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

Michael Callen† Saad Gulzar‡ Ali Hasanain§ Yasir Khan¶

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Abstract

In many developing countries, public sector absence is both common and resistant to reform. One explanation for this is that politicians provide public jobs with limited work requirements as patronage. We test this patronage hypothesis in Pakistan using: (i) a randomized controlled 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 and; (iv) surveys of connections between local politicians and health staff. Four results support this view. First, while doctors are present at 42 percent of clinics in competitive constituencies, they are present at only 13 percent of clinics in uncompetitive constituencies. Second, doctors who know their local parliamentarian personally are present at an average of 0.727 of three unannounced visits, while doctors without this connection are present at 1.309 of the three visits. Third, around 40 percent of inspectors and health administrators report interference by politicians when they try to sanction doctors. Fourth, the effect of the smartphone monitoring technology, which almost doubled inspection rates, is highly localized to competitive constituencies. 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 officials using an online dashboard. These effects are also largest in politically competitive constituencies. Our results have implications for the study of bureaucratic incentives in fragile states and are potentially actionable for policymakers trying to build state capacity.

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† University of California, Los Angeles. email: mjcallen@ucsd.edu
‡ New York University. email: saad.gulzar@nyu.edu
§ Lahore University of Management Sciences. email: hasanain@lums.edu.pk
¶ International Growth Centre - Pakistan. email: yasir.khan@theigc.org

1 Introduction

Patronage politics often leads to the selection of inefficient policies. In clientelistic 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 to be intractable. 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

[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).

three settings, the beneficiaries commonly rewarded politicians with votes, party campaign 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).

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. We investigate whether public worker absence is linked to the usefulness of jobs with minimal attendance requirements for political patronage.

We pursue five lines of analysis to investigate the links between clientelism and public sector absence. First, we combine data on parliamentary election outcomes with independently collected data on doctor absence. Second, we directly interview doctors to examine whether their connections to politicians are related to their job performance and to the desirability of their posting. Third, we interview both inspectors and health administrators, directly inquiring about the frequency of interference. 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

[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.

the degree of local political competition.[4] Last, we manipulate the salience of health staff absence in summaries 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 five main results which link health service provision to local political outcomes. First, absence is more severe in less competitive political constituencies. Second, politically connected doctors are more frequently absent. Third, reports of interference by politicians in bureaucratic decisions related to sanctioning health workers is very common and is concentratedin politically uncompetitive constituencies. Fourth, 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 18 percent. 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, our smartphone monitoring system, which required only 90 smart phones to implement, more than doubled health inspections in half of province with a population the size of Germany.

[4] 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.

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[5] (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.[6] 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 Officer, 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.

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

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

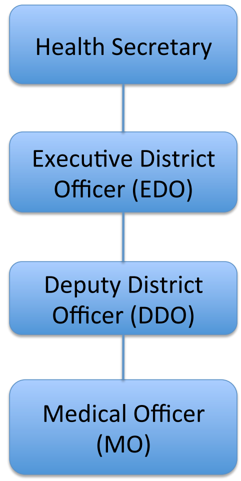

Figure 1: Health Sector Administration in Punjab

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.[7] He is supported by several Deputy District Officers, typically one for each tehsil.[8] Figure 1 depicts the (simplified) health administration hierarchy in Punjab, Pakistan.

The central 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. This officer is required

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

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

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, suspension and withholding pay (in case of contract staff). The Executive District Officer relies entirely on this subordinate officer to ensure staff presence. As the administrative head of the health department in the district, the Executive District Officer desires smooth functioning of the setup at minimum acceptable level. He relies on the Deputy District Officer to ensure this smooth function by sanctioning underperforming facilities in terms of staff attendance, medicine availability and cleanliness etc.

2.1.2 Career Concerns and Internal Agency Problems

The Executive District Officer faces a severe agency problem 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 hold 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. This lack of opportunity to move to a leadership position outside of the district setup diminishes immediate interest in improving the outcomes in the Tehsil, and creates misaligned interests between them and the Executive District Officers.

2.1.3 Doctors 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 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.

There are two different hiring processes for the Medical Officers currently in practice. The first process of hiring is through Punjab Provincial Service Commission (PPSC). Through this route the 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 various arms of the provincial government. The commission floats an advertisement with details of the hiring process[1]. Individuals who have completed MBBS 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 contract basis. In order to become permanent, long term contractual MOs 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 Dengue 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.

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. 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-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 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

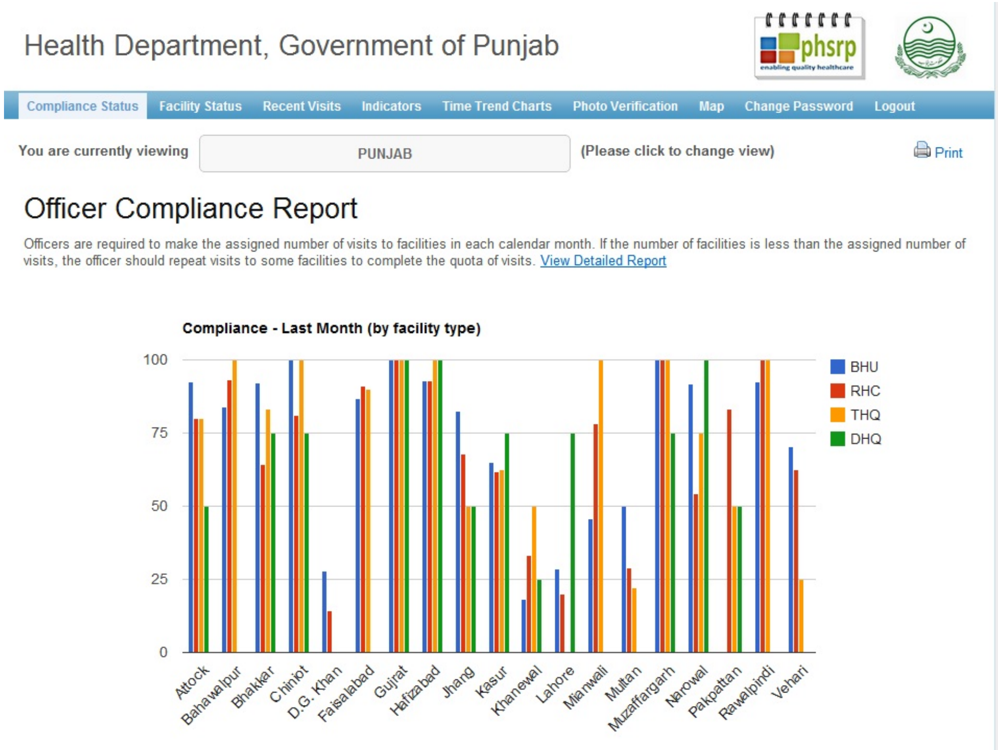

Figure 2: Online Dashboard - Summary of Inspection Compliance by District

of the treatment districts.

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 the district of 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 inspections 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.

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. All districts in

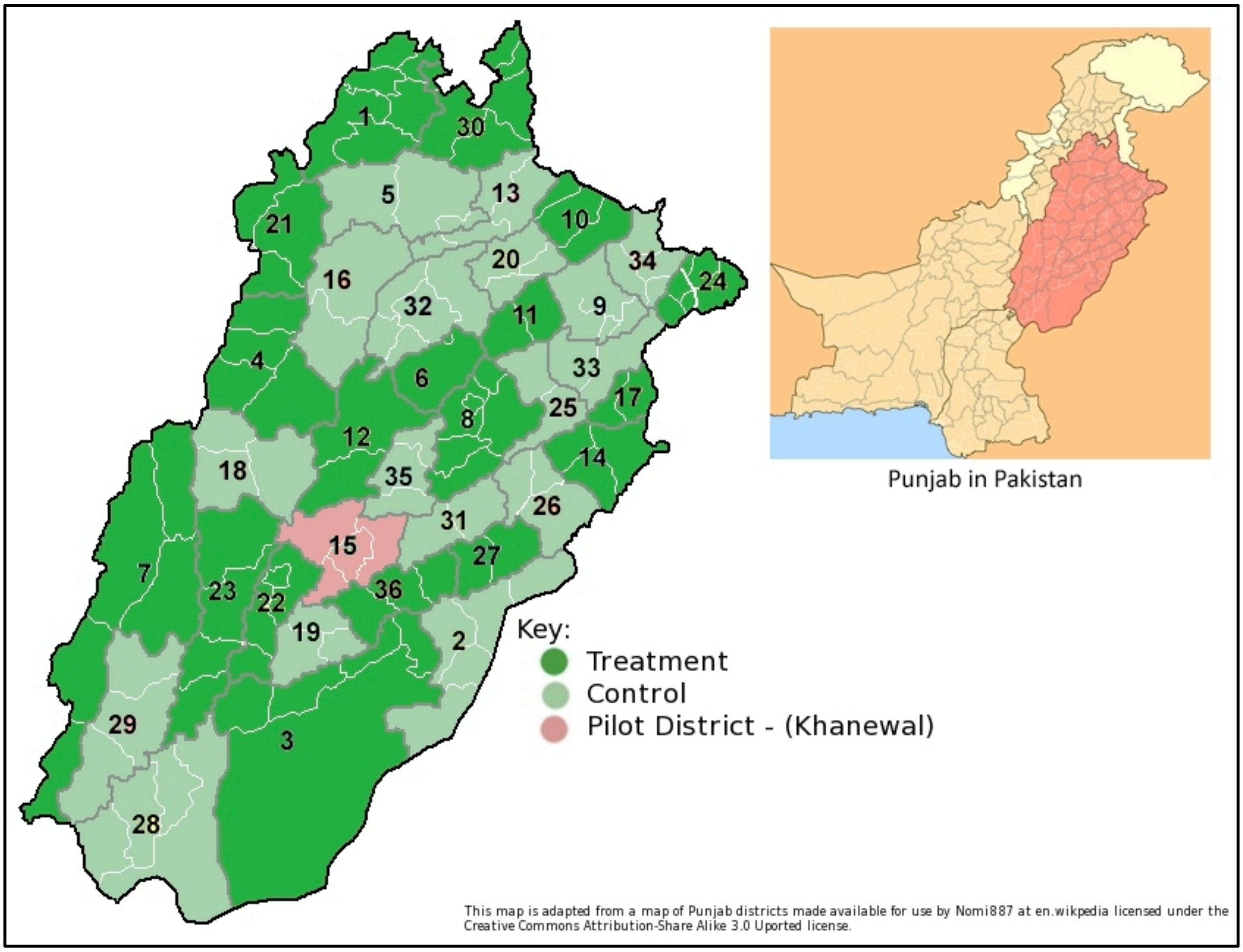

Figure 3: Treatment and Control Districts

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 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.[9] 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.

[9] 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

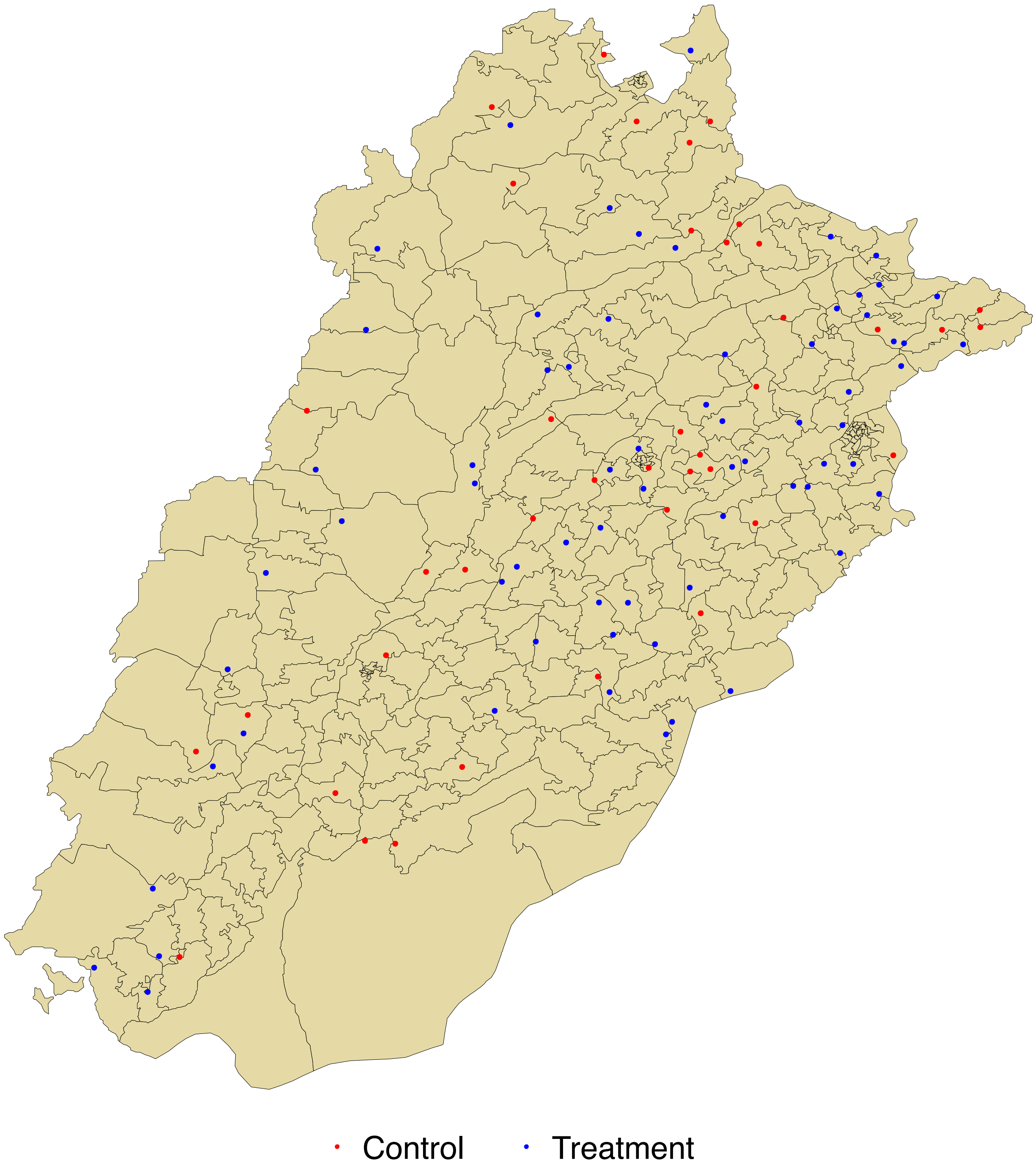

Figure 4: Locations of Basic Health Units in the Experimental Sample

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 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.

Table 1 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 doctor personally.

Table 1: Summary Statistics

Variable	Mean	Standard Deviation	# Observations
Doctor Present (=1)	0.223	0.417	1186
Doctor Posted at Clinic (=1)	0.531	0.499	1186
Doctor Knows Local MPA Personally (=1)	0.24	0.428	569
Distance to Doctors Hometown (minutes)	123.222	302.738	203
Doctor's Months of Service	98.872	98.769	195
Distance to District Headquarters (km)	49.226	28.748	1252
Catchment Population (1,000)	24.767	8.567	1243
Political Concentration (0 - 1)	0.664	0.151	1247
Victory Margin Share	0.17	0.152	1253

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.

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. We construct two measures of the degree of local electoral capture: "political concentration," a normalized Herfindahl index computed as the sum of squared vote shares for each party in the constituency divided by the maximum Herfindahl score in our sample (0.52) and "Victory Margin Share" which is simply the victory margin for the winning candidate as a share of total votes cast in the local election. We drop two clinics in parliamentary constituency number 124 from our analysis as the Herfindahl-Hirschman 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 normalized political concentration ranges from 0.272 in the most competitive constituency to one in the least competitive constituency.[10] The victory margin share in these 123 constituencies ranges from 0.0015 percent to one in uncontested districts. Figure 5 maps the political concentration measure for each constituency in Punjab. The degree of political contestation appears only weakly correlated with geography.

In Table 2 we report correlations between these measures of local political competition and doctor attendance. Columns (1) - (3) report regressions using the normalized political concentration measure as an explanatory variable and (4) - (6) report the same specifications using victory margin share. We find that doctors attend work more often in competitive constituencies. In all specifications, we include 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 of doctor postings. While there are a range of plausible omitted variables prohibiting a causal interpretation, we find that the correlation is robust to including controls for catchment population, distance to the district center, and whether a doctor was reported by other staff to be posted.

The results in Table 2 are consistent with two theories. First, it may be that in highly competitive districts politicians face stronger incentives to make sure health services are

[10]Before dividing by the maximum Herfindahl score in our sample, political concentration ranges from 0.14 to 0.52

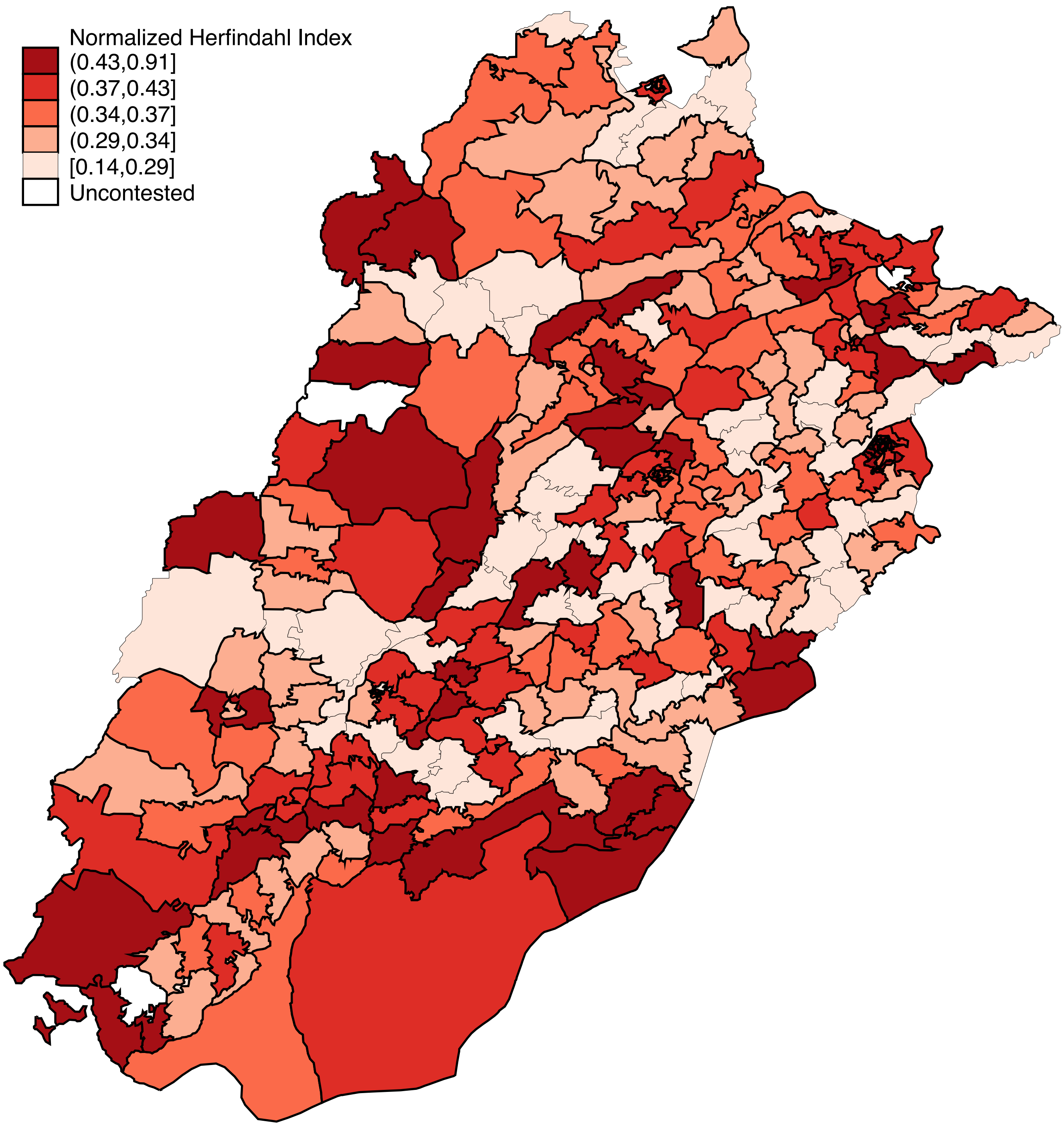

Figure 5: Electoral Competitiveness in Punjab (Normalized Herfindahl Index)

Table 2: Political Competition and Doctor Attendance

Dependent Variable:	Doctor Present (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Political Concentration	-0.289**	-0.276**	-0.124			
	(0.120)	(0.118)	(0.082)			
Victory Margin				-0.171*	-0.220**	-0.184***
				(0.101)	(0.096)	(0.067)
Distance to District Center (in minutes)		-0.002***	-0.001**		-0.003***	-0.001**
		(0.001)	(0.000)		(0.001)	(0.001)
Catchment Population (1,000)		0.004**	0.001		0.004**	0.001
		(0.002)	(0.002)		(0.002)	(0.002)
Doctor Assigned (=1)			0.402***			0.405***
			(0.031)			(0.031)
Constant	0.422***	0.449***	0.115*	0.261***	0.306***	0.065
	(0.081)	(0.099)	(0.069)	(0.023)	(0.056)	(0.047)
# Constituences	122	122	122	123	123	123
# Observations	1179	1171	1171	1184	1176	1176
R-Squared	0.158	0.171	0.322	0.152	0.166	0.321

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Sample: Control district clinics. Survey waves 1 - 3. Standard errors clustered at the provincial assembly constituency level reported in parentheses. Political Concentration is a Herfindahl index computed as the sum of squared vote shares for each party in a constituency ranging from 0.272 in the most competitive district to 1 in uncontested districts. All regressions include Tehsil (county) and survey wave fixed effects.

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 them.

Table 3 examines whether doctors with a direct connection to the provincial assembly member serving in their constituency are more likely to be absent. We run regressions of the form:

$$Present_i = \beta_0 + \beta_1 Knows\ Parliamentarian_i + \epsilon_i \qquad (1)$$

for each doctor i in our sample. We record whether doctors are present on three separate visits. $Present_i$ therefore ranges between 0 and 3. Summary statistics for this cross-section are reported in Table A3.

Columns (1) - (4) report results using only the 188 doctors posted in our control sample.

Column(5) reports the same specification for our entire sample. Doctors who do not know their local parliamentarian directly are present at an average of 1.309 of our 3 visits, while doctors who do know their parliamentarian are present at only 0.727 visits. These effects are robust to including either district or Tehsil fixed effects, and including a range of controls. We provide further support for the arguments that connected doctors enjoy preferential benefits in Table A8. We find that doctors who know their local parliamentarian are able to obtain postings closer to their hometown, which are widely thought to be more desirable.

Table 3: Political Connections and Doctor Attendance

Dependent Variable:	Number of Times Doctor Present (Max = 3)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Doctor Knows Local MPA Personally (=1)	-0.573***	-0.586***	-0.617***	-0.448**	-0.526*	-0.390***	-0.556***
	(0.132)	(0.144)	(0.218)	(0.221)	(0.309)	(0.144)	(0.212)
Patients Treated		0.000	-0.000	0.000	0.000	0.000**	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Catchment Population (1,000)		0.000	0.007	-0.003	0.003	0.006	0.016*
		(0.007)	(0.013)	(0.014)	(0.020)	(0.006)	(0.009)
Distance to District Center (km)		0.004**	-0.009*	-0.003	-0.009	-0.000	-0.001
		(0.002)	(0.005)	(0.005)	(0.009)	(0.003)	(0.004)
Doctor Assigned (=1)		1.000***	1.015**	0.318	0.726	0.983***	1.335***
		(0.206)	(0.488)	(0.354)	(0.662)	(0.205)	(0.371)
Big5 Index			0.090		0.154		0.111
			(0.144)		(0.206)		(0.132)
Public Service Motivation Index			0.141		-0.001		0.049
			(0.157)		(0.220)		(0.141)
Constant	1.300***	0.204	0.656	1.221**	0.854	0.179	-0.448
	(0.063)	(0.260)	(0.533)	(0.539)	(0.863)	(0.272)	(0.483)
Tehsil County Fixed Effects	No	No	Yes	No	No	No	No
Constituency Fixed Effects	No	No	No	Yes	Yes	Yes	Yes
Sample	Controls	Controls	Controls	Controls	Controls	Full Sample	Full Sample
# Doctors	213	212	149	212	149	505	355
R-Squared	0.061	0.146	0.567	0.608	0.711	0.563	0.680

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Robust standard errors reported in parentheses. Sample: control district Basic Health Units (BHUs). All regressions include Tehsil (county) and survey wave fixed effects.

These correlations suggest that local politicians may secure office by providing sinecures to supporters. This theory has predictions 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.

5.1 Interference in Inspector Decisions

For politicians to influence the reporting requirements of doctors, they need to interfere in bureaucratic decisions. In this section, we review the responses of inspectors and Executive District Officers to the following questions:

- Have you personally ever been pressured by a person with influence to either (a) not take action against doctors or other staff that were performing unsatisfactorily in your tehsil or district or (b) assign them to their preferred posting?

- If yes, then identify the type of influential person from the following list:
  Member of National Assembly; Member of Provincial Assembly; Other Politician; Senior Bureaucrat; Police; Powerful private person; Other; No response

- How many of these incidents occurred in the last year?

The results are striking. Around 40 percent of both inspectors and administrators report political interference in their decisions. In Table 4 we present results indicating that this type of interference is much more common for inspectors overseeing politically uncompetitive constituencies. On average, inspectors overseeing competitive constituencies report two incidents of members of the provincial assembly interfering in their decision over the course of two years. This number is twice as large (four incidents) in uncompetitive constituencies. This result is robust to restricting our data to political constituencies which are wholly contained with in a single inspector's jurisdiction.

Table 4: 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 A1 and further details about the frequency and source of political interference is provided in Table A2. 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.

6 Experimental Results

With this motivation as background, we now present our experimental results. Table 5 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.[11]

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 of the form:

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

Y_{dit} is health worker attendance or official inspection, where i refers 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

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

Table 5: Randomization Verification

	Conventional Monitoring (=1)	Smartphone Monitoring (=1)	Difference	P-value
BHU open during visit (=1)	0.926	0.930	-0.004	0.907
	[0.262]	[0.256]	(0.032)	
Inspector Has Visited in the Last Month (=1)	0.234	0.214	0.020	0.722
	[0.424]	[0.411]	(0.057)	
Number of Staff Present	2.728	2.874	-0.146	0.428
	[1.516]	[1.638]	(0.182)	
Number of Staff Assigned	5.117	5.286	-0.169	0.188
	[0.925]	[0.941]	(0.125)	
Doctor Present (Assigned only)	0.422	0.552	-0.130	0.057
	[0.495]	[0.498]	(0.066)	
Health Technician Present (=1)	0.518	0.474	0.044	0.486
	[0.500]	[0.500]	(0.063)	
Dispenser Present (=1)	0.735	0.804	-0.069	0.245
	[0.442]	[0.397]	(0.059)	
SHNS Present (=1)	0.347	0.340	0.007	0.901
	[0.477]	[0.474]	(0.059)	
Lady Health Visitor Present (=1)	0.636	0.656	-0.020	0.694
	[0.482]	[0.476]	(0.051)	
Midwife Present (=1)	0.538	0.474	0.064	0.164
	[0.499]	[0.500]	(0.045)	
Political Concentration (0 - 1)	0.664	0.661	0.003	0.917
	[0.151]	[0.147]	(0.025)	
High Competition Constituencies (Bottom Tercile)	0.320	0.355	-0.036	0.618
	[0.467]	[0.479]	(0.071)	
Medium Competition Constituencies (Middle Tercile)	0.373	0.287	0.086	0.240
	[0.484]	[0.453]	(0.072)	
Low Competition Constituencies (Top Tercile)	0.308	0.358	-0.050	0.475
	[0.462]	[0.480]	(0.069)	
# of Observations	419	427		

Notes: Variable standard deviations reported in brackets. Standard errors reported in parentheses.

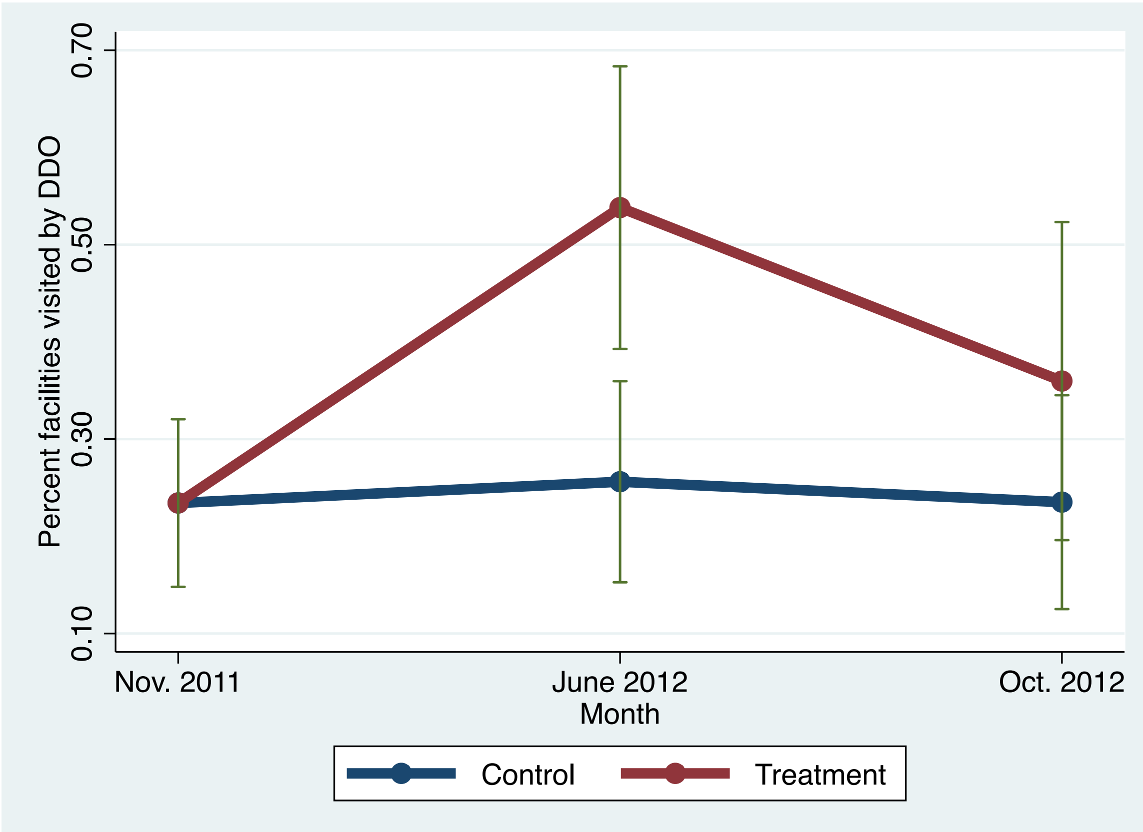

Figure 6: Effects by Survey Wave

somewhat over the life of the program. Inspections remain 89% higher than they were at baseline. Figure 6 depicts attendance in treatment and control groups by wave. Future data collection will indicate whether this downward trend sustains. In columns (2) - (5), we again see no evidence of impact.

6.1 Treatment Effects on Inspector Time Use

Table 7 presents results on the time use of inspectors. We collected data on time use by asking inspectors to provide detailed data on how they had used their time over the previous two days. These data were collected after the experiment had been operating for about seven months. The effects are consistent with the increase in inspections documented in Table 6. Doctors increase their time inspecting by an average of about 44 minutes. There is also weak evidence that they increase their time in duties unrelated to facility inspection

Table 6: 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)	0.223***	-0.025	0.032	-0.016	-0.023
	(0.062)	(0.230)	(0.202)	(0.044)	(0.038)
# Staff Assigned			0.435***		
			(0.039)		
Doctor Assigned (=1)					0.369***
					(0.035)
Constant	0.217***	2.802***	0.540**	0.326***	0.086***
	(0.022)	(0.076)	(0.213)	(0.015)	(0.028)
# Districts	35	35	35	35	35
# Clinics	836	846	846	846	846
# Observations	2163	2536	2536	2408	2408
R-Squared	0.055	0.006	0.139	0.005	0.108

Panel B - Effects By Survey Wave	Inspected (=1)	Number of Staff Present		Doctor Present (=1)	
	(1)	(2)	(3)	(4)	(5)
Monitoring x Wave 2	0.302***	-0.142	-0.062	-0.035	-0.035
	(0.076)	(0.252)	(0.217)	(0.056)	(0.050)
Monitoring x Wave 3	0.149*	0.092	0.126	0.002	-0.012
	(0.078)	(0.246)	(0.217)	(0.054)	(0.048)
# Staff Assigned			0.434***		
			(0.038)		
Doctor Assigned (=1)					0.369***
					(0.034)
Constant	0.217***	2.802***	0.545**	0.326***	0.086***
	(0.021)	(0.076)	(0.209)	(0.015)	(0.027)
# Districts	35	35	35	35	35
# Clinics	836	846	846	846	846
# Observations	2163	2536	2536	2408	2408
R-Squared	0.063	0.008	0.141	0.006	0.108

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.

or management. Cumulatively, the effect is to increase time working by an average of about 74 total minutes per day.

To protect against the potential for experimenter demand effects, in asking these questions, we asked administrative assistants to corroborate these data and we also made sure that surveyors had no clear connection to the government-sponsored inspection program.

6.2 Heterogeneity by Political Concentration

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 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 8 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. To test robustness to the linear specification, we interact treatment with political concentration, with separate dummies for the lower, mid, and highest 33 percentiles in Table A5.

Table 7: Treatment Effects on Time Use

	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			
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.

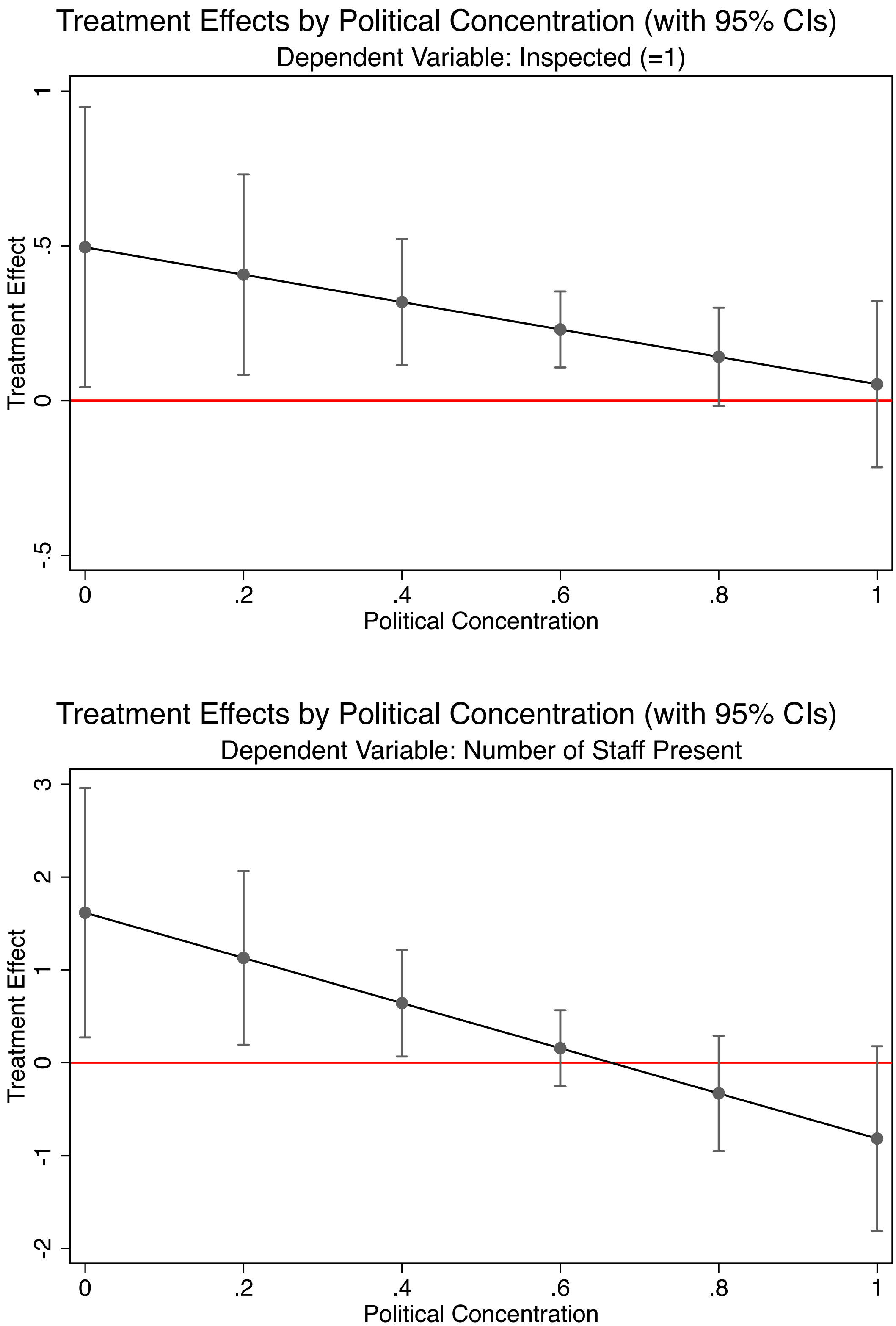

Figure 7: Treatment Effects by Political Concentration

Table 8: Treatment Effects by Political Concentration

Dependent Var.	Inspected (=1)	Number of Staff Present		Doctor Present (=1)	
	(1)	(2)	(3)	(4)	(5)
Smartphone Monitoring (=1)	0.524**	1.615**	1.679**	0.286*	0.238
	(0.232)	(0.683)	(0.710)	(0.159)	(0.143)
Monitoring x Political Concentration	-0.455	-2.429**	-2.457**	-0.454**	-0.392**
	(0.344)	(1.110)	(1.077)	(0.216)	(0.191)
# Staff Assigned			0.430***		
			(0.036)		
Doctor Assigned (=1)					0.368***
					(0.036)
Constant	0.217***	2.799***	0.561***	0.324***	0.086***
	(0.022)	(0.074)	(0.195)	(0.014)	(0.028)
# Districts	35	35	35	35	35
# Clinics	829	838	838	838	838
# Observations	2145	2513	2513	2390	2390
R-Squared	0.058	0.017	0.146	0.008	0.109

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.

6.3 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 online dashboard. This dashboard is only visible to Executive District Officers, the Health Secretary for Punjab, and the Director General of Health for Punjab. Figure 8 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

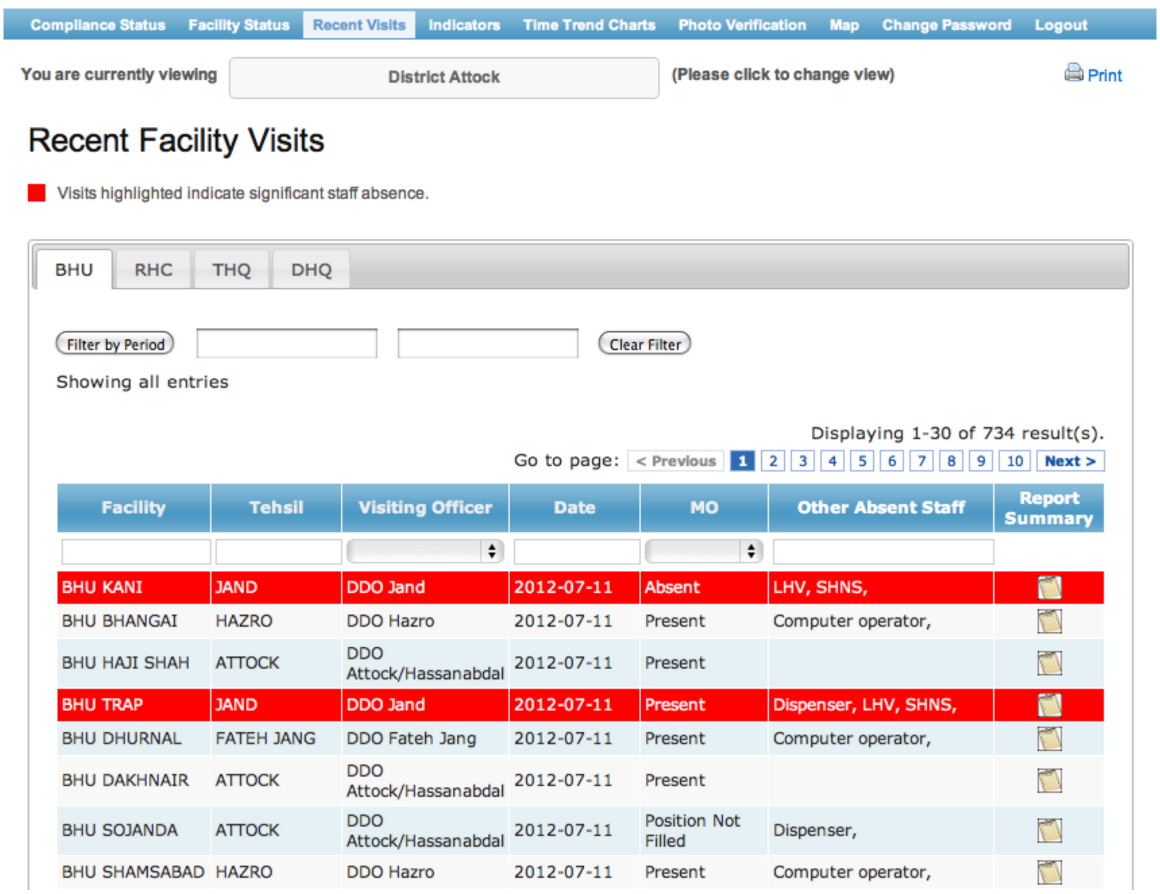

Figure 8: Highlighting Underperforming Facilities to Test Mechanisms

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 9 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) and (4), we report results only for our sample where either two or three doctors were absent. We call this the "discontinuity" sample. Columns (5) - (8) repeat this analysis for doctors only. Our coefficients suggest that absence in the month after an inspection is reduced by about 20 percent if the facility is flagged.

Placebo Tests

Our identifying assumption is that, conditional on whether a doctor was recorded absent on the dashboard the month prior to inspection, the assignment of the flag is random. We perform placebo tests of this assumption by assuming that facilities are flagged if four or more staff are absent. Table 9 Panel B repeats the specifications from Panel A with the placebo flag. Columns (1) and (2) report estimates for our complete sample and (3) and (4) restrict the sample to facilities where either three or four doctors were reported absent. We find no evidence of impact on facilities reaching the placebo absence threshold.

6.4 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

Table 9: Effect of Flagging Underperformance on the Dashboard

	Doctor Absent in Unannounced Visit (=1)			
Panel A - Discontinuity Estimates	(1)	(2)	(3)	(4)
Facility Flagged as Underperforming on Dashboard	-0.121**	-0.090*	-0.120	-0.124*
	(0.051)	(0.049)	(0.076)	(0.068)
Reported Absent on Dashboard	0.218***	0.193***	0.276***	0.224**
	(0.065)	(0.066)	(0.092)	(0.105)
Constant	0.641***	0.625***	0.555***	0.547***
	(0.035)	(0.035)	(0.074)	(0.075)
District FEs	No	Yes	No	Yes
# Observations	523	523	178	178
# Staff	348	348	152	152
R-Squared	0.025	0.149	0.050	0.334
Sample	Full	Full	Discontinuity	Discontinuity

	Doctor Absent in Unannounced Visit (=1)			
Panel B - Placebo Flags	(1)	(2)	(3)	(4)
Placebo Flag	-0.047	0.014	0.123	0.145
	(0.071)	(0.069)	(0.098)	(0.094)
Staff Reported Absent on Dashboard	0.186***	0.157**	0.275***	0.227**
	(0.066)	(0.068)	(0.096)	(0.112)
Constant	0.618***	0.601***	0.408***	0.367***
	(0.035)	(0.034)	(0.081)	(0.083)
District FEs	No	Yes	No	Yes
# Observations	523	523	121	121
# Staff	348	348	105	105
R-Squared	0.014	0.143	0.080	0.334
Sample	Full	Full	Discontinuity	Discontinuity

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. Explanatory variables reflect data from the most recent official inspection recorded on the dashboard the month before our unannounced visit.

Table 10: The Effect of Flagging by Political Concentration

	Doctor Absent in Unannounced Visit (=1)			
	(1)	(2)	(3)	(4)
Flagged x Concentration (bottom 33%)	-0.219***	-0.153**	-0.253***	-0.250***
	(0.066)	(0.067)	(0.095)	(0.081)
Flagged x Concentration (mid 33%)	-0.063	-0.007	-0.025	0.015
	(0.093)	(0.084)	(0.119)	(0.119)
Flagged x Concentration (top 34%)	-0.001	-0.058	0.019	-0.042
	(0.078)	(0.069)	(0.110)	(0.092)
Staff Reported Absent on Dashboard	0.206***	0.194***	0.237**	0.204**
	(0.068)	(0.067)	(0.094)	(0.096)
Constant	0.640***	0.624***	0.559***	0.541***
	(0.036)	(0.035)	(0.074)	(0.075)
District FEs	No	Yes	No	Yes
# Observations	523	523	178	178
# Staff	348	348	152	152
R-Squared	0.036	0.153	0.080	0.358
Sample	Full	Full	Discontinuity	Discontinuity

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.

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.[12]

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 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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[12] 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.)"

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A Additional Tables and Figures

Table A1: 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
# Observations	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

Notes: This table reports the frequency of interference by politicians in health inspectors decisions by the level political competition. 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. 63 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. Columns 4 through 6 drop constituencies spanning multiple jurisdictions. *Level of significance:* $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the jurisdiction (tehsil) level reported in parentheses.

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: 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 A3: Summary Statistics for Doctor Cross-section

Variable	Mean	Standard Dev.	# Obs.
Doctor Present (Max = 3)	1.22	0.847	214
Doctor Knows Local MPA Personally (=1)	0.154	0.362	214
Patients Treated Monthly	1397.897	664.72	214
Catchment Population (1,000)	26.757	8.871	214
Distance to District Headquarters(km)	44.709	27.707	213

Notes: Sample: Control district clinics with doctors responding to question on connection to the local MPA. Survey waves 1 - 3 are collapsed to a single doctor cross-section.

Table A4: Randomization Verification

	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: Treatment Effects by Non-Linear Political Concentration

Dependent Var.	Inspected (=1)	Number of Staff Present		Doctor Present (=1)	
	(1)	(2)	(3)	(4)	(5)
Monitoring x Low Pol. Concentration	0.261***	0.646***	0.621***	0.100	0.616**
	(0.074)	(0.233)	(0.224)	(0.064)	(0.248)
Monitoring x Mid Pol. Concentration	0.227	-0.316	-0.161	-0.074	-0.367
	(0.137)	(0.265)	(0.254)	(0.067)	(0.266)
Monitoring x High Pol. Concentration	0.184**	-0.339	-0.305	-0.066	-0.375
	(0.080)	(0.381)	(0.318)	(0.061)	(0.304)
# Staff Assigned			0.426***		
			(0.035)		
Doctor Assigned (=1)					0.455***
					(0.087)
Constant	0.216***	2.799***	0.584***	0.324***	2.609***
	(0.022)	(0.072)	(0.193)	(0.014)	(0.079)
# Districts	35	35	35	35	35
# Clinics	829	838	838	838	838
# Observations	2145	2513	2513	2390	2390
R-Squared	0.057	0.024	0.149	0.010	0.044

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 A6: Falsification Tests

	Inspected (=1)			Doctor Present (=1)		
	Distance to District HQ	PRSP District	# Out-Patient Department	Distance to District HQ	PRSP District	# Out-Patient Department
	(1)	(2)	(3)	(4)	(5)	(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[13]. 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

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

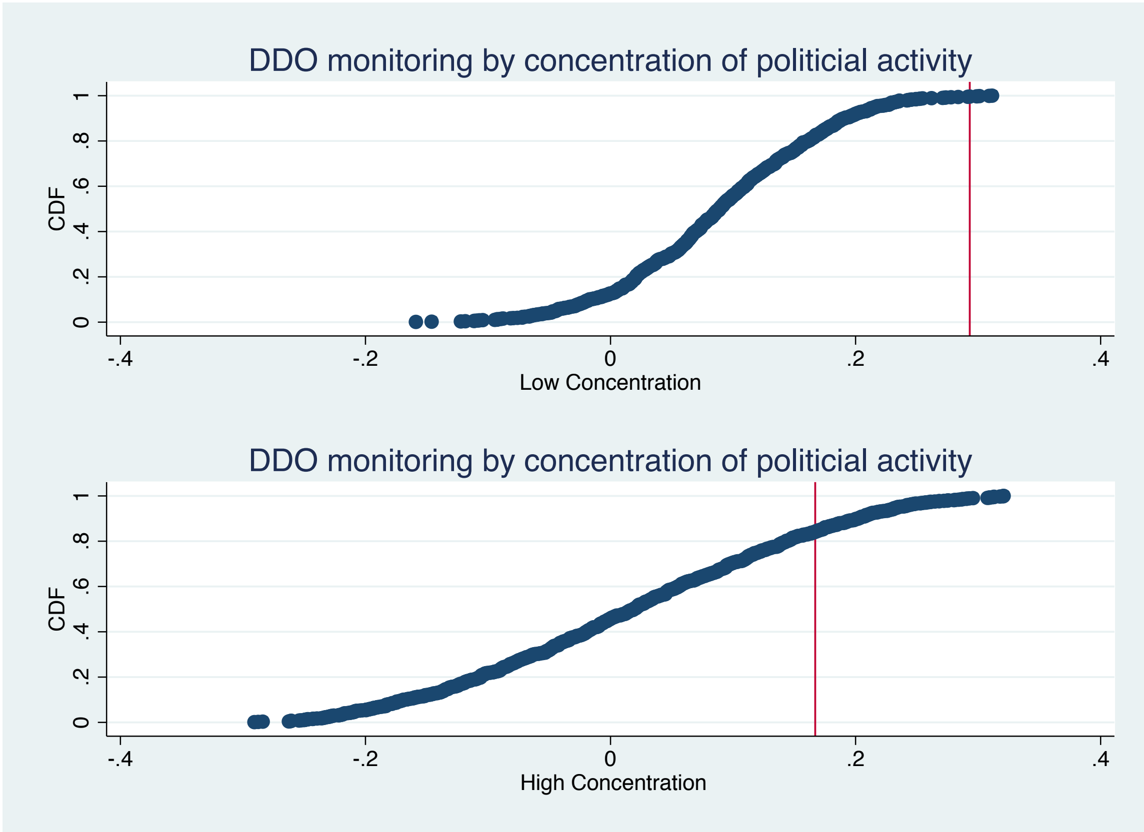

Figure A1: Estimated Distributions of Impacts by Political Concentration

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.

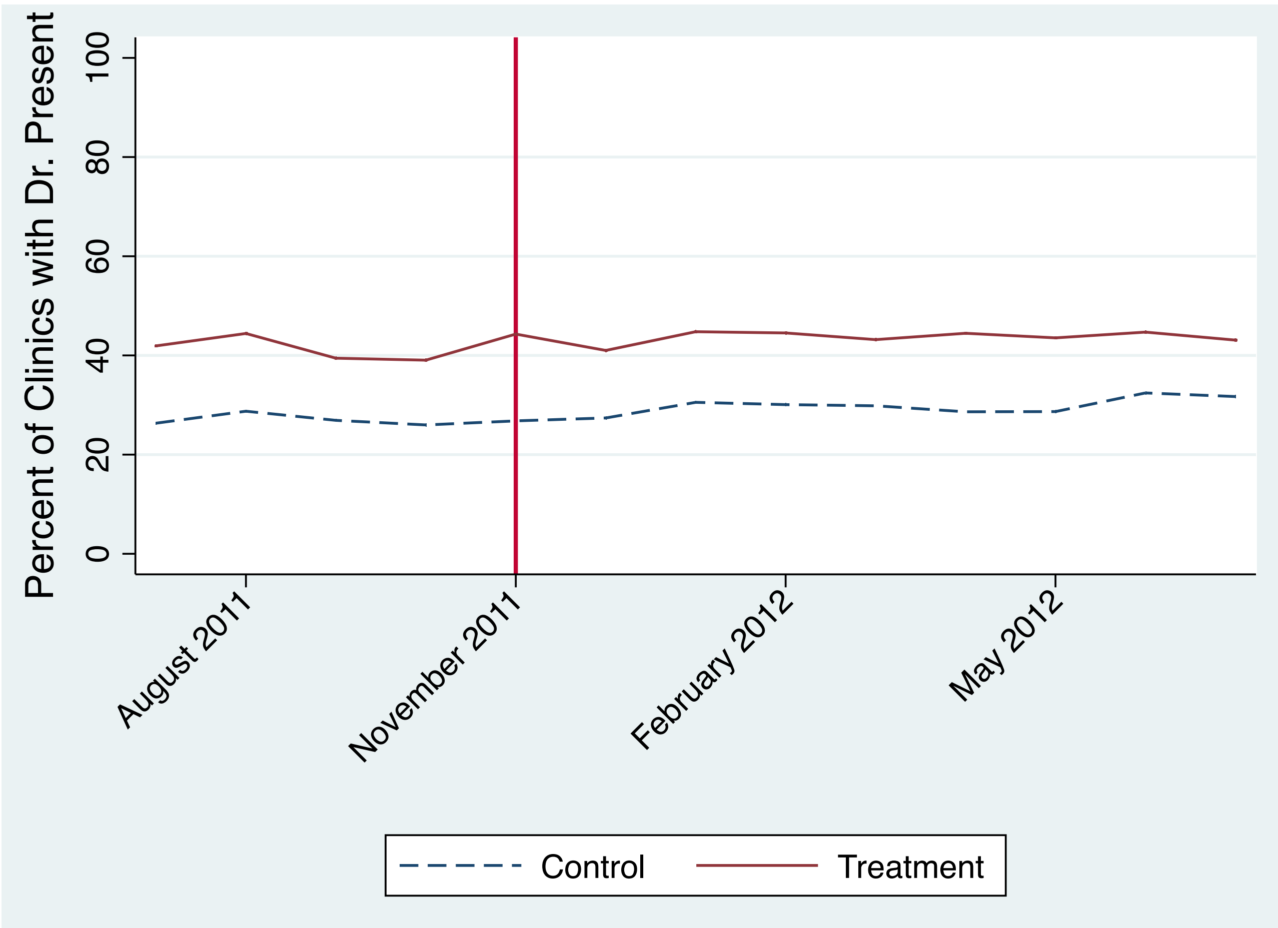

Figure A2: Average Doctor Attendance Before and After Treatment