# The Political Economy of Public Sector Absence: Experimental Evidence from Pakistan*

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September 9, 2014

**Abstract**

In many developing countries, public sector absence is both common and resistant to reform. One explanation is that politicians preferentially provide public jobs with limited work requirements as patronage. We test this patronage hypothesis in Pakistan using: (i) a randomized evaluation of a novel smartphone absence monitoring technology; (ii) data on election outcomes in the 240 constituencies where the experiment took place; (iii) attendance recorded during unannounced visits; (iv) surveys of connections between politicians and health staff; and (v) a survey of the universe of health supervisors. Four sets of results are consistent with this view. First, 36 percent of health officers report interference by a politician in the previous year when sanctioning an employee and report this twice as often in uncompetitive constituencies. Second, doctors are 21 percentage points less likely to be present if they know their politician, 32 percentage points less likely to be present if they work in an uncompetitive constituency, and are only at work during 10 percent of normal reporting hours if both conditions are true. Third, the effect of the smartphone monitoring technology, which almost doubled inspection rates, is highly localized to competitive constituencies and to monitored employees who do not know their politician. Last, we find evidence that program impact is in part due to the transmission of information to senior officers. We test this by manipulating the salience of staff absence in data presented to senior officials using an online dashboard. Highlighting absence leads to larger subsequent improvements in attendance for facilities located in a competitive constituencies.

Keywords: Clientelism, Information Communication Technology, Corruption
JEL Codes: D72, D73

* *Authors' Note*: We thank Farasat Iqbal for championing and implementing the project and, Asim Fayaz, and Zubair Bhatti for designing the smartphone monitoring program. Support is generously provided by the International Growth Centre (IGC) political economy program and the IGC Pakistan Country Office. We thank Erlend Berg, Eli Berman, Leonardo Bursztyn, Ali Cheema, Ruben Enikolopov, Naved Hamid, Gordon Hanson, Asim Ijaz Khwaja, Craig McIntosh, Ijaz Nabi, Aprajit Mahajan, Monica Martinez-Bravo, Gerard Padro-i-Miquel, Karthik Muralidharan, Jacob N. Shapiro, Christopher Woodruff, Oliver Vanden Eynde, Ekaterina Zhuravskaya and various seminar participants for insightful comments. Excellent research assistance was provided by Muhammad Zia Mehmood, Haseeb Ali, and Arman Rezaee. We thank Ali Cheema and Farooq Naseer for kindly sharing their data on election outcomes.

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# 1 Introduction

In clientelistic political systems, politicians win office by providing targeted benefits to supporters at the cost of services which provide broader collective benefits, with negative implications for political stability, economic, and human development.[1] Government jobs are commonly used for patronage. In developing countries, government employees are also frequently absent despite being generally well-compensated.[2] Moreover, public sector absence also tends resist reform. Many policies aimed at improving attendance only work temporarily. We investigate whether the persistence of public sector absence in developing countries is linked to the use of public jobs as patronage.

Governments jobs are ideal for patronage; they can be targeted to individuals, provide a credible stream of benefits, and are reversible (Robinson and Verdier 2002). This is particularly true if politicians can minimize the actual work required in the position. Historically, jobs have been used as patronage in many settings. Chubb (1983) argues that, under the control of the Christian Democrats in Naples and Palermo during the 1950s, politicians allocated public sector jobs "on the basis of political favoritism, often having nothing to do with effective work loads or even with the actual presence of the employee in his office." Sorauf (1956) describes a similar system for road workers in Centre County, Pennsylvania and Johnston (1979) for unskilled public sector jobs in New Haven, Connecticut. Wilson (1961) describes the centrality of public jobs in maintaining the Tammany Hall political machine in New York and the Democratic Party machine in Chicago in the early 20th century. In all three settings, the beneficiaries commonly rewarded politicians with votes, party campaign

[1] Bates (1981) provides the authoritative account relating to Africa's development, arguing that African governments deliberately overvalued their exchange rates in order to subsidize politically powerful urban elites with cheaper imports at the expense of the rural poor. Khwaja and Mian (2005) and Fisman (2001) provide evidence that politicians provide preferential government benefits to firms and Dube et al. (2011) find patterns in stock returns consistent with the U.S. government providing insider information to investors about future international interventions. Dahlberg and Johansson (2002) show that the Swedish central government allocated discretionary government grants for ecologically sustainable development based primarily on the number of swing voters.

[2] We find that 68.5 percent of doctors are absent prior to our intervention. This compares with the average across Bangladesh, Ecuador, India, Indonesia, Peru and Uganda of 35 percent reported in Chaudhury et al. (2006).

work, monetary contributions, and by swinging blocs of voters.[3]

The development literature identifies public worker absence as key obstacle to delivering services to the poor (Banerjee and Duflo 2006; Chaudhury et al. 2006). With the notable exception of a camera monitoring initiative in Udaipur, Rajasthan reported in Duflo et al. (2012), absence appears unresponsive to increasing inspections, particularly when inspectors are not assisted by technologies that limit their discretion. Banerjee and Duflo (2006) review unsuccessful monitoring initiatives in Kenya and India, and Banerjee et al. (2008) details the complicity of the local health administration in the failure of a monitoring initiative in rural Rajasthan. These findings support the broader position that the effects of anti-corruption initiatives tend to attenuate over time (Olken and Pande 2012).[4]

We pursue five lines of analysis to investigate the links between clientelism and public sector absence. First, we interview nearly all of the most senior district level health officials (Executive District Officers) and monitors (Deputy District Officers) posted at the time of our study.[5] We directly inquire about how common it is for politicians and other powerful actors to interfere with the sanctioning of subordinate staff. Second, we combine data on parliamentary election outcomes with independently collected data on doctor absence. Third, we examine whether doctors political connections to politicians are related to their job performance and to the desirability of their posting. Fourth, we experimentally evaluate a novel smartphone attendance monitoring program across 240 of the 297 (81 percent) of the Provincial Assembly constituencies in Punjab, examining whether impact depends on the degree of local political competition.[6] Last, we manipulate the salience of health staff

[3]Sorauf (1956) shows that the road crew organizers were more politically active than their subordinates, arguing that the strongest supporters should be placed in jobs where they have the most influence.

[4]These studies propose several solutions. Banerjee et al. (2008) encourage increasing senior level ownership and improving incentives for senior managers to make sure their subordinates are present. Chaudhury et al. (2006) explore the possibility of local monitoring, acknowledging that decentralized management systems may be more prone to local capture.

[5]In total we interviewed, 34 of 36 possible EDOs. EDO Kasur district was not interviewed as Kasur district is not part of the experimental sample, while EDO Faisalabad was not available for interview. We interview all of the 116 posted Deputy District Officers in Punjab.

[6]There are 371 seats in the Punjab Provincial Assembly. Of these, 66 are reserved for women and eight are reserved for non-muslims, leaving 297 elected seats.

absence in on-line data visualizations presented to senior officials on an internet dashboard and check if the response of politicians to these data depends on the outcomes of elections.

This investigation yields four main sets of results which link health service provision to local political outcomes. First, 39 percent of Executive District Officers and Deputy District Officers report a politician interfering in their decision to sanction an underperforming employee in the previous year. Officers report an average of 2.79 instances of interference; in the least competitive tercile of constituencies officers report an average of 4.11.[7] Second, doctors are 21 percentage points less likely to be present if they know their politician, 32 percentage points less likely to be present if they work in an uncompetitive constituency, and are only at work during 10 percent of normal reporting hours if both conditions are true. Third, while the smartphone monitoring program almost doubled health worker attendance, the effects of the program are highly localized to competitive districts. Last, we directly examine whether impacts on doctor attendance result in part from the smartphone system channeling information to senior health officials. We do this by selecting an arbitrary threshold at which facilities are flagged as underperforming on an online dashboard visible to senior officials. Flagging a facility reduces subsequent doctor absence by about 25 percentage points. These effects are highly localized to competitive constituencies. Placebo tests of alternative arbitrary thresholds support the causal interpretation of these findings.

We point to three central implications. First, our data link the finding in development economics that absence is both severe and difficult to address to the observation in political science that public jobs represent a core means of patronage. Second, remedying the problem of absence faces the challenge of well-protected government jobs being an attractive means of patronage, both for politicians and constituents. This suggests that lasting improvements to health worker attendance may require strictly limiting the ability of elected politicians to interfere in the allocation of public sector jobs. Additionally, policies which reduce politicians reliance on patronage may address the problem of absence. Last, using Information Com-

[7] See Table 2 for details on these results. We measure competitiveness of each provincial assembly constituency using a Herfindahl index computed as $\sum_i s_i^2$ where $s_i$ is the vote share of party $i$.

munication Technology for monitoring applications is a promising avenue for policy. Our smartphone monitoring system, which required only 90 smart phones to implement, more than doubled health inspections in half of a province with a population the size of Germany. This suggests promise for Information Communications Technology as a means of improving the monitoring of public service delivery.

The paper proceeds as follows: Section 2 provides institutional details of the public health sector and describes the smartphone monitoring technology. Section 3 describes the experimental evaluation. Section 4 reviews the primary data on absence. Section 5 presents our non-experimental analysis of election outcomes and doctor absence. Section 6 provides results from the experiment and Section 7 concludes.

# 2 Background

## 2.1 The Public Health System

In Punjab province, the provision of health care services is managed by the Department of Health, which is based at the provincial headquarters in Lahore. There are five major types of facilities: (1) Basic Health Unit (BHU); (2) Rural Health Center (RHC); (3) Tehsil Headquarter Hospital[8] (THQ); (4) District Headquarter Hospital (DHQ); (5) Teaching Hospitals.

We focus on Basic Health Units (BHUs). BHUs are the smallest public health care units. They are designed to be the first stop for patients seeking medical treatment in government facilities. (Hereafter in this paper, we use the word 'clinic' interchangeably to describe BHUs). There are 2496 BHUs in Punjab.[9] They largely serve rural populations; almost all such clinics are exclusively operating in rural and peri-urban areas. These clinics provide several services, including out-patient services, neo-natal and reproductive healthcare, and vaccinations against diseases. Each facility is headed by a doctor, known as the Medical Offi-

[8] In Punjab, a Tehsil is the largest sub-division of a district

[9] Each Basic Health Unit serves approximately one Union Council (Union Councils are smallest administrative units in Pakistan).

cer, who is supported by a Dispenser, a Lady Health Visitor, a School Health and Nutrition Supervisor, a Health/Medical Technician, a Mid-wife and other ancillary staff. Officially, clinics are open, and all staff are supposed to be present, from 8am to 2pm, Monday through Saturday.

### 2.1.1 Health Sector Administration

District governments are responsible for managing local health facilities. The District Health Department is headed by an Executive District Officer who reports both to the chief bureaucrat of the district and to the most senior provincial health officials.[10] He is supported by several Deputy District Officers, typically one for each tehsil.[11] Figure 1 depicts the (simplified) health administration hierarchy in Punjab, Pakistan.

The provincial health department department has also established a parallel entity known as the Punjab Health Sector Reform Program (PHSRP). PHSRP is tasked with initiating programs to reform the primary health system with support from international and donor organizations. PHSRP is responsible for the implementation of the smartphone monitoring program we evaluate in this paper.

The Deputy District Officer is the lowest position in the officer-cadre of district health administration. He inspects all health facilities in a given Tehsil. On average there are 18.47 clinics in a Tehsil (standard deviation = 10.68). This officer is required to visit every clinic at least once a month and record information collected during the visit on a standard form. The Deputy District Officer has authority to punish the clinic's absent staff by issuing a show-cause notice, which requires staff to explain their absence to the Executive District Officer. They can also suspend and withholding pay from contract staff. In severe cases of persistent absence, staff are usually transferred to less desirable locations. The Executive District Officer relies entirely on this subordinate officer to ensure staff presence.

[10] The Director General of Health Services and the Secretary of the Health Department

[11] The Executive District Officer is also supported by other staff, but they are excluded for clarity because they are irrelevant to our discussion here.

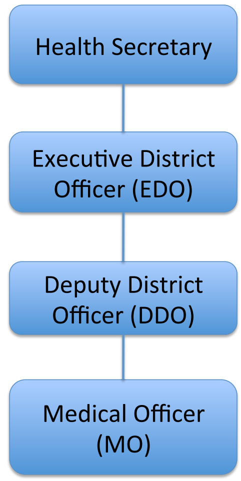



Figure 1: Health Sector Administration in Punjab

#### 2.1.2 Career Concerns and Internal Agency Problems

The Executive District Officer faces agency problems in managing his deputy inspectors. This is for several reasons. First, he has limited visibility into the inspectors' activities. Second, he has only two weak means of sanctioning an inspector. He can either issue a verbal reprimand or, in serious cases, send a written request for investigation to provincial authorities. The investigation process is long, highly bureaucratic, and prone to interference by elected politicians.

The career concerns of the Executive District Officer and his deputy inspectors are also fundamentally different. The Executive District Officer reports directly to senior provincial authorities who face few bureaucratic hurdles to sanctioning and holding him directly accountable for service delivery in his district. Performance for the Executive District Officer is commonly rewarded with appointment to a higher office. In contrast, the Deputy District Officers are neither officially nor practically accountable for health service delivery. Appointees to this position have to serve for years before they are considered for promotion to the next level in the district and infrequently ascend to leadership positions.

### 2.1.3 Doctors, Inspectors and Politicians

Influence over public sector positions provide politicians two means of patronage. First, politicians help health officials obtain postings in their region of choice (often their home union council). Second, once posted, health officials also appeal to politicians for protection against suspension, transfer, and other sanctions for underperformance.

Many staff members at the clinics belong to politically powerful clans and families. These staff can provide three types of favors to politicians. First, they can activate their networks to mobilize votes. Second, health staff are commonly recruited to assist the election commission with drawing up voter lists and overseeing polling on election day. Third, they can provide preferential care to supporters, or condition care on support.

Table 1 reports summary statistics on self-reported incidents of pressure experienced by inspectors and EDOs. We asked the respondents to report the number of instances where a person of influence pressured the respondent's colleagues or the respondent himself into a) not taking action against doctors or other staff that were performing unsatisfactorily in their tehsil or district or b) assigning doctors or other staff to their preferred posting. If yes, the respondents were asked to identify the type of people who tried to influence behavior, and to recall the number of such incidents and the times when decisions were not changed as a result of the pressure exerted.

The results show that about fifty percent of bureaucrats experienced pressure from several kinds of persons with influence. Conditional on pressure, up to ninety percent of respondents reported receiving suce pressure from elected legislators (MNAs and MPAs).

The summary statistics indicate that supervisors, the Executive District Officers, on general have a higher probability of facing pressure. This is consistent with the story where the supervisors, in their capacity as managers of the health infrastructure in the districts, must oblige requests by people with influence.

We provide details regarding the hiring process of doctors in Appendix D.

Table 1: Summary statistics

| Variable | Mean | SD | N |
|---|---|---|---|
| *Panel A: Senior Officials and Monitors* | | | |
| Ever influenced by Any Powerful Actor | 0.4 | 0.492 | 150 |
| Ever Influenced by Provincial Assembly Member | 0.322 | 0.469 | 149 |
| Instances of Interference by Provincial Assembly Member | 13.49 | 48.368 | 149 |
| *Panel B: Senior Officials Only* | | | |
| Ever influenced by Any Powerful Actor | 0.441 | 0.504 | 34 |
| Ever Influenced by Provincial Assembly Member | 0.441 | 0.504 | 34 |
| Instances of Interference by Provincial Assembly Member | 34 | 84.779 | 34 |
| *Panel C: Monitors Only* | | | |
| Ever influenced by Any Powerful Actor | 0.388 | 0.489 | 116 |
| Ever Influenced by Provincial Assembly Member | 0.287 | 0.454 | 115 |
| Instances of Interference by Provincial Assembly Member | 7.426 | 28.179 | 115 |

*Notes*:

## 2.2 Smartphone Monitoring

Our project attempts to explore the use of audits by government monitors as a solution to the problem of absence. As in Duflo et al. (2012), we explore a technology-based initiative that seeks, in part, to detect absence. There is increasing interest in using ICT to rapidly collect information that is useful to auditors and decision makers. Solving intra-bureaucracy agency problems is a potential application. We implement a smartphone-based solution that allows health system inspectors to upload the results of their assigned visit to a basic health facility to an aggregating website (dashboard), which instantly updates reports at different levels of aggregation (zonal and provincial) with the information captured by this most recent visit.

The “Monitoring the Monitors” program replaced the traditional paper-based monitoring system, which collects data on facility utilization, resource availability, and worker absence, with an android-based smartphone application. Data are transmitted to a central database using a General Packet Radio Service (GPRS) in real time. Data are then aggregated and summary statistics, charts, and graphs are presented in a format designed in collaboration with senior health officials. That data are: (i) aggregated in the province in real time; (ii) geo-

Table 2: Interference in Inspector Decisions and Political Competition

| Dependent Variable: | Instances of Political Interference | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Medium Competition | 0.569 | 0.549 | 0.254 | 1.281 | 1.285 | 0.585 |
| | (0.743) | (0.764) | (0.677) | (0.905) | (0.913) | (0.854) |
| Low Competition | 2.210* | 2.412** | 2.141* | 2.011* | 2.087* | 1.664 |
| | (1.138) | (1.203) | (1.102) | (1.093) | (1.143) | (1.079) |
| Inspector Tenure | | 0.167 | 0.149 | | 0.075 | 0.063 |
| | | (0.126) | (0.120) | | (0.118) | (0.120) |
| Time Spent Monitoring Clinics (minutes) | | | -0.004 | | | -0.002 |
| | | | (0.010) | | | (0.008) |
| Inspector knows Local MPA Personally (=1) | | | -3.994*** | | | -3.323** |
| | | | (1.407) | | | (1.454) |
| Constant | 1.902*** | -1.789 | 0.954 | 1.341** | -0.298 | 2.142 |
| | (0.600) | (2.543) | (2.900) | (0.669) | (2.878) | (3.638) |
| # Tehsils | 99 | 99 | 99 | 75 | 75 | 75 |
| # Tehsil - Constituencies | 276 | 276 | 276 | 137 | 137 | 137 |
| R-Squared | 0.019 | 0.041 | 0.128 | 0.018 | 0.023 | 0.097 |
| Mean of Dependent Variable (full sample) | 2.790 | 2.790 | 2.790 | 2.511 | 2.511 | 2.511 |
| Mean of Dependent Variable (High Competition) | 1.902 | 1.902 | 1.902 | 1.341 | 1.341 | 1.341 |
| Sample | | Full | | Non-overlapping constituencies | | |

*Notes*: This table reports the frequency of interference by politicians in health inspectors decisions by the level political competition. The unit of observation is a tehsil-constituency. The dependent variable is a count of the number of times that inspectors report Members of the Provincial Assembly pressuring them to either (a) not take action against doctors or other staff that were performing unsatisfactorily in their jurisdiction (tehsil) or (b) assign doctors to their preferred posting in the previous two years. Of the 122 inspectors covering our experimental sample, 102 provided responses to this question. We drop three reports which indicate more than 100 instances of interference (99th percentile). These three observations are more than four standard deviations from the mean. The remaining 99 inspectors are responsible for facilities spanning 213 provincial assembly constituencies. 76 of the constituencies belong to multiple inspectors' jurisdictions. Columns (1) through (3) report OLS regressions of the instances of interference on indicator variables for the degree of political competition in the full sample of 213 constituencies. Jurisdictions spanning multiple constituencies are repeated with the level of political competition in each constituency providing an observation. Columns (4) through (6) drop constituencies spanning multiple jurisdictions. Results for only experimental control districts are reported in Table **??** and further details about the frequency and source of political interference is provided in Table A5. The political competition index is a Herfindahl index computed as the sum of squared candidate vote shares in each constituency. Low competition is a dummy variable equal to one for constituencies in the top tercile of this index and medium competition is a dummy variable for constituencies in the middle tercile. *Level of significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors clustered at the jurisdiction (tehsil) level reported in parentheses.

tagged, time-stamped, and complemented with facility staff photos to check for reliability; and (iii) available in real time to district and provincial officers through an online dashboard. Figure 2 Panel A shows one view of the online dashboard. It presents a bar chart that gives the number of inspections as a proportion of total assigned inspections made by each of the treatment districts. Panel B provides a summary spreadsheet of each report, highlighting in red instances where three or more staff are absent. We examine the effect of highlight specific reports on subsequent attendance in Section 6 below.

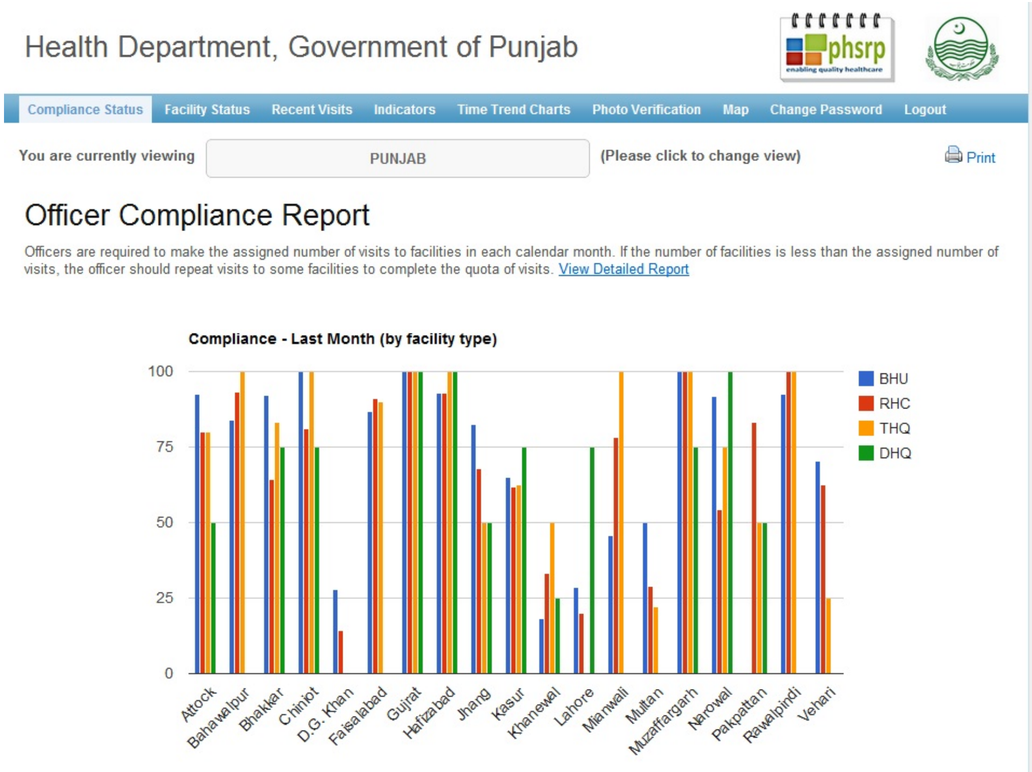
Application development started in August 2011. After developing the application and linking it to a beta version of the online dashboard, the system was piloted in the district of Khanewal. We remove Khanewal district from the experimental sample. Health administration staff were provided with smartphones and trained to use the application. The main purpose of the pilot was to ensure that the technology was working and to refine the application and the dashboard. During the pilot, several inspectors requested that the program require pictures of all staff in attendance, not just the inspector because they thought it might reduce pressure from health staff to falsify attendance.

# 3 Experiment

Our experimental sample comprised all health facilities in 35 of the 36 districts in Punjab, which has a population of 100 million. Tens of millions of public sector health users therefore stood to benefit from the program. While we have administrative data for all facilities, we monitor a subsample of 850 clinics, drawn to be representative of facilities in the province, using independent inspections. We randomly implemented the program in 18 of the 35 districts in our experimental sample. In assigning treatment we stratified on baseline attendance and the number of clinics in a district to ensure a roughly even number of treatments and controls. Figure 3 depicts control and treatment districts.

We randomized at the district level. The intervention channels information about in-

Panel A: Summary of Inspection Compliance by District




Panel B: Highlighting Underperforming Facilities

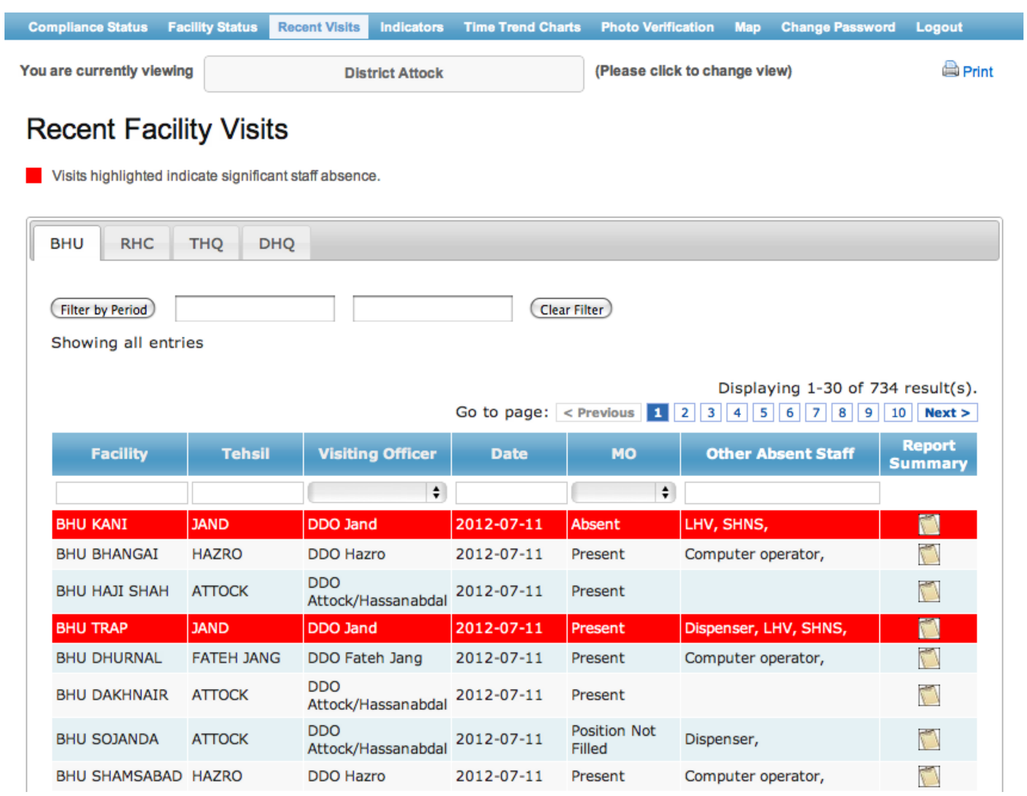



Figure 2: Online Dashboard Screenshots

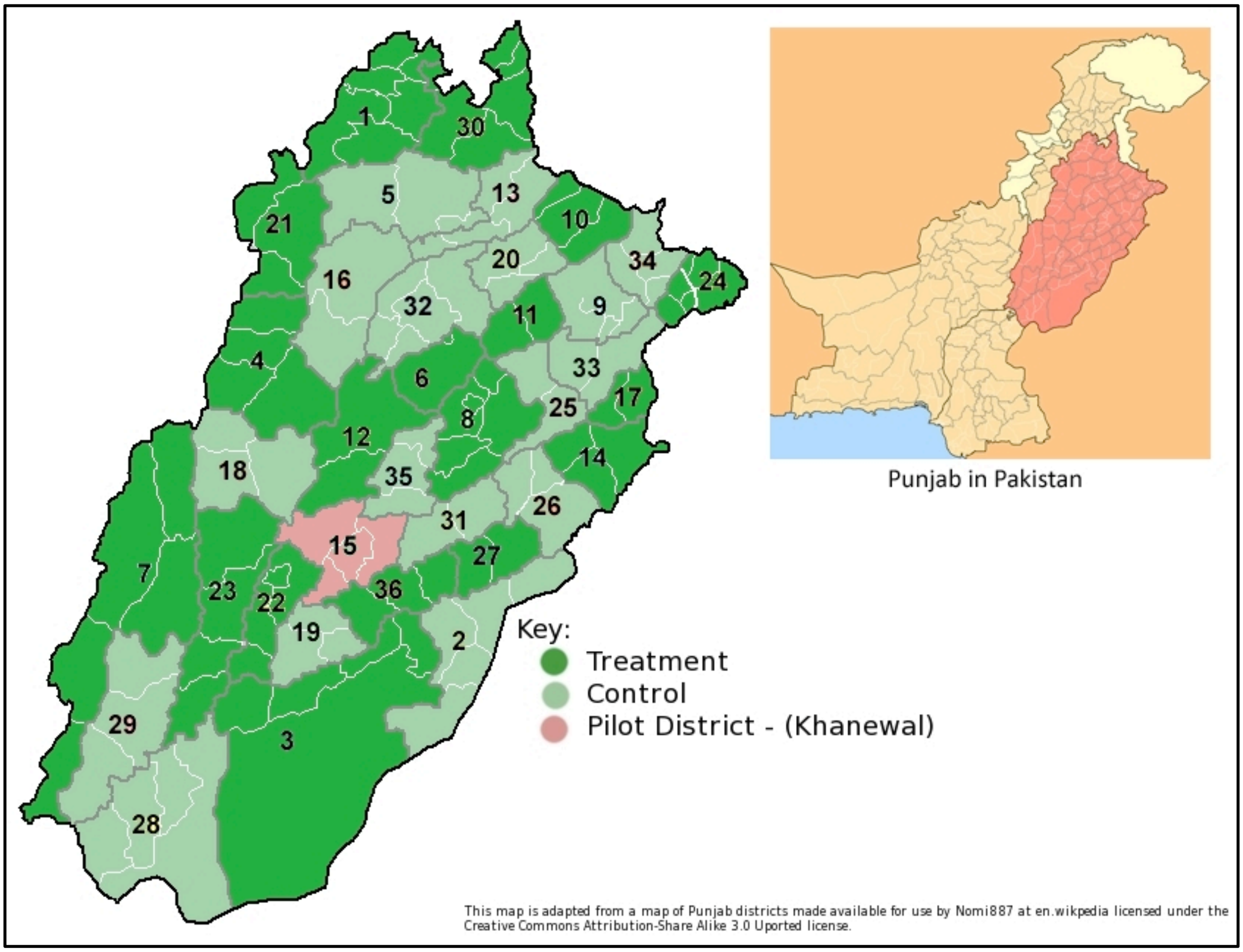



Figure 3: Treatment and Control Districts

spections to district health officials; randomization at a finer level is therefore very likely to generate externalities. The Department of Health also determined that sub-district randomization was not administratively feasible. Cluster randomization also allays some concerns about externalities generated by interactions between inspectors in the same district. All inspectors in a district are required to attend monthly meetings. While they typically have frequent interactions within districts, these relations are much weaker across districts.

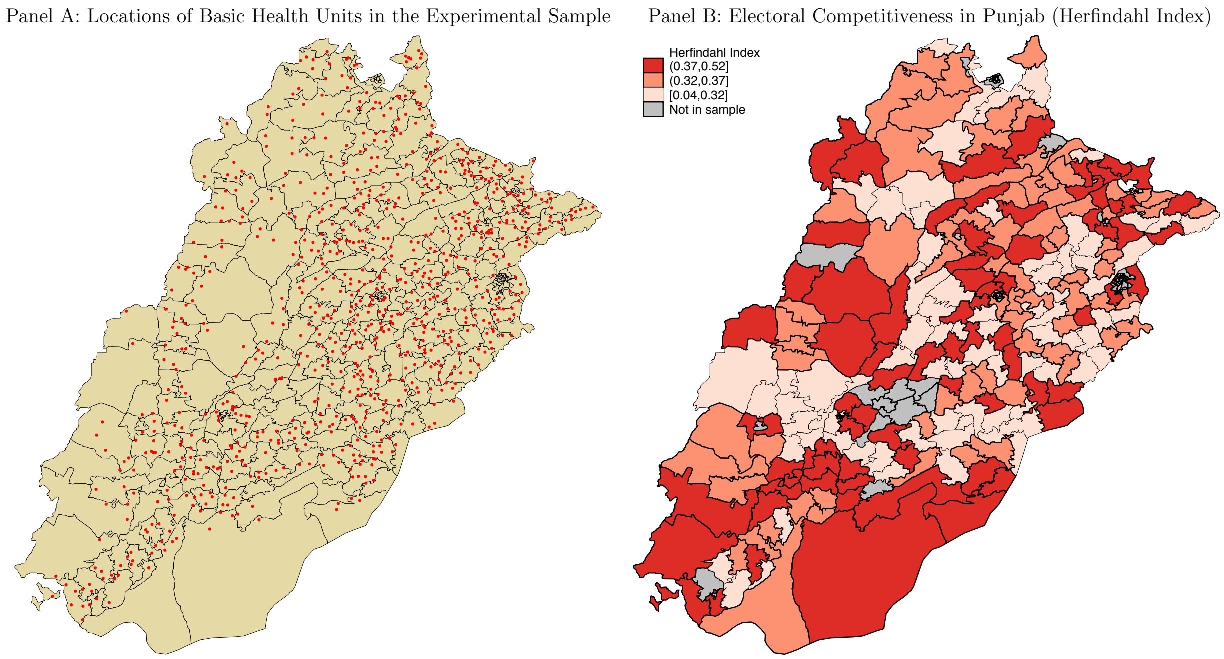



Figure 4: Experimental Sample and 2008 Political Outcomes by Constituency

# 4 Data

## 4.1 Primary Data

We collected primary data on a representative sample of BHUs 850 (34 percent) of the 2,496 Basic Health Units in Punjab. We made unannounced visits to these facilities three times, first in November 2011, then in June 2012 and in October 2012. BHUs were selected randomly using an Equal Probability of Selection (EPS) design, stratified on district and distance between the district headquarters and the BHU. Therefore, our estimates of absence are self-weighting, and so no sampling corrections are used in the analysis.[12] All districts in Punjab except Khanewal are represented in our data. To our knowledge, this is the first representative survey of BHUs in Punjab. Figure 4 provides a map of the Basic Health Units in our experimental sample along with the different Provincial Assembly constituencies in Punjab.

In our sample of 850 clinics, we collected data through independent inspection. Our team

[12]We sampled an equal proportion of clinics within each stratum to preserve an equal probability of selection.

collected information on staff absence and facility usage. Our staff interviewed the Medical Officer, the Dispenser or Health/Medical Technician, and the Lady Health Visitor before physically verifying the attendence of the Mid-Wife and the School Health and Nutrition Specialist. Our survey teams were trained at regional hubs (four in total) where they were trained by senior enumerator trainers and our team members. Following these trainings, the teams made visits to BHUs in their assigned districts and remained in regular contact with their team leaders and our research team. Surveys took three weeks to field for each wave. The attendance sheet for the staff was filled out at the end of the interviews and in private. Data collection and entry followed backchecks and other validation processes consistent with academic best practice.

### 4.2 Election Data

We also make use of election data for the 2008 Punjab Provincial Assembly elections.[13] These data provide candidate totals by constituency for all candidates running in the election. Constituencies for the Punjab Provincial Assembly are single-member. In cases of by-elections, we consider data from the election that most immediately preceded our program. Appendix C describes the protocol for identifying the constituency corresponding to each health facility.

## 5 Elections and Health Worker Attendance

To motivate our analysis, we present a few correlations which suggest a relationship between the strength of local politicians and doctor attendance. During our doctor interviews, we collected data on doctors' tenure in their post, the distance of their post from their hometown, and whether they know the local Member of the Provincial Assembly (MPA) personally. To ensure sampling of doctors who were not present at their clinics during any of our three

[13]We thank Ali Cheema and Farooq Naseer for kindly sharing this data. In cases where a by-election has happened since 2008, we take the most recent election in advance of our study

visits, we pursued the absent doctors until we could find them and interview them. For this analysis, we restrict ourselves to control districts to avoid reporting correlations induced by our treatment.[14]

Table A1 summarizes the data used for this analysis. The data reveal that doctor attendance in our control districts is quite low. While our visits took place during normal operating hours, we were able to locate doctors in only 22.3 percent of our visits. All BHUs are supposed to have doctors posted. However, because of a combination of a shortage of doctors, a lack of interest in rural postings, and perhaps misreporting to disguise absence, we find that only 53.1 percent of BHUs have doctors posted. Even accounting for this low rate of posting, doctor are present at only 42.1 percent of actual postings. Of the set of doctors we observe, 24 percent report knowing the MPA personally.

As we describe in Section 4, we identified the provincial assembly constituency in which each of our clinics are located. In our control districts, we have clinics in 123 constituencies. Using party vote shares at the Provincial Assembly constituency level for 2008 we compute a Herfindahl index as $\sum_i s_i^2$ where $s_i$ is the vote share for party $i$. We drop two clinics in one constituency (number 124) from our analysis as the Herfindahl Index is 0.786, which is 5.5 standard deviations from the mean and more than 3 standard deviations from the next highest constituency. On this sample, our Herfindahl ranges from 0.14 to 0.52. Figure 4 maps the political concentration measure for each constituency in Punjab. The degree of political contestation appears only weakly correlated with geography.

Table 3 examines relations between political connections, local political competition, and doctor attendance by running several variants of the specification:

$$Present_{ciw} = \beta_0 + \beta_1 Knows\ MP_{ic} + \beta_2 Pol\ Comp_c + \beta_3 Knows\ MP_{ic} \times Pol\ Comp_c + \beta_4 \mathbf{X}_{ciw} + \varepsilon_{ciw} \quad (1)$$

where $Present_{ciw}$ is a dummy variable equal to one if doctor $i$ in constituency $c$ is present

[14]Because treatment is randomized, it should be uncorrelated with pre-determined characteristics such as electoral outcomes which preceded our intervention. Our findings are robust to using the complete experimental sample.

during unannounced inspection wave $w$, $Knows\ MPic$ is a dummy equal to one if a doctor reports knowing their provincial assemblyman personally, $Pol\ Comp_c$ is the constituency-level normalized Herfindahl Political Competition, and $\mathbf{X}_{ciw}$ is a collection of additional covariates, inspection wave fixed effects, and Tehsil (county) or constituency fixed effects.

The estimates in Columns 1 and 2 indicate that doctors who know their parliamentarian personally are 21 percentage points less likely to be present. The reported specifications include constituency fixed effects which, because the constituencies are single-member, control both for politician heterogeneity and other constituency-level institutional confounds.[15] Columns 2 and 3 replace the right-hand side variable with our constituency-level measure of competition. In this case, we find that moving from the most competitive to the least competitive constituency is associated with a reduction in doctor attendance of about 32 percentage points. Columns 5, 6, and 7 interact these two measures. Doctors who both know their politicians and work in uncompetitive constituencies are rarely found during inspections. Estimates in columns 4, 5, and 6 are from specifications including Tehsil (county) fixed effects, which restricts our variation to geographically proximate political constituencies that should be broadly similar in terms of remoteness, climate, and desirability. Including constituency fixed effects in column 7 causes the interaction term to lose significance, possibly because the within-constituency variation is limited, though the point estimate remains large and negative.

The results in Table 3 are consistent with two theories. First, it may be that in highly competitive districts politicians face stronger incentives to make sure health services are effectively delivered. Second, it may be that politicians who can capture districts are more likely to provide sinecures as patronage. Doctors in patronage jobs may be expected to work less. To investigate which of these is operative, we asked doctors whether they knew their local provincial parliamentarian personally. 266 doctors were absent during all of our three visits. After our third visit to the facilities, we pursued all 266 until we were able to interview

[15] These results are also robust to using Province, Tehsil, or no fixed effects and to restricting the data to only single wave cross-sections (unreported).

Table 3: Political Connections, Competition, and Doctor Attendance

| Dependent Variable: | Doctor Present (=1) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Doctor Knows Parliamentarian Personally (=1) | -0.207** | -0.208** | | | 0.194 | 0.191 | 0.318 |
| | (0.084) | (0.084) | | | (0.268) | (0.257) | (0.369) |
| Political Competition Index | | | -0.327* | -0.321* | -0.067 | -0.093 | |
| | | | (0.187) | (0.186) | (0.248) | (0.242) | |
| Doctor Knows × Political Competition Index | | | | | -0.641* | -0.635* | -0.812 |
| | | | | | (0.370) | (0.357) | (0.527) |
| Distance to District Center (in minutes) | | -0.000 | | -0.001 | | 0.001 | -0.000 |
| | | (0.001) | | (0.001) | | (0.001) | (0.001) |
| Catchment Population (1,000) | | -0.006 | | -0.002 | | -0.004 | -0.005 |
| | | (0.006) | | (0.005) | | (0.004) | (0.006) |
| Constant | 0.572*** | 0.721*** | 0.656*** | 0.762*** | 0.619*** | 0.695*** | 0.722*** |
| | (0.035) | (0.160) | (0.128) | (0.172) | (0.170) | (0.196) | (0.164) |
| # Constituencies | 91 | 91 | 105 | 105 | 91 | 91 | 91 |
| # Observations | 514 | 514 | 622 | 622 | 514 | 514 | 514 |
| R-Squared | 0.256 | 0.257 | 0.154 | 0.156 | 0.201 | 0.203 | 0.261 |
| Constituency Fixed Effects | Yes | Yes | No | No | No | No | Yes |
| Tehsil Fixed Effects | No | No | Yes | Yes | Yes | Yes | No |

*Notes*: This table reports on the relationship between doctor attendance and interactions between the political connections of doctors and the degree of political competition. The dependent variable is a dummy equal to one if a doctor is present during an unannounced facility inspection performed by our survey team. The political competition index is a Herfindahl index computed as the sum of squared candidate vote shares in each provincial assembly constituency divided by the maximum observation in our sample (0.545). The raw Herfindahl varies between 0.040 and 0.545. All specification samples are restricted to basic health unit facilities in control districts with a doctor assigned. Samples in columns 1, 2, 5, 6, and 7 specifications are further restricted to observations with complete data on doctor connections, political competition, and on all covariates. Samples in columns 3 and 4 are restricted to observations with complete data on political competition and on all covariates. Results are robust to removing these restrictions. All specifications are OLS and include survey wave fixed effects. *Level of significance*:$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

them.

These correlations suggest that, for a doctor, having a connection to a politician allows them to be absent more often. This finding has implications for the effectiveness of our experiment. Politically connected inspectors and doctors should be less sensitive to monitoring. While monitoring innovations increase the probability they are detected shirking, these incentives will not be binding for bureaucrats who are protected by their relations to local politicians.

# 6 Experimental Results

With this motivation as background, we now present our experimental results. Table A2 verifies balance in our experiment. As we discuss in Section 3, we stratified treatment on the share of staff present during our baseline interview. While this achieved balance for five of the six categories of staff that are supposed to be present at BHUs, we have a large and significant imbalance for doctors. Figure A2 reports a long time series of administrative data on doctor attendance from paper records. We find that the difference in levels does not reflect a difference in pre-treatment trends, allaying some concerns that our fixed effects estimates are not causal.[16]

We begin by examining the impact of treatment on health worker attendance. We test for impacts on inspectors, where the program provides the sharpest incentives, doctors, and total staff.

We estimate regressions using the difference-in-difference specification:

$$Y_{dit} = \alpha + \beta Treatment_{dit} + \sum_{i=1}^{3} \delta_t + \lambda_i + \varepsilon_{dit} \tag{2}$$

$Y_{dit}$ is health worker attendance or official inspection and $Treatment_{dit}$ is a variable equal to 1 for treated districts during the post-treatment periods (waves 2 and 3) , where $i$ refers

[16] Note that this depicts the sample average. The effects we find on doctor attendance are localized to the subsample of clinics in competitive districts.

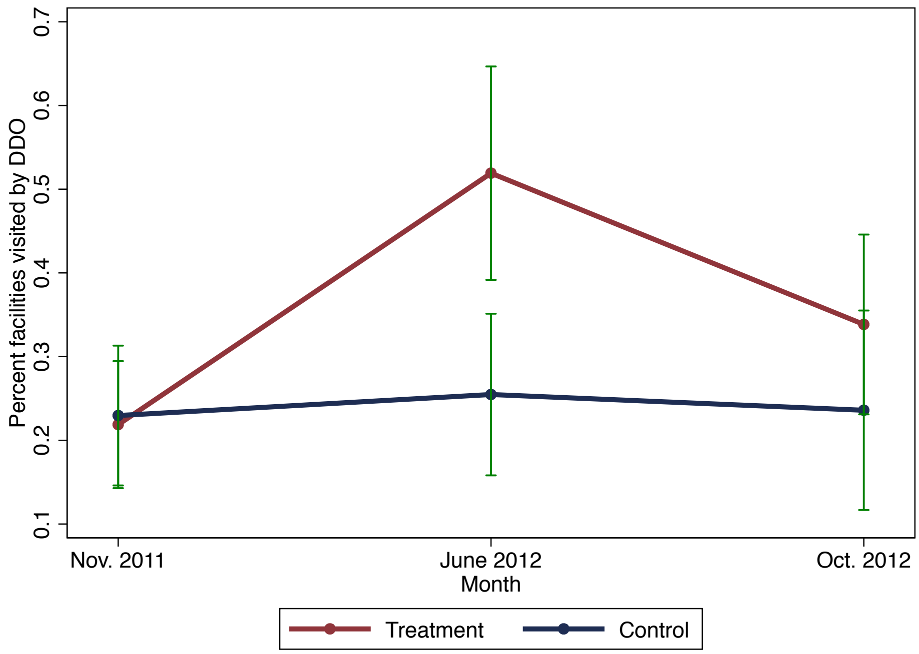



Figure 5: Effects by Survey Wave

to the clinic, $d$ refers to the district, and $t$ to the survey wave. We cluster all standard errors at the district level. With only 35 districts, we also use randomization inference. Figure A1 shows our actual impact against impacts estimated from 1,000 hypothetical treatment assignments.

The first column verifies that the program increased inspections. The smartphone monitoring system directly impacts health inspectors, as their activities are geostamped, timestamped, and observed in real time. We do not observe any significant average impacts on doctor or overall staff attendance.

Panel B reports results splitting the treatment by survey wave 2 (May 2012) and wave 3 (October 2012). In column one, we see that the large impact on inspection has attenuated somewhat over the life of the program. Inspections remain 89% higher than they were at baseline. Figure 5 depicts attendance in treatment and control groups by wave.

## 6.1 Inspector Time Use

In Figure 5 we show that Inspectors in treatment districts conduct more inspections due to the cell phone treatment. The interpretation of this result is dependent on where the additional time required to conduct these visits comes at the cost of more pressing tasks that the supervisors are assigning to these inspectors. In such cases, the increase in shirking penalties, brought about by our program, may drive the inspectors away from more efficient outcomes. In the ideal scenario, the cell phone treatment should be driving shirking inspectors to do their job.

We test for this by administering a time use survey on the universe of health inspectors in Punjab. Respondents were asked to list the time they spent on a variety of tasks during the two working days prior to our survey.[17] We interviewed inspectors during February and March of 2013, a period when the effects of our program were already attenuating (as shown in Figure 5). Therefore, any treatment effects on time use would be understated.

We present our analysis in Table 4. In addition to conducting standard hypothesis tests on the difference in the *average* treatment effect between inspectors under the treatment and control conditions, we also conduct the Fisher Exact test to see if our results are different from the null hypothesis of no effects *inspector by inspector*. We report p-values from both tests in the table.

We note three results. First, inspectors in treatment districts reported working about 72 extra minutes *overall*. Second, they reported 43 extra minutes of inspections overall, and 21 extra minutes of inspections for clinics in treatment districts. Third, treatment inspectors also report spending less time managing clinics and hospitals at their office.

The correlations we find in Section 5 above suggest the possibility of heterogeneity by the degree of political concentration. Popular accounts of local politics in Pakistan characterize it broadly as a clientelistic system—a view strongly supported by our interviews with a select

[17] Inspectors picked upto three out of 10 possible categories of work to account for each hour between 8am and 6pm. In addition, they were asked to identify when they arrived for, and left from work.

Table 4: The Effect of Smartphone Monitoring

| | Treatment (1) | Control (2) | Difference (3) | p-value Mean Diff (4) | p-value Exact Test (5) |
|---|---|---|---|---|---|
| Panel A: Treatment Effects on the Rate of Inspections | | | | | |
| Facility Inspected in the Previous Month (=1) | 0.426 | 0.242 | 0.183 | 0.008 | 0.001 |
| | (0.048) | (0.044) | (0.065) | | |
| # of Observations | 759 | 760 | | | |
| Wave 2 only | 0.519 | 0.253 | 0.266 | 0.002 | 0.003 |
| | (0.063) | (0.047) | (0.079) | | |
| # of Observations | 366 | 372 | | | |
| Wave 3 only | 0.338 | 0.232 | 0.106 | 0.178 | 0.057 |
| | (0.053) | (0.057) | (0.077) | | |
| # of Observations | 393 | 388 | | | |
| Panel B: Time-use of Inspectors | | | | | |
| *Breaks During Official Duty* | | | | | |
| Lunch, Prayer, or Tea Break | 16.189 | 22.500 | -6.311 | 0.338 | 0.716 |
| | (4.993) | (4.151) | (6.494) | | |
| *Inspections of Facilities* | | | | | |
| Inspecting Clinics | 68.648 | 46.324 | 22.324 | 0.183 | 0.083 |
| | (14.373) | (7.959) | (16.430) | | |
| Inspecting Hospitals | 52.541 | 30.637 | 21.904 | 0.217 | 0.186 |
| | (15.457) | (7.973) | (17.392) | | |
| (i) Total Time Inspecting | 121.189 | 76.961 | 44.228 | 0.105 | 0.073 |
| | (24.152) | (10.966) | (26.525) | | |
| *Management of Facilities* | | | | | |
| In Head Office, Managing Clinics | 23.484 | 36.765 | -13.281 | 0.272 | 0.739 |
| | (7.201) | (9.468) | (11.895) | | |
| In Head Office, Managing Hospitals | 24.344 | 32.721 | -8.376 | 0.589 | 0.702 |
| | (7.588) | (13.365) | (15.369) | | |
| (ii) Total Time Managing In Head Office | 47.828 | 69.485 | -21.657 | 0.273 | 0.808 |
| | (9.440) | (16.976) | (19.424) | | |
| *Official Duty Unrelated to Facility Management* | | | | | |
| Managing Immunization Drives | 94.918 | 92.770 | 2.148 | 0.933 | 0.452 |
| | (20.484) | (15.260) | (25.544) | | |
| Official Meetings Unrelated to Facility Management | 112.500 | 55.441 | 57.059 | 0.046 | 0.110 |
| | (21.217) | (17.598) | (27.565) | | |
| Other Official Duty | 74.385 | 81.765 | -7.379 | 0.851 | 0.539 |
| | (29.151) | (25.875) | (38.978) | | |
| (iii) Duty Unrelated to Facility Management | 281.803 | 229.975 | 51.828 | 0.258 | 0.121 |
| | (30.167) | (33.481) | (45.067) | | |
| *Total Official Duty* | | | | | |
| Total Minutes Working (i) + (ii) + (iii) | 450.820 | 376.422 | 74.398 | 0.082 | 0.045 |
| | (18.380) | (37.163) | (41.460) | | |
| # of Observations | 122 | 102 | | | |

*Notes*: This table reports average treatment effects on the number of inspections (Panel A) and the time use patterns of inspectors (Panel B). The standard errors, reported in parentheses, are clustered at the district level. The unit of observation in Panel A is the clinic, and data come from primary unannounced surveys after the treatment was launched (wave 2 and 3). The dependent variable is an indicator variable that equals 1 if an inspector visited a clinic within a month prior to the survey, and 0 otherwise. The regression reports differences between treatment and control clinics. p-values reported in column (4) are for the difference between treatment and control clinics. Column (5) reports the Fisher Exact Test p-values that places column (4) p-values in the distribution of p-values obtained from a 1000 random draws of treatment assignment. Data for results in Panel B come from the survey of the universe of health inspectors in Punjab. The unit of observation for Panel B are these inspectors. Column (1) shows the average, in minutes, of how inspectors in treatment districts spend their time over the last two days on several tasks. Column (2) shows the same for control districts. Column (3) reports the difference between the two.

Table 5: Treatment Effects by Political Concentration

| Dependent Var. | Inspected (=1) | Number of Staff Present | | Doctor Present (=1) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Monitoring x Low Pol. Concentration | 0.230*** | 0.650*** | 0.620*** | 0.115* | 0.169* |
| | (0.065) | (0.234) | (0.224) | (0.067) | (0.099) |
| Monitoring x Mid Pol. Concentration | 0.213* | -0.316 | -0.162 | -0.074 | -0.110 |
| | (0.125) | (0.265) | (0.254) | (0.067) | (0.082) |
| Monitoring x High Pol. Concentration | 0.190** | -0.339 | -0.305 | -0.066 | -0.034 |
| | (0.073) | (0.381) | (0.318) | (0.061) | (0.100) |
| # Staff Assigned | | | 0.425*** | | |
| | | | (0.035) | | |
| Constant | 0.197*** | 2.797*** | 0.584*** | 0.324*** | 0.515*** |
| | (0.020) | (0.072) | (0.192) | (0.014) | (0.020) |
| # Districts | 35 | 35 | 35 | 35 | 35 |
| # Clinics | 838 | 842 | 842 | 842 | 664 |
| # Observations | 2257 | 2521 | 2521 | 2398 | 1518 |
| R-Squared | 0.065 | 0.024 | 0.149 | 0.010 | 0.015 |
| Only Clinics with Doctors | No | No | No | No | Yes |

*Notes*: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors clustered at the district level reported in parentheses. All regressions include clinic and survey wave fixed effects.

group of experienced parliamentarians. Parliamentarians can influence both the allocation of public sector jobs, and the enforcement of reporting requirements. We use the large degree of variation in competitiveness across the 240 constituencies in our sample to check for impact heterogeneity.

Consistent with the correlations presented in Section 5, we find that monitoring leads to a larger increase in attendance in competitive districts. The first column of Table 5 indicates that our increase in monitoring is localized to competitive constituencies. Similarly, in columns (2) and (3), we find that treatment results in roughly an additional worker being present in the most competitive districts. Last, in columns (4) and (5) we find that doctors are present at about 30 percent more facilities in competitive constituencies, with no effect in noncompetitive constituencies.

## 6.2 Mechanisms - Highlighting Absence

Our set up allows a direct test of the mechanism creating an increase in doctor attendance. Data from inspections are aggregated and presented to Executive District Officers on an on-line dashboard. This dashboard is visible to Executive District Officers, the Health Secretary for Punjab, and the Director General of Health for Punjab. Figure 2 Panel B provides an example of a dashboard view visible to the Executive District Officer.

To test whether actions by senior officers are affecting absence, we directly manipulated the data on the dashboard to make certain facilities salient. Specifically, we highlighted entries that found three or more staff to be absent in red on the dashboard. We examine whether this manipulation affected subsequent doctor absence with the following specification:

$$Absent\ Survey_{jt} = \alpha + \beta_1 Flagged_{jt-1} + \beta_2 Absent\ Dashboard_{jt-1} + \sum_{i=1}^{3} \delta_t + \eta_{jt} \quad (3)$$

$Absent\ Survey_{jt}$ is equal to one if doctor $j$ was absent during our unannounced visit in wave $t$, $flagged_{it-1}$ is a dummy equal to one if the facility was flagged in red on the dashboard the month prior to survey wave $t$, and $Absent\ Dashboard_{jt-1}$ is equal to one if the doctor was noted as absent in the period prior to our survey during the official inspection.

Facilities are flagged only if three or more staff members are absent. Consequently, if we restrict our sample to only facilities where, in the month prior to our unannounced visit, only two or three staff were absent, we can estimate the effect of flagging on a sample where the only difference might plausibly be whether the facility was flagged.

Table 6 reports results from this test. In columns (1) and (2) we report results for our entire sample looking at total staff attendance. In columns (3), we report results only for our sample where either two or three doctors were absent. We call this the "discontinuity" sample. Our coefficients suggest that absence, in the month after a facility is flagged, is reduced by about 55 percent if the facility is flagged.

Table 6: Effect of Flagging Underperformance on the Dashboard

| | Doctor Present in Unannounced Visit (=1) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Flagged | 0.124** | 0.254*** | | |
| | (0.058) | (0.070) | | |
| Flagged x High Competition | | | 0.223*** | 0.319*** |
| | | | (0.086) | (0.114) |
| Flagged x Med Competition | | | 0.014 | 0.195 |
| | | | (0.110) | (0.126) |
| Flagged x Low Competition | | | 0.021 | 0.137 |
| | | | (0.107) | (0.128) |
| High Competition | | | 0.028 | 0.101 |
| | | | (0.082) | (0.111) |
| Med Competition | | | -0.007 | 0.045 |
| | | | (0.083) | (0.106) |
| Low Competition | | | 0.000 | 0.000 |
| | | | (0.000) | (0.000) |
| Constant | 0.458*** | 0.339*** | 0.454*** | 0.294*** |
| | (0.038) | (0.051) | (0.060) | (0.073) |
| Flagged x High Competition = Flagged x Mid Competition (p-value) | | | 0.138 | 0.465 |
| # Clinics | 265 | 166 | 263 | 166 |
| # Reports | 368 | 198 | 366 | 198 |
| R-Squared | 0.014 | 0.064 | 0.032 | 0.092 |
| Sample | Full | Flagged | Full | Flagged |

*Notes*: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the clinic level reported in parentheses. The Discontinuity sample are facility-month observations where either two or three (the threshold to trigger the underreporting red flag) are recorded on the dashboard. All regressions include survey wave fixed effects. Delay is 11, length is 14.

Figure 6 shows average doctor absence. The horizontal axis uses absence reports provided by inspectors on the online dashboard. For each doctor absence level on the horizontal axis, the vertical axis shows average doctor absence in a subsequent primary data collection visit by our survey team. Absence levels have an overall lower average in the flagged zone - the area to the right of the vertical red bar- versus places that were not flagged. This figure is generated for survey visits fifteen to thirty days after the flagging. The results are robust to several configurations of this window.

## 6.3 Heterogeneity by Political Concentration

District health officials have reported facing pressure and obstacles from influential persons to sanction underperforming health staff. In our survey 44% of the Executive District Officers and 38% of the Deputy District Officers reported to have faced such pressure. If senior health officials face more political obstacles to sanctioning absent doctors with stronger patrons,

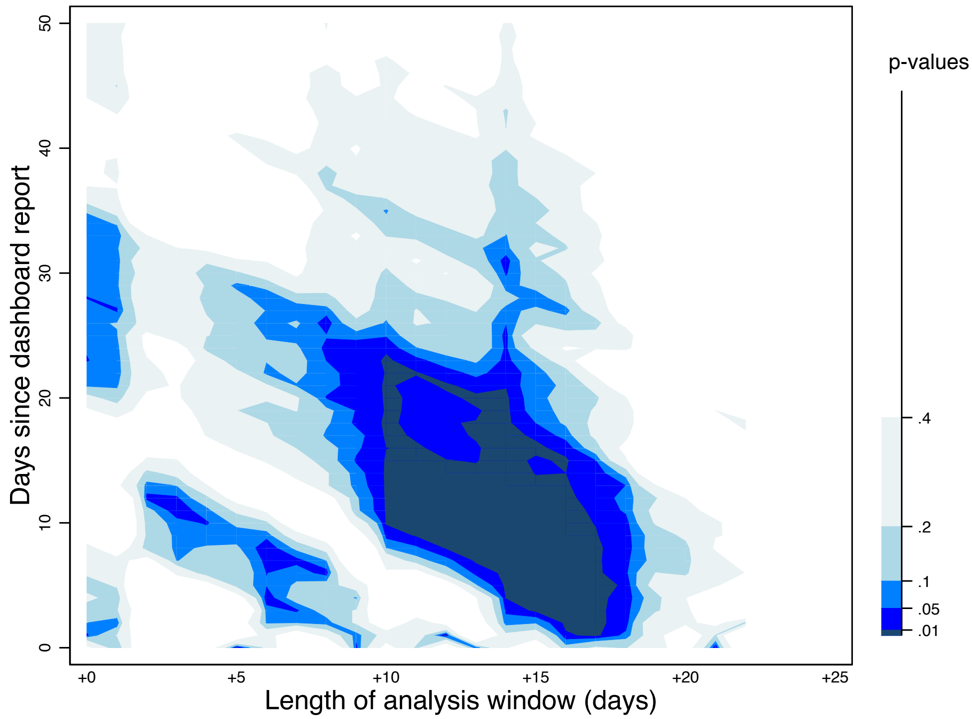



Figure 6: Average Absence after Flagging

then we should find that the effect of highlighting a facility as underperforming should be localized to competitive districts. This permits a fairly direct test of whether the reason that absence is both more severe and also less responsive to our smartphone monitoring intervention is due to powerful parliamentarians shielding doctors from sanction. Columns (4) to (6) of Table 6 examine this directly. We find that being flagged as absent results in a decrease in absence of about 30 percentage points for constituencies in the bottom 33 percentiles according to the vote share Herfindahl index. We also find similar effects for the facilities that belong to the middle 33 percentile bin of the political concentration index. However, there are no effects of flagging facilities on the dashboard in the more politically captured places.

# 7 Conclusion

In clientelistic systems, politicians gain office by providing targeted goods to supporters instead of by effectively providing public goods. We examine a particular case: doctors may be absent and unavailable to provide health care because their position is a sinecure provided in return for political support. Four findings support this explanation for public worker absence. First, absence is significantly more severe in less competitive districts. Second, politically connected workers are absent more frequently. Third, the effects of a novel monitoring technology on the performance of government monitors remain localized to competitive districts. Fourth, highlighting employee absence to senior managers only results in subsequent decreases in absence in competitive districts.

Doctor, teacher, and other public worker absence is a serious obstacle to effective public service delivery in developing countries (Banerjee and Duflo 2006; Chaudhury et al. 2006). In many cases, it is also highly resistant to interventions aimed at promoting attendance. Understanding the political rationale for public worker absence opens a broader set of interventions to combat the problem. First, professionalizing the civil service, and eliminating politicians involvement in decisions related to bureaucratic hiring, firing, promotion, and posting would remove the opportunity to use these positions as patronage. Second, increasing voters awareness of public worker absence might amplify the political costs from voters not motivated by patronage.[18]

Our experiment also demonstrates the promise of using Information Communication Technology to improve public sector monitoring. These technologies can rapidly gather and aggregate information useful to an auditor at very low cost. Our intervention was cheap and straightforward to implement and more than doubled inspections in a country where they were happening at only 22 percent of the officially prescribed rate. Moreover, such

[18]Along these lines, Wilson (1961) states "organized guardians of the civic purse will not permit corrupt politicians to increase city expenditures through certain kinds of projects (for example, urban renewal, street-lighting, street-cleaning, building inspection, fire and police protection) but not through others (increasing the staffs of aldermen, multiplying executive secretariats, and hiring men to do jobs which machines can do better—such as operating elevators, sweeping streets, etc.)"

approaches require little if any international support, and may be incentive-compatible, and so sustainable, for senior policymakers and politicians who would like to reduce absence but merely lack the information to do so.

More generally, anti-corruption efforts often face challenges in sustaining effect. Our findings suggest that in some cases the resilience of public sector corruption may be because it is maintained for reasons of political expedience. Given the huge potential payouts to politicians from facilitating corruption, future research in the economics of corruption might consider the political rationale for corruption. Such investigations could broaden the set of anti-corruption policies and increase their impact.

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**APPENDIX: NOT FOR PUBLICATION**

# A Appendix

Table A1: Summary Statistics

| Variable | Mean | Standard Deviation | # Observations |
|---|---|---|---|
| Doctor Present (=1) | 0.226 | 0.418 | 1191 |
| Doctor Posted at Clinic (=1) | 0.531 | 0.499 | 1191 |
| Doctor Knows Local MPA Personally (=1) | 0.253 | 0.435 | 269 |
| Distance to Doctor's Hometown (minutes) | 123.216 | 286.306 | 269 |
| Doctor's Months of Service | 96.027 | 93.237 | 261 |
| Distance to District Headquarters (km) | 48.969 | 29.298 | 1369 |
| Catchment Population (1,000) | 22.26 | 6.961 | 1367 |
| Political Concentration (0 - 1) | 0.664 | 0.157 | 1369 |
| Victory Margin Share | 0.155 | 0.105 | 1369 |

*Notes*: Sample: Control district clinics, survey waves 1 - 3. Political Concentration is a Herfindahl index computed as the sum of squared vote shares for each party in a Provincial Assembly constituency ranging from 0.272 in the most competitive district to one in uncontested districts.

# B Finding Doctors

Doctors were frequently absent during our unannounced visits. Consequently, we had to make a concerted effort to find all of the doctors assigned in our sample. We tracked down 541 doctors after the completion of our three unannounced field visits and an additional announced visit that was specifically carried out to interview doctors that were absent in the previous waves. Table A7 describes the breakdown of our sample.

## Table A2: Randomization Verification

| | Conventional Monitoring (=1) | Smartphone Monitoring (=1) | Difference | P-value | Control Observations | Treatment Observations |
|---|---|---|---|---|---|---|
| BHU open during visit (=1) | 0.926 | 0.930 | -0.004 | 0.899 | 417 | 428 |
| | [0.263] | [0.256] | (0.033) | | | |
| Inspector Has Visited in the Last Month (=1) | 0.230 | 0.219 | 0.012 | 0.836 | 330 | 320 |
| | [0.422] | [0.414] | (0.056) | | | |
| Number of Staff Present | 2.722 | 2.883 | -0.161 | 0.379 | 330 | 320 |
| | [1.516] | [1.637] | (0.181) | | | |
| Number of Staff Assigned | 5.115 | 5.285 | -0.170 | 0.169 | 417 | 428 |
| | [0.926] | [0.940] | (0.121) | | | |
| Doctor Present (Assigned only) | 0.430 | 0.547 | -0.116 | 0.078 | 223 | 309 |
| | [0.496] | [0.499] | (0.064) | | | |
| Health Technician Present (=1) | 0.516 | 0.477 | 0.039 | 0.519 | 312 | 302 |
| | [0.501] | [0.500] | (0.060) | | | |
| Dispenser Present (=1) | 0.733 | 0.805 | -0.071 | 0.224 | 390 | 399 |
| | [0.443] | [0.397] | (0.057) | | | |
| SHNS Present (=1) | 0.347 | 0.341 | 0.006 | 0.921 | 403 | 413 |
| | [0.477] | [0.475] | (0.060) | | | |
| Lady Health Visitor Present (=1) | 0.631 | 0.662 | -0.031 | 0.548 | 374 | 396 |
| | [0.483] | [0.474] | (0.050) | | | |
| Midwife Present (=1) | 0.659 | 0.650 | 0.008 | 0.863 | 328 | 303 |
| | [0.475] | [0.478] | (0.048) | | | |
| Political Concentration (0 - 1) | 0.348 | 0.346 | 0.002 | 0.872 | 414 | 423 |
| | [0.083] | [0.078] | (0.014) | | | |
| High Competition Constituencies (Bottom Tercile) | 0.312 | 0.362 | -0.050 | 0.489 | 414 | 423 |
| | [0.464] | [0.481] | (0.072) | | | |
| Medium Competition Constituencies (Middle Tercile) | 0.377 | 0.284 | 0.093 | 0.209 | 414 | 423 |
| | [0.485] | [0.451] | (0.073) | | | |
| Low Competition Constituencies (Top Tercile) | 0.312 | 0.355 | -0.043 | 0.543 | 414 | 423 |
| | [0.464] | [0.479] | (0.070) | | | |

*Notes*: This table checks balance between treatment and control clinics. The unit of observation is the clinic (basic health unit). The first ten rows report data from the baseline survey of health facilities which involved making unannounced visits to facilities in November, 2011. The last four rows report data based on the February 2008 parliamentary election election. The political competition index is a Herfindahl index computed as the sum of squared candidate vote shares in each provincial assembly constituency. Variable standard deviations are reported in brackets. Standard errors are reported in parentheses.

Table A3: Impact on Inspections and Health Worker Attendance

| Panel A - Average Effects | Inspected (=1) | Number of Staff Present | | Doctor Present (=1) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Smartphone Monitoring (=1) | 0.212*** | -0.042 | 0.020 | -0.010 | -0.005 |
| | (0.064) | (0.228) | (0.201) | (0.043) | (0.068) |
| # Staff Assigned | | | 0.436*** | | |
| | | | (0.039) | | |
| Constant | 0.217*** | 2.802*** | 0.532** | 0.326*** | 0.518*** |
| | (0.023) | (0.076) | (0.215) | (0.014) | (0.021) |
| # Districts | 35 | 35 | 35 | 35 | 35 |
| # Clinics | 839 | 849 | 849 | 849 | 669 |
| # Observations | 2169 | 2541 | 2541 | 2414 | 1527 |
| R-Squared | 0.053 | 0.006 | 0.139 | 0.006 | 0.009 |
| Only Clinics with Doctors | No | No | No | No | Yes |

| Panel B - Effects By Survey Wave | Inspected (=1) | Number of Staff Present | | Doctor Present (=1) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Monitoring x Wave 2 | 0.294*** | -0.158 | -0.066 | -0.031 | -0.045 |
| | (0.075) | (0.251) | (0.218) | (0.056) | (0.080) |
| Monitoring x Wave 3 | 0.137 | 0.073 | 0.105 | 0.009 | 0.039 |
| | (0.083) | (0.242) | (0.212) | (0.054) | (0.089) |
| # Staff Assigned | | | 0.435*** | | |
| | | | (0.038) | | |
| Constant | 0.217*** | 2.802*** | 0.539** | 0.326*** | 0.518*** |
| | (0.022) | (0.076) | (0.210) | (0.014) | (0.021) |
| # Districts | 35 | 35 | 35 | 35 | 35 |
| # Clinics | 839 | 849 | 849 | 849 | 669 |
| # Observations | 2169 | 2541 | 2541 | 2414 | 1527 |
| R-Squared | 0.062 | 0.008 | 0.140 | 0.006 | 0.011 |
| Only Clinics with Doctors | No | No | No | No | Yes |

*Notes*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the district level reported in parentheses. All regressions include clinic and survey wave fixed effects.

Table A4: Randomization Verification Within Subgroups

| | High Political Competition | | | Mid Political Competition | | | Low Political Competition | | |
|---|---|---|---|---|---|---|---|---|---|
| | Control | Treatment | p-value | Control | Treatment | p-value | Control | Treatment | p-value |
| BHU open during visit (=1) | 0.893 | 0.907 | 0.813 | 0.912 | 0.934 | 0.590 | 0.976 | 0.953 | 0.383 |
| | [0.310] | [0.291] | | [0.284] | [0.250] | | [0.153] | [0.212] | |
| DDO Has Visited in the Last Month (=1) | 0.160 | 0.209 | 0.472 | 0.276 | 0.229 | 0.612 | 0.262 | 0.198 | 0.467 |
| | [0.368] | [0.409] | | [0.449] | [0.423] | | [0.442] | [0.400] | |
| Number of Staff Present | 2.565 | 2.974 | 0.170 | 2.635 | 2.777 | 0.506 | 3.032 | 2.820 | 0.444 |
| | [1.504] | [1.865] | | [1.532] | [1.508] | | [1.486] | [1.461] | |
| Number of Staff Assigned | 4.954 | 5.252 | 0.165 | 5.201 | 5.223 | 0.881 | 5.183 | 5.360 | 0.318 |
| | [1.066] | [1.103] | | [0.855] | [0.944] | | [0.833] | [0.744] | |
| Doctor Present (Assigned only) | 0.388 | 0.570 | 0.032 | 0.375 | 0.565 | 0.029 | 0.515 | 0.518 | 0.974 |
| | [0.491] | [0.497] | | [0.487] | [0.499] | | [0.503] | [0.502] | |
| Health Technician Present (=1) | 0.403 | 0.390 | 0.881 | 0.363 | 0.291 | 0.357 | 0.444 | 0.349 | 0.251 |
| | [0.493] | [0.490] | | [0.482] | [0.456] | | [0.499] | [0.478] | |
| Dispenser Present (=1) | 0.683 | 0.794 | 0.132 | 0.656 | 0.795 | 0.094 | 0.798 | 0.745 | 0.540 |
| | [0.467] | [0.406] | | [0.477] | [0.406] | | [0.403] | [0.437] | |
| SHNS Present (=1) | 0.333 | 0.418 | 0.242 | 0.325 | 0.291 | 0.623 | 0.390 | 0.295 | 0.312 |
| | [0.473] | [0.495] | | [0.470] | [0.456] | | [0.490] | [0.458] | |
| Lady Health Visitor Present (=1) | 0.545 | 0.624 | 0.260 | 0.592 | 0.641 | 0.459 | 0.629 | 0.617 | 0.861 |
| | [0.500] | [0.486] | | [0.493] | [0.482] | | [0.485] | [0.488] | |
| Midwife Present (=1) | 0.553 | 0.529 | 0.753 | 0.529 | 0.444 | 0.175 | 0.540 | 0.443 | 0.199 |
| | [0.499] | [0.501] | | [0.501] | [0.499] | | [0.500] | [0.498] | |
| Political Concentration (0 - 1) | 0.832 | 0.820 | 0.547 | 0.664 | 0.654 | 0.191 | 0.490 | 0.508 | 0.329 |
| | [0.082] | [0.083] | | [0.026] | [0.025] | | [0.088] | [0.067] | |

Table A5: Political Interference in Service Delivery

| | Inspectors | | | Supervisors | | |
|---|---|---|---|---|---|---|
| | Mean | SD | N | Mean | SD | N |
| **Colleague ever influenced?** | 0.479 | 0.502 | 117 | 0.537 | 0.502 | 67 |
| by MNA | 0.857 | 0.353 | 56 | 0.889 | 0.319 | 36 |
| by MPA | 0.893 | 0.312 | 56 | 0.889 | 0.319 | 36 |
| by other Politician | 0.161 | 0.371 | 56 | 0.306 | 0.467 | 36 |
| by senior Bureaucrat | 0.143 | 0.353 | 56 | 0.222 | 0.422 | 36 |
| by Police | 0.054 | 0.227 | 56 | 0.056 | 0.232 | 36 |
| by Private Person | 0.125 | 0.334 | 56 | 0.167 | 0.378 | 36 |
| # of times pressure, last year | 7 | 56.761 | 55 | 10 | 19.019 | 35 |
| # of times decision not changed, last year | 2 | 14.765 | 52 | 1 | 25.871 | 33 |
| # of times pressure, last 2 years | 14 | 85.219 | 55 | 10 | 21.607 | 33 |
| # of times decision not changed, last 2 years | 3 | 23.282 | 52 | 2.500 | 27.050 | 30 |

*Notes:* We trim all variables in the lower panel at the 99 percentile.

Table A6: Falsification Tests

| | Inspected (=1) | | | Doctor Present (=1) | | |
|---|---|---|---|---|---|---|
| | Distance to District HQ (1) | PRSP District (2) | # Out-Patient Department (3) | Distance to District HQ (4) | PRSP District (5) | # Out-Patient Department (6) |
| Smartphone Monitoring (=1) | 0.261** | 0.271*** | | 0.019 | -0.033 | |
| | (0.120) | (0.087) | | (0.113) | (0.068) | |
| Monitoring x Column Variable | -0.001 | -0.122 | 0.000 | -0.001 | 0.037 | 0.000 |
| | (0.002) | (0.105) | (0.000) | (0.002) | (0.132) | (0.000) |
| Constant | 0.221*** | 0.219*** | 0.185*** | 0.518*** | 0.517*** | 0.275*** |
| | (0.022) | (0.020) | (0.058) | (0.021) | (0.021) | (0.055) |
| # Districts | 34 | 35 | 35 | 34 | 35 | 35 |
| # Clinics | 807 | 836 | 827 | 639 | 667 | 596 |
| # Observations | 2088 | 2163 | 1512 | 1450 | 1522 | 985 |
| R-Squared | 0.052 | 0.058 | 0.029 | 0.014 | 0.009 | 0.028 |

*Notes*: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the district level reported in parentheses. All regressions include clinic and survey wave fixed effects. OPD estimates are post-treatment differences since OPD is measured only after treatment.

Table A7: Breakdown of Doctor Surveys

| | Wave 1 | Wave 2 | Wave 3 | Wave 4 | Total |
|---|---|---|---|---|---|
| Doctors Assigned in Sample | 537 | 509 | 488 | | |
| Total Interviews | 266 | 252 | 226 | 141 | 885 |
| Number of New Doctors Interviewed | 266 | 128 | 60 | 87 | 541 |
| Balance | 271 | 115 | 34 | | |

Table A8: Connections and Perks

| Dependent Variable: | Distance to Doctor's Hometown (minutes) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Doctor Knows MP Personally (=1) | -131.628*** | -112.918*** | -127.607*** | -95.366** | -270.811*** | -314.565 | -393.636* |
| | (35.431) | (35.675) | (41.792) | (46.485) | (83.030) | (188.270) | (212.932) |
| Doctor's Years of Service | | | 0.093 | 0.035 | | | 1.977 |
| | | | (0.307) | (0.361) | | | (1.578) |
| Catchment Population (1,000) | | | -1.950 | -1.417 | | | -5.550 |
| | | | (2.579) | (2.471) | | | (11.668) |
| Distance to District Center (km) | | | 1.066 | 2.023 | | | 0.995 |
| | | | (0.899) | (1.240) | | | (4.310) |
| Constant | 198.698*** | 185.783*** | 191.748** | 126.098 | 449.808*** | 460.512*** | 444.783 |
| | (47.187) | (42.578) | (95.577) | (90.661) | (105.185) | (99.948) | (364.098) |
| District Fixed Effects | No | Yes | Yes | No | No | Yes | Yes |
| Tehsil (County) Fixed Effects | No | No | No | Yes | No | No | No |
| Sample | Full | Full | Full | Full | >50 mins | >50 mins | >50 mins |
| # Observations | 204 | 204 | 194 | 194 | 60 | 60 | 56 |
| R-Squared | 0.045 | 0.214 | 0.233 | 0.385 | 0.063 | 0.429 | 0.494 |

*Notes*: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors clustered at the Basic Health Unit (BHU) level reported in parentheses. Sample: Full - control district BHUs; >50 minutes - control BHUs where doctor is further than 50 minutes from their hometown. All regressions include Tehsil (county) and survey wave fixed effects.

# C Matching Clinics to Political Constituencies

We followed a two pronged strategy to place the clinics in their relevant electoral constituencies:

First, we gathered the GPS coordinates of each clinic in our sample during field surveys. These coordinates were compared with those provided to us by the Health Department and then verified in cases of disagreement. This enables us to place clinics on a geo referenced map of constituencies.

The Election Commission of Pakistan has publicly released maps of all provincial and national constituencies in the Portable Document Format (PDF) on their website[19]. As these maps lack vector information that is required for direct use with GPS coordinates, we manually converted the PDFs to shape files so that we can place each clinic in the correct constituency polygon. The quality of this approach however, is affected by the reliability of these base maps prepared by the Election Commission of Pakistan.

A second approach helps ensure that the placement of clinics does not hinge solely on the quality of these maps. During the second round of our surveys, we asked all responders in a clinic to identify the constituency where the clinic is located. In cases where respondents did not know the constituency number, we asked them to name the elected representative from the area. To corroborate this further, we asked the most senior official present at the clinic to identify the political constituency in consultation with colleagues during the third round of the surveys.

We manually compared the names of elected politicians provided by the clinic staff with official lists available on the website of Punjab Assembly. We assigned a constituency number if the name matched with information on the website. At the end of this exercise we had constituency information from multiple responders. We proceeded by taking the mode of these responses to assign clinics to political constituencies. In cases with disagreements, we manually compared the data with official lists of district-wise constituencies and corrected

[19]http://ecp.gov.pk/Delimitation/ConstituencyMap/PA.aspx

cases with obvious typos. For instance, a district with a constituency number 191 had a reported constituency number of 91, which we corrected.

Through this procedure, we were able to match all but a few clinics to constituencies. We used geo-spatial information and Election Commission of Pakistans maps to break the tie between the remaining few clinics.

## D Hiring Process for Doctors

There are two different hiring processes for the Medical Officers. The first process of hiring is through Punjab Provincial Service Commission (PPSC). Through this route a Medical Officer becomes part of the bureaucracy either temporarily or permanently depending on the nature of positions that are being filled. PPSC is a statuary body tasked with hiring of human resources for several arms of the provincial government. The commission floats an advertisement with details of the hiring process. Individuals who have passed the doctor certifications (M.B.B.S.), and are registered with Pakistan Medical and Dental Council, are eligible to apply to these positions. The top candidates are called in for a test and further shortlisted candidates are interviewed by a selection committee. The committee consists of senior officials from PPSC, the Health Department, and the Director General Health Services office, and a senior medical expert. Merit lists generated based on performance in the interview are then communicated to the Health Department by PPSC. The department then decides on the postings based on these lists.

The second process for hiring Medical Officers is devolved at the District Level. The EDO health office advertises vacant positions locally, and shortlisted applicants are interviewed by the EDO himself. The candidates might also be given a test designed by the EDO on the same day. Recommendations of the EDO are conveyed to the Establishment Division of the Health Department, which then issues offer letters to the successful applicants. However, these doctors are only hired on a contractual basis. In order to become permanent employees, long term contractual doctors have to clear a promotion exam at PPSC. EDOs also have the power to hire and appoint temporary MOs during times of high demand of services, such as in the case of an outbreak of the Dengue virus, or flood prone epidemics. Some of these MOs can be considered preferentially for filling vacancies once the demand normalizes. However, temporary MOs also have to clear a test at PPSC in order to become permanent employees.

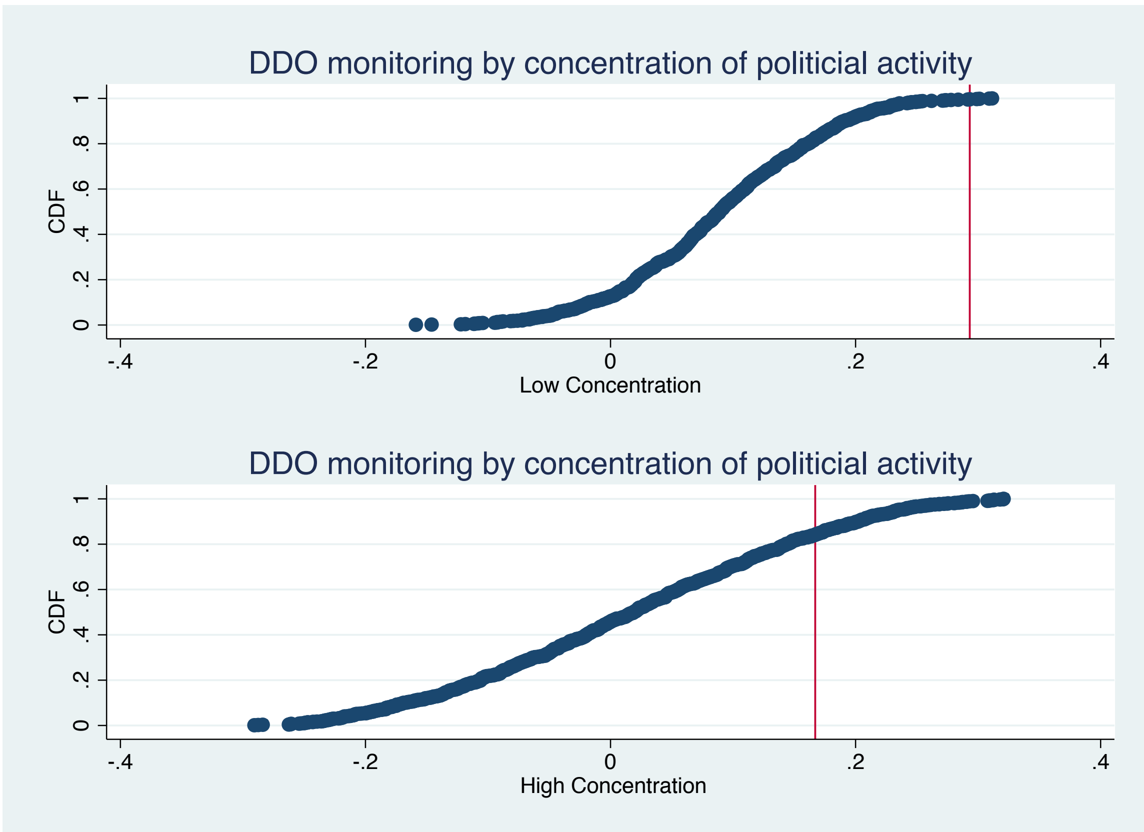


Figure A1: Estimated Distributions of Impacts by Political Concentration

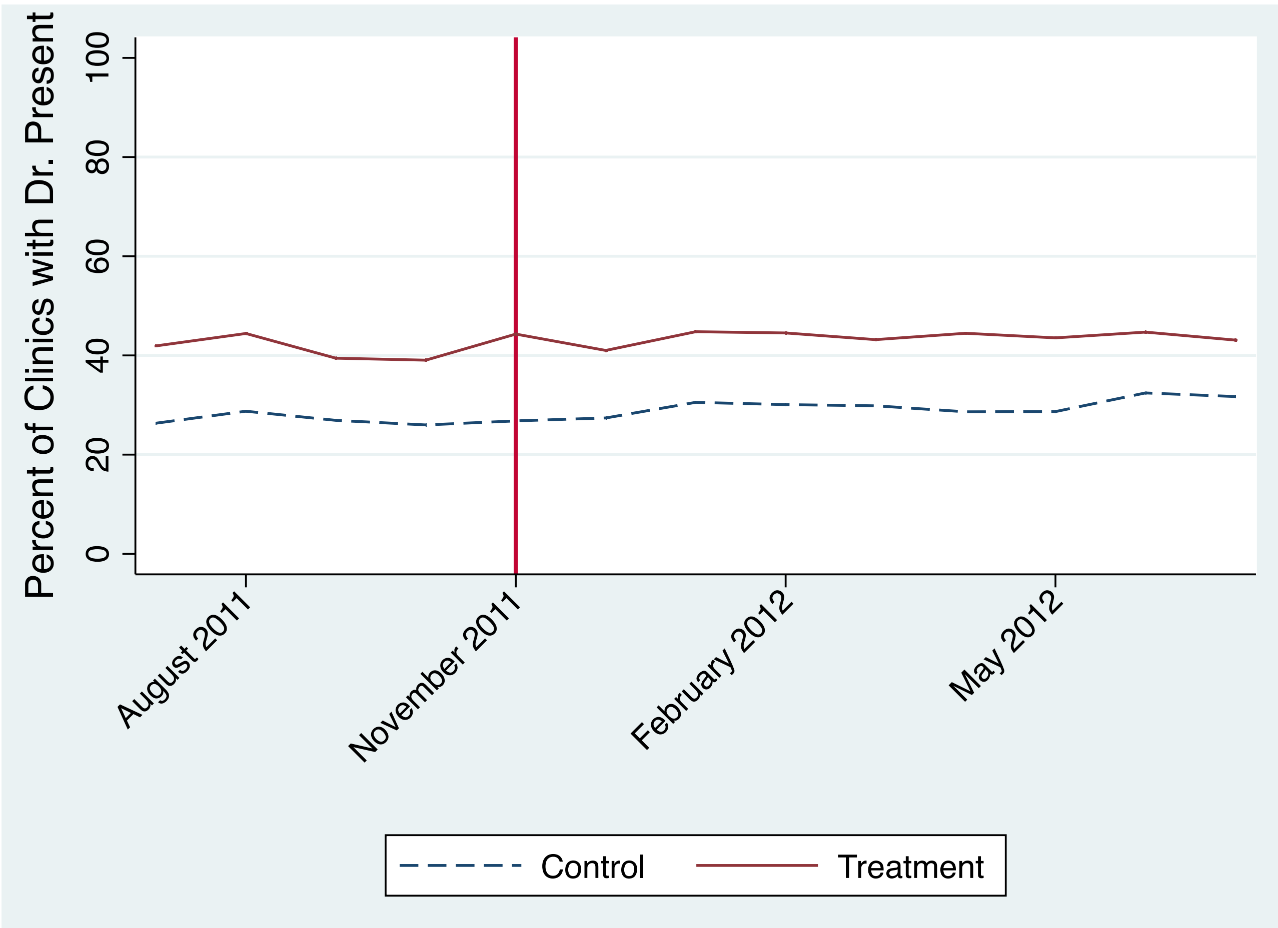


Figure A2: Average Doctor Attendance Before and After Treatment

Table A9: Main Effects Randomization Inference

| Dependent Variable | Sample | Constant | Treatment Effect | P-value (t-test) | P-value (Fisher) |
|---|---|---|---|---|---|
| Inspected (=1) | Full | 0.217 | 0.210 | 0.003 | 0.000 |
| | | (0.023) | (0.065) | | |
| Inspected (=1) | High Competition | 0.221 | 0.244 | 0.007 | 0.006 |
| | | (0.030) | (0.084) | | |
| Inspected (=1) | Mid Competition | 0.251 | 0.228 | 0.108 | 0.013 |
| | | (0.048) | (0.137) | | |
| Inspected (=1) | Low Competition | 0.180 | 0.177 | 0.030 | 0.099 |
| | | (0.028) | (0.078) | | |
| Number of Staff Present | Full | 2.802 | -0.040 | 0.861 | 0.850 |
| | | (0.075) | (0.227) | | |
| Number of Staff Present | High Competition | 2.912 | 0.630 | 0.006 | 0.031 |
| | | (0.069) | (0.211) | | |
| Number of Staff Present | Mid Competition | 2.683 | -0.317 | 0.249 | 0.973 |
| | | (0.098) | (0.269) | | |
| Number of Staff Present | Low Competition | 2.799 | -0.358 | 0.355 | 0.886 |
| | | (0.125) | (0.381) | | |
| Doctor Present (=1) | Full | 0.327 | -0.010 | 0.813 | 0.644 |
| | | (0.014) | (0.043) | | |
| Doctor Present (=1) | High Competition | 0.336 | 0.103 | 0.115 | 0.057 |
| | | (0.021) | (0.064) | | |
| Doctor Present (=1) | Mid Competition | 0.300 | -0.058 | 0.393 | 0.867 |
| | | (0.021) | (0.067) | | |
| Doctor Present (=1) | Low Competition | 0.337 | -0.066 | 0.285 | 0.900 |
| | | (0.020) | (0.061) | | |