0 | 0.0548 | 0.171 | 0.173 |
| PD-R+ PD-R* Baseline Reciprocity = 0 | 0.237 | 0.0233 | 0.0767 |
| MP+ MP* Baseline Reciprocity = 0 | 0.00254 | 0.00977 | 0.112 |

Notes: Clustered standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Wild bootstrap p-values reported in square brackets. The Complaint Box (CB) treatment is the omitted category. Returned/Received ratio measures the proportion of money providers send back to clients relative to the amount initially sent by clients. This can range from 0 to 3. Columns 1 and 2 use the continuous variable, while Columns 3 to 6 use binary variables. Baseline Reciprocity is the R/R ratio in the Baseline Trust Game played before the Reporting Game. Controls include dummies for the amount received from clients, the percent returned in Baseline Trust Game, age, gender, private sector, health worker job title (a clinical officer vs nurse), how many patients the provider knows, and a dummy for knowing at least one other health provider.

**Table 11**
**Amounts sent by patients in the Reporting Game**

| | Complaint Box (CB) | Monetary Penalty (MP) | Peer Disclosure (PD) | Peer Disclosure with Retaliation (PD-R) |
|---|---|---|---|---|
| % sending a positive amount | 64% | 83%** | 67% | 89%*** |
| Trusting patient sample | | | | |
| % sending 200 | 50% | 44% | 54% | 50% |
| % sending 400 | 38% | 33% | 28% | 44% |
| % sending 600 | 13% | 19% | 15% | 6% |
| % sending 800 | 0% | 5% | 3% | 0% |

Note: The asterisks refer to p-values generated by pair-wise Chi-square test where CB is the comparison treatment.
*** p<0.01, ** p<0.05, * p<0.1

## Table 12
## Patients' Trusting Decisions in the Reporting Game

| | Sent Positive Amount to Provider (OLS) Full Sample | | Amount Sent to Provider (OLS) (Conditional on Sending >0) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Peer Disclosure (PD) | 0.032 | 0.000 | 8.333 | 20.753 |
| | (0.057) | (0.082) | (42.684) | (43.845) |
| | [0.620] | [0.970] | [0.808] | [0.704] |
| PD with Retaliation (PD-R) | 0.253*** | 0.231*** | -13.000 | -3.330 |
| | (0.055) | (0.074) | (40.796) | (41.323) |
| | [0.000] | [0.002] | [0.752] | [0.952] |
| Monetary Penalty (MP) | 0.187*** | 0.172** | 42.442 | 60.674 |
| | (0.063) | (0.072) | (39.832) | (38.704) |
| | [0.016] | [0.042] | [0.376] | [0.186] |
| Constant | ` | 0.587*** | 325.000*** | 182.285* |
| | (0.037) | (0.205) | (37.987) | (94.837) |
| | [0.000] | [0.008] | [0.000] | [0.080] |
| Additional Controls | N | Y | N | Y |
| Observations | 216 | 204 | 164 | 154 |
| R-squared | 0.060 | 0.107 | 0.019 | 0.081 |
| Mean of Control Group (CB) | 0.64 | 0.653 | 325 | 325 |
| P-Values for Test of Equality of Coefficients | | | | |
| PD=MP | 0.0310 | 0.0218 | 0.149 | 0.124 |
| PD=PD-R | 0.00127 | 0.000581 | 0.393 | 0.315 |
| PD-R = MP | 0.325 | 0.368 | 0.00803 | 0.00616 |

Notes: Clustered standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Wild boostrap p-values reported in square brackets. The Complaint Box (CB) treatment is the omitted category. Sent Positive Amount is a binary variable that is equal to one if patients sent any money to providers. Amount sent is conditional on sending a positive amount. This can range from 0 to 800. Additional controls include age, gender, wealth, education, whether the patient recognizes at least one health worker, satisfaction with the care they received, and the patient's social status ranking of doctors.

## Table 13
## Willingness to Complain and Intensity of Complaints

| | Complain | | Number of Cards Sent | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Peer Disclosure (PD) | -0.098** | -0.101** | 1.066*** | 1.053** |
| | (0.039) | (0.038) | (0.356) | (0.389) |
| | [0.044] | [0.032] | [0.040] | [0.052] |
| PD with Retaliation (PD-R) | -0.103*** | -0.078* | 0.190 | 0.563** |
| | (0.029) | (0.039) | (0.207) | (0.262) |
| | [0.006] | [0.098] | [0.396] | [0.054] |
| Monetary Penalty (MP) | -0.074** | -0.088* | 0.623** | 0.771** |
| | (0.032) | (0.045) | (0.282) | (0.315) |
| | [0.058] | [0.122] | [0.042] | [0.020] |
| Constant | 0.044 | 0.242** | 0.927* | 1.102 |
| | ` | (0.113) | (0.525) | (0.904) |
| | [0.126] | [0.064] | [0.104] | [0.214] |
| Basic Controls | Y | Y | Y | Y |
| Additional Controls | N | Y | N | Y |
| Observations | 931 | 879 | 203 | 194 |
| R-squared | 0.400 | 0.429 | 0.153 | 0.171 |
| Mean of Control Group (CB) | 0.293 | 0.293 | 2.436 | 2.436 |
| P-Values for Test of Equality of Coefficients | | | | |
| PD=MP | 0.575 | 0.751 | 0.289 | 0.472 |
| PD=PD-R | 0.893 | 0.586 | 0.0333 | 0.212 |
| PD-R = MP | 0.393 | 0.840 | 0.144 | 0.552 |

Notes: Clustered standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Wild boostrap p-values reported in square brackets. The Complaint Box (CB) treatment is the omitted category. Complain is a binary variable that is equal to one if patients sent at least one frowning face card to a provider. Number of Cards sent measures the number of frowning face (complaint) cards sent to providers. This is conditional on complaining. Basic controls include broad controls for amount sent to providers and the amount received back. Additional controls include age, gender, wealth, education, whether the patient recognizes at least one health worker, satisfaction with the care they received, and the patient's social status ranking of doctors.

## Table 14
## Treatment effects by wealth and knowledge of provider

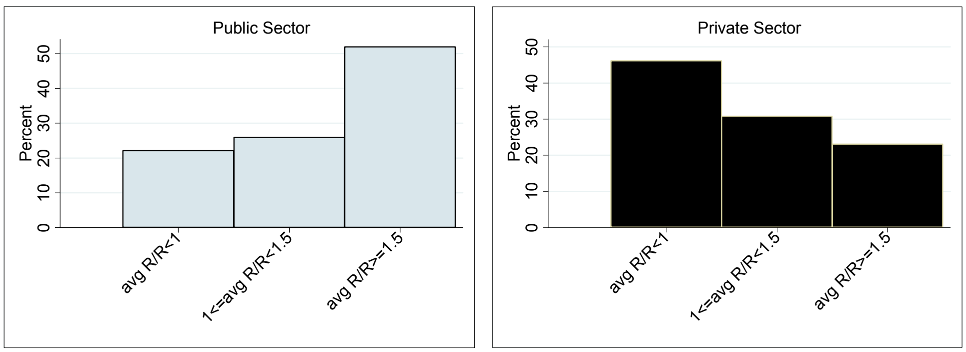
| | Complain | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Peer Disclosure (PD) | -0.084** | -0.096** | -0.047 | -0.061 |
| | (0.037) | (0.038) | (0.064) | (0.046) |
| | [0.031] | [0.018] | [0.465] | [0.198] |
| PD with Retaliation (PD-R) | -0.082** | -0.082** | -0.103** | -0.062* |
| | (0.033) | (0.036) | (0.049) | (0.036) |
| | [0.021] | [0.034] | [0.045] | [0.099] |
| Monetary Penalty (MP) | -0.067* | -0.073 | -0.028 | -0.038 |
| | (0.038) | (0.045) | (0.046) | (0.046) |
| | [0.093] | [0.120] | [0.539] | [0.422] |
| Covariate X PD | ` | -0.016 | -0.107 | -0.080 |
| | (0.030) | (0.024) | (0.120) | (0.099) |
| | [0.317] | [0.503] | [0.382] | [0.427] |
| Covariate X PD-R | 0.001 | 0.007 | -0.002 | -0.033 |
| | (0.043) | (0.036) | (0.086) | (0.060) |
| | [0.975] | [0.841] | [0.984] | [0.590] |
| Covariate X MP | 0.076** | 0.073** | -0.116 | -0.121** |
| | (0.036) | (0.035) | (0.088) | (0.058) |
| | [0.045] | [0.046] | [0.200] | [0.048] |
| Wealth | -0.039* | -0.056** | | -0.039* |
| | (0.022) | (0.026) | | (0.019) |
| | [0.099] | [0.040] | | [0.050] |
| Know Health Worker | | -0.018 | 0.051 | 0.030 |
| | | (0.031) | (0.074) | (0.043) |
| | | [0.563] | [0.496] | [0.502] |
| Constant | 0.034 | 0.202* | 0.023 | 0.200* |
| | (0.027) | (0.110) | (0.037) | (0.111) |
| | [0.224] | [0.080] | [0.539] | [0.086] |
| Interacted Covariate | Wealth | Wealth | Know Health Worker | Know Health worker |
| Basic Controls | Y | Y | Y | Y |
| Additional Controls | N | Y | N | Y |
| Observations | 887 | 879 | 931 | 879 |
| R-squared | 0.414 | 0.435 | 0.404 | 0.431 |
| Mean of Control Group (CB) | 0.293 | 0.293 | 0.293 | 0.293 |
| P-Values for Test of Equality of Coefficients | | | | |
| PD=MP | 0.705 | 0.601 | 0.790 | 0.715 |
| PD=PD-R | 0.966 | 0.732 | 0.394 | 0.975 |
| PD-R=MP | 0.740 | 0.865 | 0.135 | 0.691 |
| P-Values for Test of Sum of Coefficients | | | | |
| PD+ PD x Covariate = 0 | 0.0199 | 0.00522 | 0.0544 | 0.0761 |
| PD-R+ PD-R x Covariate = 0 | 0.265 | 0.247 | 0.0660 | 0.115 |
| MP+ MP x Covariate = 0 | 0.894 | 0.999 | 0.0330 | 0.0133 |

Notes: Clustered standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Wild boostrap p-values reported in square brackets. The Complaint Box (CB) treatment is the omitted category. Complain is a binary variable that is equal to one if patients sent at least one frowning face card to a provider. Basic controls include broad controls for amount sent to providers and the amount received back. Additional controls include age, gender, wealth, education, whether the patient recognizes at least one health worker, satisfaction with the care they received, and the patient's social status ranking of doctors.

# Figures

**Figure 1**

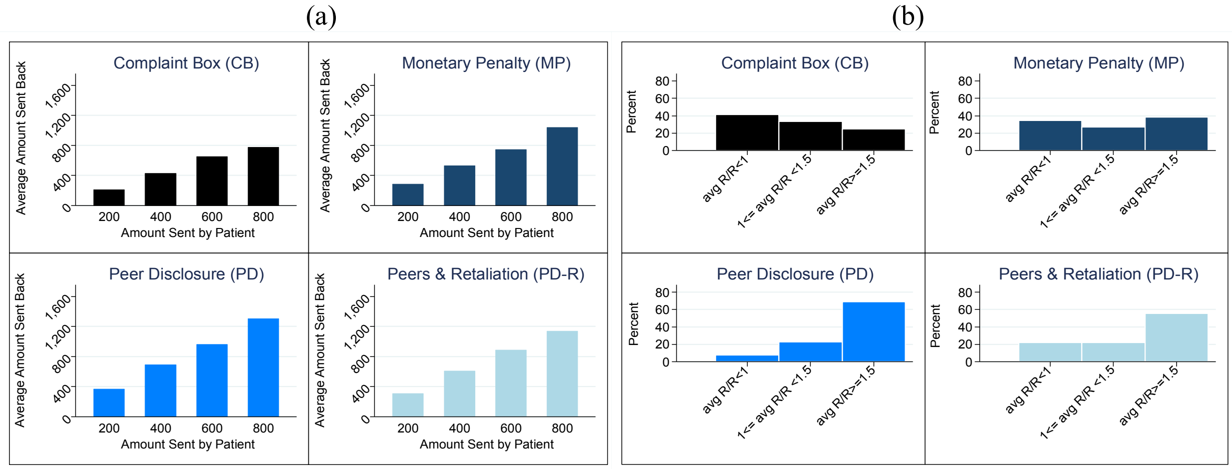
**Providers' behavior in the Baseline Trust Game by sector of employment**




Note: The figure shows the percentages of public sector and private sector providers whose average returned-received ratios are lower than 1, between 1 and 1.5, and equal to or greater than 1.5.

**Figure 2**

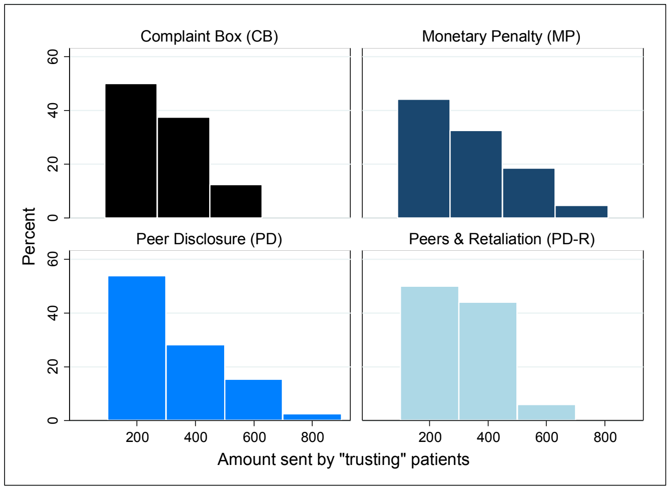
**Amount returned by providers across treatments**




Note: (a) shows the average amounts sent back by providers when receiving 200, 400, 600 and 800 from the matched patients. (b) shows the percentages of providers whose average returned-received ratios are lower than 1, between 1 and 1.5, and equal to or greater than 1.5

**Figure 3**

**Amount sent to providers by “trusting” patients**



# Appendix

**Figure A1**

**Timing and structure of data collection**