Ruling Parties, Bureaucratic Performance and Service Delivery in Democracies*

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Abstract

Electoral accountability in democracies has been credited with providing better services to voters. Examining highly politically competitive environments in Punjab, Pakistan I contend that reelection incentives for ruling party politicians can have perverse effects on bureaucratic performance and service delivery, but can improve their re-election rates. This occurs because ruling party politicians have higher access to state resources. I test this in the context of the public health sector by using: (i) data on election outcomes from 100 constituencies where the ruling party politicians won or lost an election in 2008, ii) bureaucratic attendance records during unannounced visits, and iii) data on tenure, connection with politicians, and facility utilization from a large new representative panel survey of rural health clinics. Three sets of results from a regression discontinuity analysis comparing ruling party areas with other constituencies support this view. First, doctors report knowing the politicians personally more often, enjoy higher tenure at the clinics they are posted at, and serve in areas closer to their hometowns. Second, ruling party area doctors are absent from work more often, especially if they know the politician, and when the subsequent elections of 2013 draw closer. This is associated with a fall in antenatal and outpatient visits, and the number of deliveries. Finally, in places where the 2008 elections were close, and the doctors are absent more often, the ruling party candidates are elected to office more often in 2013.

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1 Introduction

Studies show that democracies spend more on public goods, and can perform better in terms of welfare.[1] However, several recent papers examine how democratic incentives may in fact skew political behavior in favor of particularistic concerns.[2] For instance, Stokes (2005) shows that democracies create what she terms 'perverse accountability', where electoral candidates respond to the preferences of weakly opposed voters, whileBueno de Mesquita et al. (2005) show how democratic institutions target their efforts towards a voting core that carries sufficient political power. What is not obvious from recent work is a) how bureaucrats are affected by such perverse incentives under democratic institutions, and b) how the consequent change in bureaucratic behavior affects service delivery and development.

Public jobs are an important source of clientelism. Robinson and Verdier (2013) show that public sector jobs resolve the commitment problem of clientelism for politicians by offering a source of patronage that is a 'credible, selective, and reversible method of redistribution' (p. 261). In spite of a rich literature on bureaucratic performance (Hanna and Wang 2013; Bó et al. 2011; Banerjee et al. 2008), empirical investigations of political appropriation of the public sector rely mostly on case studies.[3] The causal effect of how democratic political institutions affect bureaucratic behavior and performance is therefore mostly unexplored.

In this paper I bring together work on the clientelistic relationship between politicians and bureaucrats, and the impact of this relationship on service delivery. I examine how political incentives in democracies can i) shape characteristics of bureaucrats; ii) perversely impact bureaucratic performance and service delivery; iii) reduce the utilization of public service delivery and iii) subsequently provide electoral benefits. To do this, I study the general elections of 2008 in Punjab, Pakistan. I contend that politicians belonging to the ruling party enjoy higher access to the resources of the state, which they exploit for political gains. One can interpret access to state resources as a positive shock to the budget constraint of ruling party politicians. By making use of state resources, ruling party politicians have the ability to further their political ends. I investigate the impact of this higher access to state resources on bureaucratic performance, service delivery and electoral performance.

Identifying the causal effect of this difference between ruling party and non-ruling party politicians is hard. To account for potential selection bias in politicians, some of whom may have won precisely because of strong political networks, I use an approximation of

[1]Stasavage (2005); Baum and Lake (2003); Martinez-bravo et al. (2013); Ross (2006); Bueno de Mesquita et al. (2005); Keefer (2007); Harding and Stasavage (2014)

[2]Vicente (2014); Gonzalez-Ocantos et al. (2012); Brusco et al. (2013); Robinson and Verdier (2013); Callen et al. (2013)

[3](Chubb 1983; Wilson 1989; Golden 2003; Mayntz and Derlien 1989; Meyer-Sahling 2006)

random allocation of political office between ruling party politicians, and politicians from other political parties. Specifically, I use a regression discontinuity design to identify the causal effect of ruling party politicians on bureaucratic characteristics and service provision.[4] In this design, the party affiliation of candidates in constituencies where elections were close are treated 'as-if' randomly allocated. This allows for the comparison of constituencies where the ruling party politicians barely won, with those where they barely lost, by treating other omitted variables as orthogonal to the party affiliation of the winning candidate.[5]

I focus on bureaucratic activity in the public health sector in Punjab, Pakistan. First, I leverage, to my knowledge, the first representative panel primary survey of rural health clinics in the province. These clinics are small facilities spread across the rural areas of Punjab, and provide the first stop for health related issues for a poor population. Second, during unannounced visits in the first wave of data collection, I find that there is a 68.5 percent chance of a doctor being absent at a representative clinic.[6] This compares with the average of 35 percent across Bangladesh, Ecuador, India, Indonesia, Peru and Uganda (Chaudhury et al. 2006). Doctor absence therefore, is a big problem for these public health facilities. Doctors posted at these clinics have received years of training, and are compensated accordingly. In spite of this, citizens are only likely to find doctors only once time in every three visits they make to a clinic. Third, bureaucratic performance in public health in Punjab has recently faced several large scale failures that have resulted deaths of patients.[7] Understanding the extent to which political failures may explain variations in bureaucratic public health performance is therefore important. In this paper, I focus on the bureaucrats performing on the frontline: doctors at rural health clinics who interact directly with citizens, and therefore potentially able to influence their political preferences.

My analysis yields three sets of results. First, I examine the characteristics of bureaucrats employed in public service in ruling party areas. I show that in ruling party constituencies, bureaucrats a) report 73 percent more connections with politicians and b) enjoy between 3 and 6 additional years of public service at clinics that are closer to their hometowns. This signals towards the propensity of ruling party politicians in engaging bureaucrats who have

[4]This research design is similar to several recent research studies. For instance, Meyersson (2014) uses close elections to study how politicians belonging to Islamic parties affect female education and empowerment in Turkey.

[5]For robustness, I also study political behavior in areas close to the geographic border between a ruling party constituency, and those that belong just on the opposite side of the border, but in a non-ruling party area.

[6]See, our companion study Callen et al. (2013) for details.

[7]These include the provision of bad medicine (see http://tribune.com.pk/story/329593/pic-medicine-disaster-cooperation-and-reticence-as-blame-game-begins/), inadequate preparedness for the spread of the dengue virus (see http://tribune.com.pk/story/263068/dengue-fever-infects-over-12000-in-pakistan/), and cases of polio (see http://tribune.com.pk/story/704397/who-recommends-travel-restrictions-on-pakistan/).

better social networks in their native regions where they have also served for longer.

Second, I show that bureaucratic performance in ruling party constituencies is poorer. I find that in three unannounced visits to clinics where the winning politician belongs to the ruling party, a) doctors are absent 75 percent more often. b) This absence is explained by doctors who report knowing the politician. c) Doctors are absent more often as the subsequent election of May 2013 draw closer, and d) the same period corresponds to a decrease in clinic utilization in terms of out-patient visits, ante-natal care visits and the number of deliveries. These results suggest that doctors who know the politicians are allowed to substituting service delivery for political purposes. This means that health care, as measured by facility utilization suffers.[8]

Finally, I show that clientelism and deteriorating service delivery carries political returns. Correlational evidence suggests that the probability of returning a ruling party candidate in the 2013 election is higher in constituencies where ruling party candidates won in 2008, and where doctors were absent more on average between 2008 and 2013.

These results contribute to several strands of literature. First, they show that democratic political institutions bring forth incentives that cause large-scale service delivery differences between constituencies that are statistically the same pre-treatment. Studies have shown that politicians from the ruling party are often able to use higher access to the government resources to their advantage (Albouy (2013); Ansolabehere and Snyder (2006); Fisman (2001); Khwaja and Mian (2005); Sukhtankar (2012) and Jayachandran (2006)).[9] This paper connects the literature on connections with studies that examine sub-national variation in democracies in terms of service delivery (Ross 2006; Nelson 2007; Fujiwara 2013).

Second, the findings provide a direct test of the broker mediated theory of clientelism in Brusco et al. (2013). In their own test of the theory, Brusco et al. primarily rely on interviews with citizens and brokers, and as a result capture clientelism via brokers ex-post. The contribution of this paper relate to a) capturing how clientelistic behavior may be initiated through the co-option of bureaucrats, b) the study of this process through behavioral outcomes instead of survey responses, and c) understanding the impacts of this process on service delivery and electoral performance. It therefore relates to a growing literature that attempts at understanding clientelism both theoretically and empirically (Robinson and Verdier 2013; Stokes 2005; Nichter 2008; Vicente and Wantchekon 2009; Gonzalez-Ocantos

[8]Unfortunately, health outcome data from Demographic Health Surveys, such as birth weight and infant mortality, is unavailable at a geographically disaggregated level for 2013. This would have allowed for tests of health impacts.

[9]For instance, 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.

et al. 2012).

Third, this paper relates directly to the literature that studies the interaction of politicians and bureaucrats through case studies.[10] While the case study method is instructive, this literature has not successfully been able to use exogenous variation in party affiliation to demonstrate causal effects on clientelistic behavior.[11]

Finally, there is a large development literature that identifies public worker absence as a key obstacle to delivering services to the poor (Banerjee et al. 2008; Chaudhury et al. 2006). Governments jobs are ideal for patronage[12]; they can be targeted to individuals, provide a credible stream of benefits, and are reversible (Robinson and Verdier 2013). This is particularly true if politicians can minimize the actual work required in the position. I discuss how pervasive absence can be a consequence of patronage politics, and lead bureaucracies to engage in socially inefficient behavior.

The rest of this paper is organized as follows: in Section 2, I present some historical and institutional background. Section 3 describes the data, before discussing the identification strategy in Section 4. I present results in Section 5, subject them to identification checks in Section 6, and discuss them in Section 7. Section 8 concludes the paper.

[10] Golden (2003), Mayntz and Derlien (1989) and Meyer-Sahling (2006) examine the behavior of politicians and bureaucrats through discussions on the emergence of machine politics in the contexts of Italy, West Germany and Hungary respectively.

[11] Dixit (1997), who provides a formalization of Wilson (1989)'s work writes that each principle, in this case the politician, can "strike a mutually beneficial deal with the agent [bureaucrat] by offering some insurance... for outcomes of tasks that are primarily of interest to other principles." A principle with more power can use this symbiotic relationship with the bureaucrat to his advantage and skew outcomes against other principles. In particular, the politician from the ruling party can strike a deal with the local bureaucrat. In return for letting them enjoy benefits of public jobs, with little oversight on outcomes, the bureaucrats help the politician in their electoral campaigns. Nichter (2011) also alludes to this by differentiating between electoral and relational clientelism. "Electoral clientelism, such as vote buying and turnout buying, delivers all benefits to citizens *before* voting, and involves the threat of opportunistic defection by citizens. By contrast, relational clientelism continues to deliver benefits to citizens *after* voting, and involves the threat of opportunistic defection by both citizens and elites."(Nichter 2011:p. 3-4). My results show that this alignment of incentives for politicians and bureaucrats often create opportunities for relational clientelism to flourish.

[12] 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 (1989) 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. There can be multiple channels through which favors are reciprocated. In all three settings above, the beneficiaries commonly rewarded politicians with votes, party campaign work, monetary contributions, and by swinging blocs of voters.

2 Background

Elections in Punjab

My analysis focuses on the province of Punjab in Pakistan, home to roughly 100 million people. On 12 October 1999, General Musharraf deposed Prime Minister Nawaz Sharif of PML(N) in a coup d'état.[13] Between 2001 and 2002, Musharraf introduced non-party local government elections across Pakistan as a means of countering local political infrastructures in 2001. "Mainstream political parties have historically seen non-partisan local governments as instruments of military regimes for creating a class of collaborative politicians to displace the parties' organization at the local level." In addition, "elected local government[s] have helped military regimes to legitimize and strengthen their control over the state" (Cheema et al. 2014).

This was complemented by General Elections in 2002 that brought Musharraf's preferred party, PML(Q), to power in Punjab and the Federal government. After Musharraf was deposed by a popular uprising by lawyers, General Elections were held in 2008 and 2013, where the 2013 elections marked the first time in Pakistan's history that a sitting parliament was able to complete its tenure in office. This summary of recent political history of Punjab allows for the appreciation of the relatively weak local political network that PML(N) started out with in 2008.

I consider the time period between the general elections of 2008 and 2013 in Punjab. The province follows a party-based single-member district electoral system. I focus on the Punjab Provincial Assembly, which is a legislative body comprising of 371 members.[14] My analysis is based on the pre-treatment results from the General Elections of 2008, when the incumbent party, Pakistan Muslim League (Quaid Group) was ousted by the Pakistan Muslim League (Nawaz Group) (PML(N)).[15] PML(N) won about thirty percent of the competitive seats in that election.

My analysis below focuses on 132 constituencies in Punjab where the PML(N) candidate either won or was the runner-up. I employ two identification strategies to account for selection bias. There were three effective number of candidates contending in each of these elections.[16]

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[13] Nawaz Sharif, the Prime Minister in 1999, and chairman of PML(N), tried removing General Musharraf from his position as the Chief of the Armed Forces, while Musharraf was away from the country. Musharraf was able to circumvent the threat, and in doing so, successfully launched a coup against the government. As a result, Nawaz Sharif, and group of close party members were forced to go in exile.

[14] "About Assembly", Provincial Assembly of the Punjab, Retrieved on Sep 7, 2013 from http://www.pap.gov.pk/index.php/faqs/listfaqs/en/12.

[15] I refer to Pakistan Muslum League (Nawaz Group) as "PML(N)" in the rest of the paper.

[16] This is calculated by inversing the party herfindahl index for each constituency. The herfindahl is a

The Public Health System

In the Punjab province, the provision of health care services are managed by the Department of Health, which is based at the provincial headquarters in Lahore. The province comprises of 36 districts and about three to four Tehsils (counties) each. Each district has on average 8 provincial assembly constituencies. There are five major types of facilities: (1) Basic Health Unit (BHU); (2) Rural Health Center (RHC); (3) Tehsil Headquarter Hospital (THQ); (4) District Headquarter Hospital (DHQ); (5) Teaching Hospitals.

I focus on Basic Health Units (BHUs), which are the smallest public health care units. They are designed to be the first stop shop for patients seeking medical treatment in government facilities. I use the word 'clinic' interchangeably to describe BHUs in the rest of the paper. There are 2496 of such clinics in Punjab, and they primarily serve rural populations.[17] These clinics provide several services, including out-patient services, ante-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.

Local administrative responsibilities reside with Executive District Officers, who report directly to the chief bureaucrat of the district and to the most senior provincial health officials.[18]

Doctors, Senior Bureaucrats, and Political Influence in Punjab

Bureaucrats are a cheap means of patronage in developing democracies. A continues stream of payment in the form of a public sector salary makes public sector employment a sought after position in rural communities. Ruling party politicians can influence the process of public service human resource management in at least two ways: first, they can exert political influence to control the process of transfers of public employees. Second, once posted, health officials also appeal to politicians for protection against suspension, transfer, and other sanctions for underperformance. I detail the hiring process of doctors in Appendix F.

The data collected for this paper was part of a large scale field experiment where we obtained data also for senior level bureaucrat, and their behavior. This allows me to establish some basic facts about the political landscape in Punjab. First, I present some summary

measure of dispersion using extensively in the industrial organization literature. In this case, it is calculated as the sum of inverse squared vote shares for each candidate.

[17]Almost all such clinics are exclusively operating in rural and peri-urban areas.

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

statistics on how senior bureaucrats are influenced routinely by politicians. This speaks to the fact that bureaucrats operate in a highly politicized environment, where politicians look out for doctors that are part of their political machines. Second, I present some instances of doctors aiding the political campaigns of candidates in the 2013 general elections.

Table 1 reports summary statistics on self-reported incidents of pressure experienced by the universe of Deputy and Executive District Officers in Punjab. I asked the respondents to report the number of instances where a person of influence put pressure on the respondent to 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. Conditional on them saying yes to this question, the respondents were asked to identify the type of people who tried to influence behavior. The results show that about fifty percent of bureaucrats experienced pressure from several kinds of persons with influence. Conditional on being pressured, up to ninety percent of respondents reported receiving it from elected legislators: the Members of the National (MNA) and Provincial MPA) Assemblies.

Table 1: Senior Bureaucrats Face Routine Pressure

	Mean	SD	N
Respondent ever influenced?	0.401	0.491	187
by MNA	0.905	0.295	74
by MPA	0.811	0.394	74
by Other Politician	0.178	0.385	73
by Senior Bureaucrat	0.257	0.440	74
by Police	0.027	0.163	74

Notes: This table reports whether senior bureaucrats faced pressure from people of influence to change their decision regarding a subordinate, such as doctors, in the past year. Conditional on saying yes, respondents were asked to identify category of that persons who put pressure on them.

Many public doctors belong to politically powerful clans and families. They 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.

The Free and Fair Elections Network (FAFEN), an independent non-governmental organization that works towards promoting clean elections in Pakistan, tweets infractions to the elections code prior to the General Election of May 2013. Figure 1 records some tweets relating to doctors and health staff behavior during the 2013 election. These suggest that health

Figure 1: Doctors as Politcal Workers

staff in rural areas may provide a good avenue for political networks and vote mobilization.[19]

3 Data

To understand this process more systematically, I make use of primary data on public health in Punjab, election data for the 2008 and 2013 general elections in Punjab.

Primary Data

I collect primary data on a representative sample of 850 (34 percent) of the 2,496 public rural clinics in Punjab.[20] Enumerators made unannounced visits to these facilities three times, first in November 2011, then in June 2012 and finally in October 2012. The clinics were selected randomly using an Equal Probability of Selection (EPS) design, stratified on district and distance between the district headquarters and the clinic. Therefore, my estimates of the dependent variables are self-weighting, and there is no sampling correction in the analysis.

[19]Figure H1 in the Appendix records some tweets that show how government bureaucrats in general help politicians during campaigning. For instance, the "Govt. High School teacher seen campaigning for PML(N)N in Garh, Tandianwala, Faisalabad" tweet shows how local bureaucrats are used by politicians for their ability to influence voters.

[20]These data are from a larger project titled "Monitoring the Monitors". See Callen et al. (2013) for details.

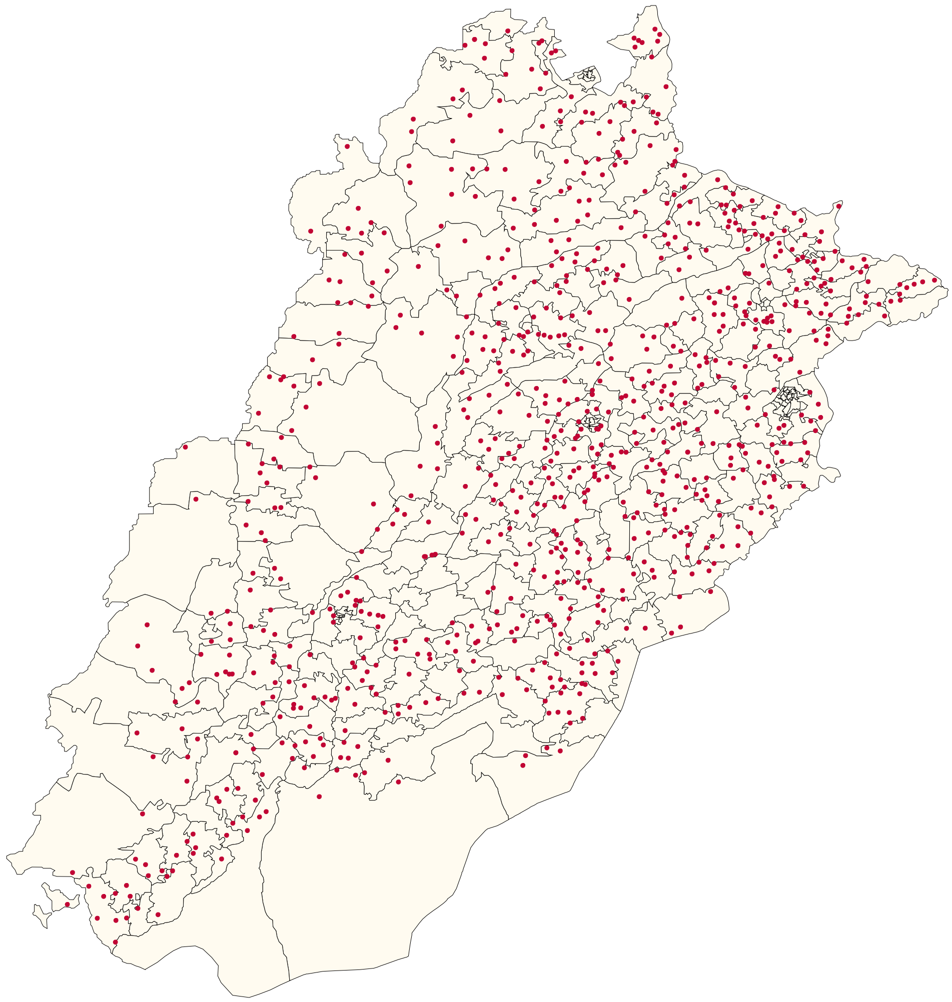

Figure 2: Locations of Clinics in Primary Data

All districts in Punjab except Khanewal are represented in the data.[21] To my knowledge, this is the first representative survey of Basic Health Units in Punjab. Figure 2 provides a map of all 850 clinics I have data on, along with the Provincial Assembly constituencies in Punjab. My sample represents about 33 percent of all rural facilities in the province. To bolster data in places where doctors were not found in all three waves, an additional fourth wave of data collection was conducted where the surveyors pre-announced their visits. I detail this process in Appendix E1. The primary data collection included detailed surveys of doctors.

[21]Khanewal is excluded in Callen et al. (2013) since it was used to pilot a cell phone technology that we introduce and test in the paper.

Election Data

I also make use of results from the 2008 and 2013 Punjab Provincial Assembly elections.[22]. These data provide candidate totals by Punjab Provincial Election constituencies for all candidates running in both elections. I consider the margin of victory for candidates where the winner or runner-up belonged to the ruling party, PML(N). Figure H5 shows PML(N) winners and runners-up in my data by their absolute margin of victory. Data are available for about 109 constituencies. Appendix G describes the protocol for identifying the constituency corresponding to each health clinic. The procedure differed for the two identification strategies I detail below.

4 Methodology

Ruling party politicians enjoy higher access to state resources. This loosening of their budget constraint allows them to further their political goals. Identifying the impact of ruling party politicians is hard because ruling party politicians may differ systematically on important dimensions from non-ruling party politicians. To deal with this, I explain below the two strategies I adopt in this paper. First, I use a naive model to show correlations between having a ruling party politicians and outcomes of interest. Second, I make use of a close elections regression discontinuity approach to identify the causal impact of ruling party politicians on outcomes.

Naive Estimates

I begin by estimating a simple ordinary least squares estimate of the effect of having a PML legislator. Though I add fixed effects for geography, so that I compare ruling party politicians with non-ruling party politicians within a small geographic location, called Tehsils, I label this approach 'naive' because there is still the possibility of systematic differences between these two types of constituencies along other important dimensions. I estimate the 'naive' specification for simple correlations as follows:

$$Y_{ijt} = \alpha + \beta PML(N)\ Winner_{ij} + \gamma_j + \epsilon_{ijt} \quad (1)$$

where Y_{ijt} refers to the outcome of interest at clinic i in Tehsil j at survey wave t. $PML(N)\ Winner_{ijt}$ is an indicator variable that equals one if the incumbent politician that corresponds to clinic i in Tehsil (county) j belongs to the ruling party, Pakistan Muslim

[22] I thank Jacob Shaprio for kindly sharing these data (Fair et al. 2013).

League (Nawaz Group). This is a deterministic function of whether the PML(N) politician won the election in 2008. γ_j refers to Tehsil or county fixed effects that take care of locational pre-treatment confounders, and add efficiency to the models.

Regression Discontinuity Estimates based on Close Elections

One way to causally identify the effect of an incumbent belonging to the ruling party is to study exogenous variation in party membership of incumbents. In an ideal experiment, I would compare the same politician when he is in two different parties at the same point in time. Therefore, naive comparisons of PML(N) legislators with legislators belonging to other parties can be biased by confounders. This makes the winners from different parties diverge on several dimensions, making the simple difference in means biased.[23]

In order to estimate the *causal* impact of ruling party incumbency, the comparison must be limited to legislators that are similar in all such aspects. They may only differ in their party membership due to plausibly random reasons. The difference in the outcome variables between these two types of politicians is defined as the causal impact of ruling party incumbency. I use the the approach suggested by Lee (2008) and Imbens and Lemieux (2008) to study the causal effect of ruling party incumbents on several outcome variables. I estimate equations of the following form:

$$Y_{ijt} = \alpha + \beta PML(N)\ Winner_{ij} + f(x_{ij}) + \gamma_j + \epsilon_{ijt} \tag{2}$$
$$\forall i\ s.t.\ x_{ij} \in (-h, h)$$

where the control function $f(x_{ij})$ corresponds to an n^{th} order polynomial of the forcing variable x_{ij} which in this context, refers to the victory margin between the winner and the runner up. The forcing variable theoretically ranges between $[-100, 100]$ but in the data, takes on values between $(-45, 48)$. The values are positive for PML(N) winners, and negative for other winners.

The coefficient of interest is β which estimates the local average treatment effect of ruling party incumbents on Y_{ijt} at zero margin of victory. I get identification of my estimate of β by using close elections as a mechanism for 'as-if' random assignment of the winner's party.

Approaches to estimating equation (2) rely on changing the control function $f(x_{ij})$ and varying the bandwidth h to obtain a sample to estimate β. By restricting h to smaller

[23] For example, incumbency disadvantages might have lead to higher political competition in places where PML(N) (Nawaz) removed a PML(N) (Quaid) politician in the 2008 elections. Higher political competition in these constituencies might independently influence outcome variables, thereby confounding the analysis. Other examples of confounders include characteristics of candidates such as wealth, status, charisma and campaign spending.

values, that is restricting the analysis to very close elections, we are in a world closer to the 'as-if' randomization of treatment assignment through the reduction of bias in β. "This resembles more closely the empirical counterfactual but comes at the expense of efficiency due to small samples" (Querubin 2013:p. 13). Due to data limitations, I use the same benchmark specifications as Lee et al. (2004).[24] A linear control function on both sides of the threshold of the forcing variable will include bias, especially as h increases and the control function has a non-zero slope. To correct for this, I use polynomial approximations to estimate β. In particular, I regress Y_{ijt} on a fourth-order polynomial in the victory margin x_{ij} on *each* side of the threshold. Each of these polynomials are interacted separately with the treatment variable to ensure a fully-flexible design. I show robustness of my results to alternate specifications and bandwidths in Appendix D, and discuss them in text below.

In the analysis that follows, I estimate equation (1) and (2) on several variables of interest. I report results using an Ordinary Least Squares model that provides consistent estimates of the local average treatment effect. I present only the coefficient on the treatment variable, `PML(N) Winner`, and the constant. The coefficients on the control function, that includes quartic polynomials, that are allowed to run separately on either side of the threshold, are not presented in the table.

I also provide estimates with Tehsil (county) fixed effects. As shown in Figure H5, the political constituencies are spread over a large geographical area. By adding in fixed effects for geographic location, I keep fixed any unobserved local confounders, and estimate the treatment effects between clinics that receive and do not receive the ruling party treatment in small geographic area.

Because the treatment of PML(N) incumbents is assigned simultaneously to several clinics in a constituency, I cluster standard errors in all models at the provincial constituency level.

For robustness, I also provide results using an alternate identification strategy that relies on a geographic discontinuity. I make use of a geographic regression discontinuity approach, where I compare clinics very close to political borders but under the jurisdiction of either a PML(N) politician *or* non-PML(N) politician. The idea is that clinics that arbitrarily close to a political border will exhibit similar characteristics, like being under the jurisdiction of the same bureaucrat, but differ only on which political constituency they fall under. I detail how I estimated treatment effects with this procedure in Appendix B.

[24] See Table A1

5 Results

I present three sets of results. First, I present results how the characteristics of public sector doctors differ in ruling party constituencies. Second, I show how service delivery deteriorates as the 2013 elections draw closer. Third, I consider the impact of this on the re-election prospects of ruling party politicians.

Appendix A presents summary statistics for the data by absolute margin of victory. These statistics, and subsequent analysis, is reported conditional on a doctor being officially assigned at the rural clinic at the time of the survey.[25]

As shown in the Table A1, I record 22 constituencies within a narrow bandwidth of 5 percent absolute victory margin.[26] Doctor attendance is higher in places which have closer elections, but is similar as you move closer to political borders. On average, 13 percent of the doctors report knowing the member of the provincial assembly (MPA) in places where elections were close, but about 21 percent reported these connections in places close to a political border.

5.1 Doctor Characteristics

I consider the impact of having a ruling party politician on doctor connections with politicians, and doctor tenure. The survey included a section on doctor connections with politician. This indicator variable records every interview where the doctor reported knowing the member of the provincial assembly. I code this variable to equal 1 if the doctor in a survey wave reports knowing the politician, and 0 otherwise. Enumerators also asked doctors about their tenure as public sector doctors, in addition to the duration for which they have served at the clinic they were interviewed at. I record information from both questions in number of months.

Doctor Connections with Politician

I first report results on doctor connections with politicians. Several studies have shown that ruling party politicians exploit their office for personal gains by showing the value of connections to politicians (Fisman 2001; Khwaja and Mian 2005). Connections with doctors

[25] I find that the treatment does not affect the probability of a doctor being assigned at the threshold using specification (2). This is robust to both OLS and Logit models, with and without Tehsil (county) Fixed Effects. It is consistent with what I have observed in conversations at the Depatment of Health. The official assignment to particular clinics is a process involving decicions at several levels of government, and is usually pursued in waves, instead of an adhoc basis. This puts considerable constraints on a politician's ability to affect the assignment of doctors in his area. However, this does not preclude him to affect the way in which doctors are moved around.

[26] I check for small sample bias with randomization inference.

can help the politicians in voter mobilization, while politicians help doctors by protecting them from shirking from work. I operationalize these connections by measuring whether the doctor knows the incumbent.

Table 2 reports the results. Columns (1) and (2) present the naive OLS model. Even with Tehsil fixed effects, there seems to be a weak relationship between having a ruling party politician and whether there are connections between doctors and politicians. Columns (3) and (4) the causal impact of a PML(N) winner. The results show that doctors in ruling party areas report up about 73 percent more connections with politicians than doctors in areas where the ruling party candidate was the runner-up. These results are local to swing areas, where margin of victory approaches zero.

Table 2: Doctors Know Politicians More in PML(N) Areas

	Knows (1)	Knows (2)	Knows (3)	Knows (4)
PML(N) Winner	-0.032	0.065	0.289***	0.728**
	(0.064)	(0.074)	(0.106)	(0.359)
Mean Dep Variable	0.186	0.186	0.186	0.186
# Constituencies	78	78	78	78
# Observations	226	226	226	226
Fixed Effects	-	Tehsil	-	Tehsil
Model	Naive	Naive	Close	Close
Sample	Full	Full	Full	Full

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

Table B1 shows that the point estimate is identical to the alternate identification strategy that relies on the geographic regression discontinuity design. Though the results are not significant, a point estimate of the same magnitude lends credence to this result presented here. In addition, Figure H2 shows these results by taking averages over bins of victory margin (top half) and distance to border (bottom half). There is a significant jump in the the likelihood of a doctor knowing the politician if the politician belongs to PML(N). I also make use of randomization inference to check for robustness to small sample bias in the close RD model. I find that there is a very small probability that the results reported are due to chance.[27] I show this result in Figure C1. Finally, Table D1 presents the robustness of this

[27] All randomization inference procedures in this paper are based on 10,000 simulations of the treatment assignment at the political constituency level.

result to alternate specifications and functional forms. The results remain significant and of similar magnitude with a cubic polynomial, though they are no longer significant in the case of quadratic and linear specifications.

Doctor Tenure

Brusco et al. (2013) suggest that political parties are likely to recruit brokers who have the highest patronage to votes conversion ratio. Therefore, local level political clients should exhibit characteristics that show their ability to be influential in this local communities. Below, I look at results on doctor tenure within the health department, as well as their tenure at the clinic they were interviewed at. Additionally, I correlate this with the distance of the clinic to their hometown. To account for outliers, I trim these variables at the ninety fifth percentile. [28]

I present the results in Table 3. In panel A, I consider overall doctor tenure. Column (1) and (2) show that there is no correlation between a PML(N) politician and overall doctor tenure. Columns (3) and (4) employ the close elections RD and finds no impact of PML(N) politician on doctor tenure.

In panel B, I run the same regressions on a doctor's tenure at the specific clinic where he was interviewed. Column (1) shows immediately that in the entire sample, the tenure of doctors at clinics is higher than their tenure in minority areas. This result is not robust to the inclusion of Tehsil fixed effects in column (2). However, once we run the close elections RD model in columns (3) and (4), the coefficient on clinic tenure is positive and significant. The point estimate in column (4) suggests that doctors in ruling party areas enjoy higher tenures at clinics by 79 months, or 6 years and 7 months.

Table B3 shows that the results are robust to the geographic RD design. I also show results of panel B in Figure H4, which exhibits a jump at the threshold. To check for small sample bias, I conduct a randomization inference procedure and find the probability of finding the results by chance is very low. Figure C2 shows this result. Finally, Table D2 reports the result in Panel B with alternate specifications and bandwidths. I show that the result is significant with a quartic, cubic and quadratic polynomial for a smaller bandwidth of 20 percentage points from the cutoff. The point estimates remain of similar magnitude.

Overall, I find that while tenure of doctors is similar across PML(N) and non-PML(N) areas, the tenure at a specific clinic is much higher in PML(N) areas. This suggests that PML(N) politicians preferred keeping doctors who had served at the clinic for longer, thereby preserving their political networks. An additional check for this is to consider if these doctors are also closer to their hometowns, where they will presumably have even larger networks.

[28] My results are robust to not trimming the data. Available on request.

Table 3: Doctor Tenure

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable - Doctor Tenure Overall (in months)				
PML(N) Winner	16.399	18.110	28.566	-23.528
	(10.916)	(19.006)	(26.790)	(80.788)
Mean Dep Variable	79.050	79.050	79.050	79.050
# Constituencies	74	74	74	74
# Observations	218	218	218	218
Fixed Effects	-	Tehsil	-	Tehsil
Model	Naive	Naive	Close	Close
Sample	Full	Full	Full	Full
Panel B: Dependent Variable - Doctor Tenure at Clinic (in months)				
PML(N) Winner	10.334*	2.592	35.218**	79.147***
	(5.597)	(7.874)	(13.975)	(23.234)
Mean Dep Variable	34.830	34.830	34.830	34.830
# Constituencies	70	70	70	70
# Observations	200	200	200	200
Fixed Effects	-	Tehsil	-	Tehsil
Model	Naive	Naive	Close	Close
Sample	Full	Full	Full	Full

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

I consider the effect of a PML(N) politician elected in a close election on how close a doctor is to his hometown in terms of travel time. Table 4 report these results.

The dependent variable is the natural log of the doctor's distance to his hometown in hours. Column (1) shows that PML(N) area doctors are on average farther to their hometowns than non-PML(N) area doctors. In column (2), I restrict the data to doctors who have below median tenure at the clinics and again find that for these doctors there are no significant differences in distance to hometown between PML(N) and non-PM areas. Finally, in column (3) I re-run the analysis on doctors who have above median tenure at the clinic. These doctors, who have not been moved recently by PML(N), are indeed significantly closer to their hometowns in PML(N) areas, suggesting that PML(N) retains doctors who have been closer to their hometowns, and therefore have presumably better networks for vote mobilization.

Table 4: Distance to Hometown by Tenure at Clinic

	Ln(Distance to Homtown in Hours)		
	(1)	(2)	(3)
PML(N) Winner	1.724***	0.250	-65.802***
	(0.598)	(2.024)	(6.598)
Mean Dep Variable	-1.984	-1.907	-2.080
# Constituencies	69	55	46
Fixed Effects	Tehsil	Tehsil	Tehsil
Model	Close	Close	Close
Sample	¬missing(Tenure)	Less Tenure	More Tenure

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. The dependent variable is the log of the Doctor's Distance to Hometown (in hours). All specifications use the Close Elections RD model. Column (1) is regressed on the entire data. Column (2) is regressed only on the data where the tenure at clinic for doctors is below the median. Column (3) is regressed only on the data where the tenure at clinic for doctors is above the median.

5.2 Service Delivery

The next set of results are related to bureaucratic performance and service delivery in Punjab. I consider impacts on doctor attendance, the variation in these impacts over time, and the effects on public health utilization. My primary survey was conducted in three waves of data collection. These were November 2011, June 2012, and October 2012. The panel structure of the data allows me to show that doctor absence increased as the 2013 elections drew nearer, suggesting that the incidence of clientelism went up over time. This time period also corresponds to a decrease in the utilization of clinics.

I measure doctor attendance in the three unannounced surveys. Survey enumerators showed up at clinics with letters from the Punjab Health Sector Reform Program.[29] The enumerator was tasked to fill out an attendance sheet once the survey was complete and he had exited the compound.[30] Places where a doctor was assigned and not present, are coded as zero, while places where a doctor was present are coded as one.

I report results on three health utilization variables: antenatal care visits to clinic (ANC), out-patient visits (OPD), and the number of deliveries conducted at the clinic. Because these are noisy measures of health usage, I use logged values of these variables. Table A1 provide summary statistics.

Doctor Attendance

If doctors prefer to shirk, they should show up to work less when under a contract with politicians. Politicians provide them the necessary protection from senior bureaucrats by shielding them from administrative sanction.

Table 5 provides results on doctor attendance. The naive OLS regression in columns (1) and (2) shows that a ruling party winner does not correlate with doctor attendance on average. The point estimates are very small. However, under the close elections model presented in columns (3) and (4), we see that the doctor attendance is significantly lower in PML(N) areas versus other areas. With tehsil fixed effects, the probability of doctor presence goes down by 74 percent in ruling party areas.

Table B2 finds that the results are robust to the geographic regression discontinuity specification. Figure H3 shows the discontinuity observed in presence. Doctors who serve in PML(N) areas are less likely to show up to work at the discontinuity. Finally, a randomization inference procedure in Figure C3 shows that these results are not driven by chance. Finally, Table D3 shows that these results are significant to several alternate specifications and bandwidths.

Together with results on doctor connections, these results show that doctors are both more likely to be connected with politicians and are more likely to be absent from their jobs in ruling party politician areas.

[29] This is a body that reports directly to the Secretary of Health.

[30] If the doctor showed up during the surveys, the enumerator was instructed to mark him as absent, as from a citizen's perspective, the doctor was not present at the clinic when the surveyor arrived.

Table 5: Doctor Attendance is Lower in PML(N) Areas

	Present (1)	Present (2)	Present (3)	Present (4)
PML(N) Winner	-0.030	-0.096	-0.444**	-0.742***
	(0.054)	(0.071)	(0.195)	(0.214)
Mean Dep Variable	0.464	0.464	0.464	0.464
# Constituencies	93	93	93	93
# Observations	658	658	658	658
Fixed Effects	-	Tehsil	-	Tehsil
Model	Naive	Naive	Close	Close
Sample	Full	Full	Full	Full

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

Doctor Absence by Political Connections

Do doctors who know the politician show up to work less often? Table 6 presents some evidence that this is indeed the case. Since the number of observations for political connections are low, I recode the variable equal to 1 if a) the doctor reported knowing the politician in any survey wave, and b) the doctor does not say anything to the contrary in another survey wave. That is, in other waves the variable is either missing or the doctor reports that he knows the politician. In the case of conflicts, I code this variable as zero.

In column (1), I restrict the sample to places where data are available both for connections and attendance. I run a simple OLS model to show that there is a significant negative correlation between PML(N) winner and doctor attendance. In columns (2) and (3), I break up the sample by whether the doctor knows the politician or not. I continue running OLS because low variation in connections makes the estimation of a regression discontinuity model impossible. Column (2) shows that the point estimate is low and not different from zero. Column (3) shows that doctors who know the politician show up to work a lot less. This is significantly different from zero.

Doctor Absence by Survey Wave

Table 7 reports doctor absence by survey wave. Column (1) replicates earlier an earlier result on doctor attendance for reference. Columns (2)-(4) break it down by survey wave to show

Table 6: Doctor Presence by Political Connections

	Present (1)	Present (2)	Present (3)
PML(N) Winner	-0.127*	-0.040	-0.542***
	(0.072)	(0.066)	(0.159)
Mean Dep Variable	0.533	0.559	0.431
# Constituencies	86	77	33
# Observations	570	454	116
Fixed Effects	Tehsil	Tehsil	Tehsil
Model	Naive	Naive	Naive
Sample	¬missing(Knows)	¬Know	Knows

Notes: *Level of significance*:$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. All specifications use a simple OLS model.

that absence becomes more pronounced in later survey waves.[31]

Health Ultilization by Survey Wave

Next, I consider effects on health sector utilization. I consider the effects on three outcomes: outpatient visits to the clinic in the last month, antenatal care visits to the clinic in the last month, and the number of deliveries at the clinic during the last month. Because the data are noisy, I trim them at the 99th percentile, and take their natural log. These data were only collected during wave 2 and 3 of the survey.

Table 8 reports the results. Column (1) shows that though there is no on-average difference in clinic outpatient visits between PML(N) and non-PML(N) constituencies, there were more visits in PML(N) areas in Wave 2. This effect disappears, and the point estimate turns negative, in Wave 3. Columns (4)-(6) report the results for ante-natal care visits, and columns (7)-(9) report results for the number of deliveries. We can see a similar pattern as outpatient visits. The results attenuate consistently in wave 3, as the 2013 elections draw nearer.[32]

[31] This result also holds with geographic RD in Table B4, where the only significantly negative treatment effect is in wave 3, which is consistent with the Supreme Court explanation.

[32] These results cannot be replicated with a geographic RD design. This is likely due to the fact that the data are very sparse. I am only able to construct a dataset for 35 political constituencies. Table available upon request.

Table 7: Doctor Attendance by Survey Wave

	Doctor Present = 1			
	All	Wave 1	Wave 2	Wave 3
	(1)	(2)	(3)	(4)
PML(N) Winner	-0.742***	-0.538	-1.153***	-0.697*
	(0.214)	(0.492)	(0.422)	(0.413)
Mean Dep Variable	0.464	0.442	0.495	0.455
# Constituencies	93	84	82	84
# Observations	658	226	212	220
Fixed Effects	Tehsil	Tehsil	Tehsil	Tehsil
Model	Close	Close	Close	Close
Sample	Full	Full	Full	Full

Notes: *Level of significance*:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. All dependent variables are logged. Survey Wave 1 was conducted in November 2011, Wave 2 in June 2012 and Wave 3 was done in October 2012. General Elections were held on Feb 18, 2008 and May 11, 2013.

Table 8: Health Outcomes by Survey Wave

	ln(Out-Patient Visits)			ln(Ante-Natal Care Visits)			ln(# Deliveries)		
	All	Wave 2	Wave 3	All	Wave 2	Wave 3	All Waves	Wave 2	Wave 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PML(N) Winner	0.241	0.852**	-0.546	0.827**	1.315*	0.768	0.209	2.949***	0.473
	(0.218)	(0.323)	(0.342)	(0.364)	(0.782)	(1.486)	(0.616)	(0.788)	(0.987)
Mean Dep Variable	7.011	6.927	7.093	4.007	4.090	4.093	1.629	2.065	1.367
# Constituencies	90	81	84	86	68	66	86	61	79
# Observations	428	210	218	416	139	132	323	121	202
Fixed Effects	Tehsil	Tehsil	Tehsil	Tehsil	Tehsil	Tehsil	Tehsil	Tehsil	Tehsil
Model	Close	Close	Close	Close	Close	Close	Close	Close	Close
Sample	Full	Wave 2	Wave 3	Full	Wave 2	Wave 3	Full	Wave 2	Wave 3

Notes: *Level of significance*:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. All dependent variables are logged.

5.3 Electoral and Health Outcomes

The final set of results focus on reelection prospects for ruling party politicians. Though correlational, these results show that reelection prospects for PML(N) politicians are higher in places with relatively close elections in 2008, and where doctors were absent more often.

Probability of Reeleciton in 2013

I check the probability of PML(N) politicians getting elected in the 2013 general elections in places we would expect them to engage most in clientelism. More specifically, we should expect to see that PML(N)'s electoral performance should be positively correlated with higher doctor absence. In addition, this relationship should be focused in swing constituencies, where the marginal returns from engaging in clientelism are highest (Brusco et al. 2013).

To test this, I consider the same 100 constituencies considered in the close elections RD analysis above. As the outcome of interest, probability of returning a PML(N) candidate in 2013, varies at the constituency level, a close elections RD model cannot be estimated. Instead, I present simple OLS correlations to show that PML(N) candidates are more likely to be elected in swing constituencies where doctors are found absent more often.

Ideally, this analysis would be carried out non-parametrically over average doctor absence, but data limitations allow for a coarser measure. By constituency, I split the data into 'above the median' and 'below the median' bins for doctor attendance averages. In addition, I create a variable 'swing' by splitting the absolute victory margin at its median value, such that a value of 0 means *above* median, and a value of 1refers to *below* median.

Table 9 shows that PML(N) candidates are more likely to win in 2013 in swing constituencies where the incidence of clientelism is higher, as proxied by lower doctor attendance. Columns (1)-(3) present the average effects, first in the full sample, then in samples split at below and above median values of doctor attendance in the constituency. While there is no average effect on the probability of PML(N) victory, there is a positive correlation between higher doctor attendance and PML(N) victory in 2013. Columns (4)-(6) interact PML(N) winner in 2008 with whether the margin of victory was below the median. While, again there seem to be no average correlations in column (4). Column (5) shows that when doctors are present less, the chance of a PML(N) winner in 2013 are higher in swing constituencies. In addition, in column (6), we can see that when doctor attendance is high, the probability of election a PML(N) candidate goes down in swing constituencies.

Table 9: Probability of PML(N) Reelection in 2013

	PML(N) Winner 2013					
	(1)	(2)	(3)	(4)	(5)	(6)
PML(N) Winner 2008	0.080	-0.086	0.247**	0.060	0.617	-0.405
	(0.086)	(0.138)	(0.106)	(0.273)	(0.425)	(0.325)
Swing				0.025	-0.333	0.286*
				(0.143)	(0.232)	(0.160)
PML(N) Winner 2008 x Swing				-0.016	0.483*	-0.452**
				(0.178)	(0.277)	(0.212)
Constant	0.730***	0.800***	0.682***	0.764***	0.333	1.071***
	(0.068)	(0.115)	(0.079)	(0.208)	(0.345)	(0.232)
# Constituencies	100	50	50	100	50	50
Sample	Full	Present	Present	Full	Present	Present
		Less	More		Less	More
Model	Naive	Naive	Naive	Naive	Naive	Naive

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Heteroskedasticity robust standard errors reported in parentheses. All analysis is at the constituency level. Swing = 1 if margin of victory in 2008 was below the median, 0 otherwise. Column (2) and (5) restrict data to constituencies where average doctor attendance was less than the median. Columns (3) and (6) restrict data to constituencies where the average doctor attendance was more than the median.

6 Identification Checks

The regression discontinuity results are only valid if identifying assumptions are satisfied. One assumption that is crucial to this analysis is that in close elections, the only difference between ruling party incumbents and those belonging to other parties, is their party membership. In other words, the differences in outcomes of interest are only generated by plausibly exogenous variation in victory, instead of underlying characteristics of the candidates, all of which are assumed continuous at over the threshold. This section analyzes some checks of these assumption.[33]

In this section, I present four identification checks: an alternate specification, sorting of observations around the cutoff, placebo regressions, and artificial manipulation of the cut-point.

[33]This analysis is limited only to pre-treatment covariates that I observe through the survey data. Other unobserved factors like "wave effects" and "plus factors" (Chandra 2004) remain unaccounted for, and therefore, assumed smooth across the discontinuity.

Alternate Specification

In Appendix B, I develop an alternative identification strategy that compares behavior at clinics that are statistically similar, but fall in different political jurisdiction. The results obtained through this geographic regression discontinuity approach are consistent with those presented in this paper.

Sorting

McCrary (2008) presents a framework for testing the existence of manipulation of the treatment assignment mechanism. If it is indeed the case that the treatment assignment is randomly assigned, then the density of units who are assigned the treatment at the threshold, should equal the density of units that are not. In other words, there must be continuity in the density of this function at the discontinuity. If politicians whose party actually wins are able to manipulate their probability of victory by affecting electoral outcomes in their favor, then we should see a break in this density.

This sorting of units is a threat to identification because it disables the 'as-if' random variation in treatment assignment. In Figure 3, I plot the density of constituencies, averaged over equal bin size. The overlapping confidence intervals suggest that there exists no 'break' in the distribution. A more formal test also reveals that there is no statistically significant break in the distribution at the threshold.[34] Note that this test is only done for the close elections RD sample, as it is not valid for the geographic RD design since there was no major construction of clinics efforts during the 2008-2013 period.[35]

Placebo Regressions

As suggested in Imbens and Lemieux (2008), one other check for validity is to see if there is balance in pre-treatment covariates around the threshold. If the estimation technique is valid, then I must only observe a treatment effect on variables that were measured after PML(N) assumed office. Additionally, there must be a theoretical reason for the observed effect in the post-treatment variable. With these two conditions in mind, I estimate equation (2) on a number of variables in Table 10. These placebo regressions should be balanced on both sides of the threshold, exhibiting no break in the densities.

Column (1) - (4) measure characteristics of constituencies. I observe that there is no treatment effect of an incumbent belonging to the ruling party on the registered number

[34] The test statistic for the difference is estimated at -0.44, with the associtated standard error of 0.49.

[35] Figure 4 presents an additional identificaiton check. It calculates the treatment effect by artificially moving the cutoff, and finds that the effects only exists at the experimental cutoffs.

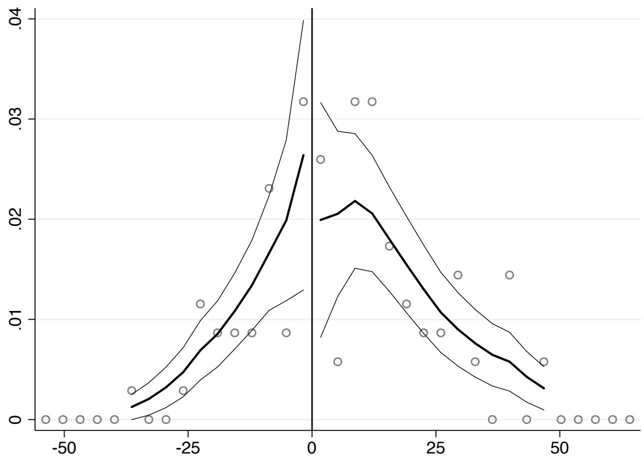

Figure 3: Conditional Density Plot to Check for Sorting

of voters, turnout, number of candidates who ran for election and political competition as measured by the Party Herfindahl Index. This is as expected since all these variables are measured for the 2008 elections which occurred *prior* to PML(N) politicians assuming office.

In column (5), I check balance on a clinic characteristic: the distance to the District headquarter, which I take as a proxy of the remoteness of the clinic. Since, the location of the clinics is fixed, it should not be affected by the treatment. Column (5) confirms this. [36]

Table 10: Placebo Regressions

	Registered Voters (1)	Voter Turnout (2)	Number of Candidates (3)	Party Herfindahl (4)	Distance to Headquarter (5)
PML(N) Winner	-0.013	-0.047	-0.111	0.008	-10.159
	(0.146)	(0.059)	(2.172)	(0.053)	(14.126)
Constant	12.004***	0.501***	7.526***	0.318***	42.659***
	(0.113)	(0.044)	(1.595)	(0.039)	(9.335)
# Constituencies	99	100	100	99	91
# Observations	99	100	100	99	648

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

[36]Columns (5) of Table 10 present results with Tehsil (county) fixed effects. The results are robust to running the specifications without these as well.

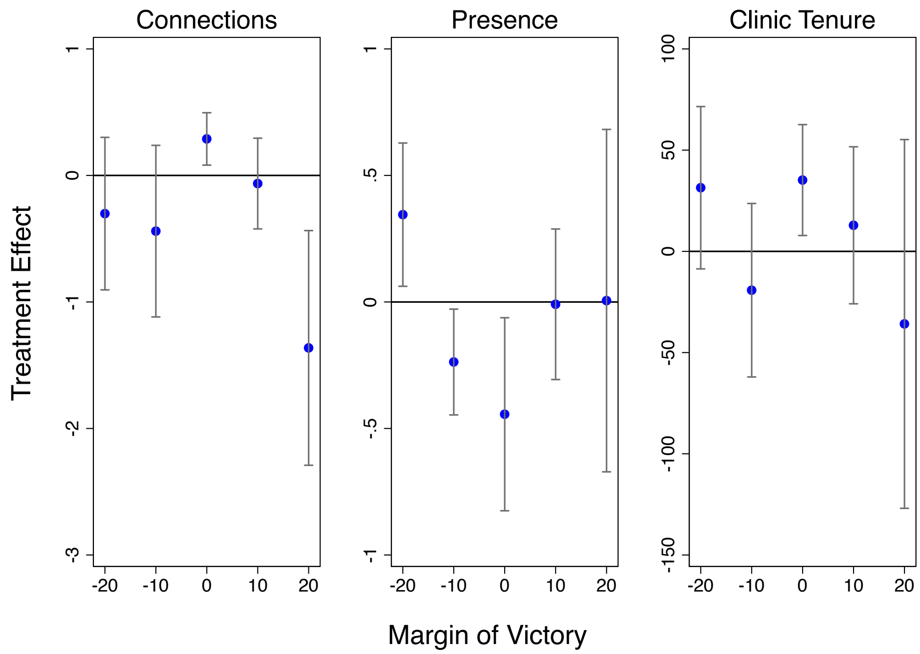

Figure 4: Manipulating the Cutoff

Manipulating the Cutoff

Finally, the treatment effect must only occur at the true threshold if the discontinuity in access to state resources occurs there. I check for this by artificially manipulate the threshold in Figure 4. I show that the treatment effect is restricted to the true cutoff.[37] For instance, I move the cutoff to 10 percent margin of victory and find that there is no consistent difference in the direction of the estimated treatment effects.

7 Discussion

Some features of the results merit further discussion. First, a motivation of this paper is to understand how democratic accountability can create perverse incentives for politicians even in the most unlikely cases. The close elections regression discontinuity design identifies local average treatment effects, that is, the results are *local* to places where the margin of victory approaches zero. These are constituencies where the degree of political competition is the highest, and where electoral accountability is presumably strongest. The results presented in this paper show that even in the most testing circumstances, differential ability to engage

[37] To estimate these effects, I use the close elections regression discontinuity model with tehsil fixed effects.

resources of the state for political purposes leads to changes with large consequences for service delivery and development outcomes. This is confirmed in Appendix B, where I show that the results are robust to a geographic discontinuity design, but only in swing areas.

Second, the identification strategy is premised on the idea that ruling party politicians look similar to non-ruling party politicians, and that the identified treatment effects, the difference between ruling party and non-ruling party election winners, occur as a *result* of a ruling party politician being elected. Therefore, the difference in connections with politicians between ruling party and non-ruling party areas arises *between* the 2008 general election and the time of the surveys. Together, the results signal towards the difference in political manipulating of doctors and public health between ruling party and non-ruling party areas.

Third, this political manipulation of the bureaucracy carries consequences for service delivery in a substantively important way. The results show that bureaucratic characteristics are associated with ruling party constituencies and that service delivery suffers in ruling party areas, particularly as subsequent elections draw nearer. This corresponds to a decrease in clinic utilization. Ruling party politicians benefit from this behavior by improving their probability of reelection. Together with preliminary evidence that suggests that politicians protect bureaucrats in Punjab (Table 1), and that doctors offer quid pro quo services in the subsequent election of May 2013 (Figure 1), it can be argued that the use of the bureaucracy for political purposes has consequences for citizen welfare. For instance, this paper shows that antenatal visits and the number of deliveries both fell in the later waves of the surveys. If antenatal visits and deliveries are not taking place in formal health institutions, we can expect adverse consequences for births and early childhood health indicators. Research shows that stunting at early ages results in long term losses in cognitive development, learning and economic productivity later in life (Dewey and Begum 2011).

Fourth, while the results presented do not show the explicit act of doctors engaging in clientelistic activities, they show an overall pattern across several outcomes, where doctor behavior changes as a result of political incentives of ruling party politicians. These results are consistent with a theory of clientelism presented in Brusco et al. (2013). First, political parties are most likely to engage in clientelism where the marginal returns form effort are greatest. In the case of Punjab, effort on raising votes in swing constituencies yields additional seats in the parliament. Both the close elections and the geographic regression discontinuity estimates strongly show that the effects are strong in swing areas. Furthermore, the results also show that politicians are most likely to let engage doctors who are likely to be good at mobilizing votes. They retain doctors who have been present at a clinic for long, and prefer those who are posted closer to their hometowns. These results again show the politician engage in rational efficiency maximizing behavior.[38] Stokes (2005) and Brusco et al. (2013) contend that in the presence of the secret ballot, compliance to the clientelistic political party is ensured through local brokers who enjoy a long-term relationship with the voters. By engaging doctors who are more likely to know locals, politicians are able to resolve this commitment problem as well. Finally, the results on timing of the effects are consistent with the story of politicians ramping up clientelistic activities closer to subsequent elections.

8 Conclusion

In this paper I examine how electoral incentives in democracies can affect bureaucratic performance service delivery. I consider the case of Punjab, Pakistan to study how PML(N) legislators, who won in the 2008 general elections, performed vis-a-vis winners from other parties. I study the state of public health in the province by using a unique primary dataset I use a close elections regression discontinuity approach to resolve selection bias in studying the impact of having a ruling party politician. I contend that as the margin of victory in the 2008 approaches zero, the party affiliation of a politician is randomly assigned. I interpret this random assignment of public office to ruling party politicians as a discontinuity in the capacity of politicians to engage in clientelism through the appropriation of state resources. Noting that the public health bureaucracy in Punjab is politically charged, I present evidence on how the politicians engage in clientelism with public sector doctors, the consequences of this for service delivery, and the associated impacts on re-electing a ruling party candidate.

I present three sets of results: first, I show that in ruling party areas, doctors are more likely to report knowing the politicians, enjoy longer tenures at clinics, and live closer to hometowns if they have not been transferred. These results show that doctors in ruling party areas differ systematically along political dimensions. Next, I consider the impacts of bureaucratic performance and show that doctors in ruling party areas are absent 75 percent more often, and that they are more likely to be absent if they know the politician. In addition, their absence ramps up as the subsequent election of May 2013 draw closer. Finally, the same time period is associated with a decrease in clinic utilization for out-patient visits, ante-natal care visits and the number of deliveries. The final set of results focuses on electoral impacts. ruling party victory in 2008 is associated with a higher probability of reelection in 2013 in places where doctors were absent greater than the median, *and* the elections of 2008 were closer than the median.

These results show how ruling party politicians, in pursuit of cementing their position in a democratic process, engage in activities contrary to democratic principles. This behavior

[38] Brusco et al. (2013) characterise this as the productivity parameter of the broker.

is induced by democratic incentives in most competitive places, often referred to as swing constituencies. The results are consistent with a theory of clientelism developed by Brusco et al. (2013). Ruling party politicians maximize the marginal returns from effort by focusing their energies on bureaucrats with presumably large networks, those with longer tenures operating in areas closer to their hometowns. They also focus more on swing constituencies where the largest concentration of marginal voters exist. Finally, they time these activities such that the efforts are maximized closest to elections.

Mis-governance as a consequence of political incentives carries consequences for development. First, the results carry consequences for the design of policies to combat public employee absence, and the efficiency of resource utilization in the government. Programs that aim to reduce corruption and improve government efficiency would benefit from understanding instances where the incentives of politicians and service providers align, such they lead to a decline in service delivery and development outcomes. Second, in the presence of these perverse democratic incentives to move bureaucratic effort away from the social optimum, other mechanisms will need to be derived to compensate for the long term impacts on citizen welfare.

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Appendix

A Summary Statistics

Table A1: Summary Statistics for Close Elections Data

Variable	Mean	Std. Dev.	Min.	Max.	N
Absolute Margin of Victory ≤ 5					
Constituencies					22
Doctor Present = 1	0.54	0.5	0	1	173
# of times Doctor Present	1.33	1.09	0	3	208
Doctor's Months of Service	60.2	46.1	0	180	80
Doctor's Months of Service at Clinic	35.86	37.14	1	156	79
Doctor Knows Politician	0.13	0.34	0	1	82
Big 5 index (z-score)	0.25	0.73	-1.28	1.89	159
PSM index (z-score)	0.04	0.61	-1.5	1.54	159
Party Herfindahl Index	0.31	0.07	0.2	0.48	278
Doctor Distance to hometown (hours)	-2.16	1.12	-5.19	1.39	78
Absolute Margin of Victory ≤ 10					
Constituencies					43
Doctor Present = 1	0.48	0.5	0	1	321
# of times Doctor Present	1.19	1.04	0	3	386
Doctor's Months of Service	72.45	64.51	0	312	142
Doctor's Months of Service at Clinic	34.77	36.39	0	156	132
Doctor Knows Politician	0.21	0.41	0	1	145
Big 5 index (z-score)	0.15	0.77	-1.28	1.89	299
PSM index (z-score)	0.01	0.63	-1.5	1.68	299
Party Herfindahl Index	0.33	0.08	0.2	0.5	521
Doctor Distance to hometown (hours)	-1.88	1.34	-5.19	1.54	137
Absolute Margin of Victory (All Data)					
Constituencies					100
Doctor Present = 1	0.46	0.5	0	1	658
# of times Doctor Present	1.1	1	0	3	822
Doctor's Months of Service	78.22	68.44	0	393	282
Doctor's Months of Service at Clinic	37.17	39.51	0	170	260
Doctor Knows Politician	0.22	0.42	0	1	290
Big 5 index (z-score)	0.04	0.76	-1.39	1.89	655
PSM index (z-score)	-0.01	0.68	-2.09	1.72	655
Party Herfindahl Index	0.35	0.08	0.16	0.52	1137
Doctor Distance to hometown (hours)	-2	1.32	-5.89	1.54	278

Notes:

Table A2: Summary Statistics for Geographic RD

Variable	Mean	Std. Dev.	Min.	Max.	N
Distance to Border $\leq$ 5 Km					
Constituencies					119
Doctor Present = 1	0.44	0.5	0	1	748
\ # of times Doctor Present	1.06	0.98	0	3	905
Doctor's Months of Service	82.88	69.07	0	393	298
Doctor's Months of Service at Clinic	37.53	39.09	0	168	263
Doctor Knows Politician	0.21	0.41	0	1	308
Big 5 index (z-score)	0.02	0.77	-1.16	1.89	729
PSM index (z-score)	-0.09	0.72	-2.09	1.68	729
Party Herfindahl Index	0.35	0.08	0.16	0.52	1214
Distance to District Headquarters (km)	39.65	25.67	5	135	1200
Absolute Victory Margin $\leq$ 5	0.19	0.39	0	1	1226
Distance to Border $\leq$ 10 Km					
Constituencies					131
Doctor Present = 1	0.47	0.5	0	1	1580
# of times Doctor Present	1.16	1.01	0	3	1918
Doctor's Months of Service	81.09	70.15	0	393	658
Doctor's Months of Service at Clinic	35.35	38.71	0	168	588
Doctor Knows Politician	0.19	0.4	0	1	689
Big 5 index (z-score)	0.01	0.78	-1.39	1.89	1579
PSM index (z-score)	-0.07	0.70	-2.09	1.72	1579
Party Herfindahl Index	0.34	0.08	0.16	0.52	2535
Distance to District Headquarters (km)	39.98	25.33	5	155	2495
Absolute Victory Margin $\leq$ 5	0.21	0.41	0	1	2571
Distance to Border $\leq$ 20 Km					
Constituencies					132
Doctor Present = 1	0.47	0.5	0	1	3130
# of times Doctor Present	1.17	1.01	0	3	3790
Doctor's Months of Service	82.73	71.84	0	393	1325
Doctor's Months of Service at Clinic	35.91	38.89	0	170	1182
Doctor Knows Politician	0.2	0.4	0	1	1377
Big 5 index (z-score)	0.03	0.79	-1.39	1.89	3128
PSM index (z-score)	-0.05	0.71	-2.09	1.72	3128
Party Herfindahl Index	0.35	0.08	0.16	0.52	5010
Distance to District Headquarters (km)	40.34	25.6	5	155	4929
Absolute Victory Margin $\leq$ 5	0.2	0.4	0	1	5066

Notes:

Table A3: Summary Statistics for Elections Analysis

Variable	Mean	Std. Dev.	Min.	Max.	N
Constituencies					100
# of times Doctor Present	0.84	0.73	0	3	100
Doctor Tenure at Clinic	38.24	31.7	1	132	82
Doctor Knows Politician	0.24	0.34	0	1	87
Margin of Victory	6.75	17.33	-35.48	46.89	100
PML(N) Vote Share, 2008	0.4	0.1	0.21	0.65	100
PML(N) Vote Share, 2013	0.43	0.14	0	0.68	99
Turnout, 2008	0.5	0.09	0.2	0.68	99
Turnout, 2013	0.59	0.05	0.49	0.72	99

Notes:

B Geographic Regression Discontinuity

An additional way of resolving the selection problem is to compare clinics in PML(N) areas with other clinics that look similar on covariates, but are located in non-PML(N) constituencies. This is possible because administrative boundaries, that govern how bureaucracy operates, do not overlap with political boundaries, which structure how politicians operate.

I use the geographic regression discontinuity approach developed in Dell (2010), and formalized in more recent work (Keele and Titiunik 2013) to study the causal effect of politician who belongs to the ruling party. This approach ensures 'as-if' random allocation of politician party to clinics that are similar. I estimate equations of the following form:

$$Y_{ibt} = \alpha + \beta PML(N)\ Winner_{ib} + f(x_{ib}) + \gamma_b + \epsilon_{ibt} \tag{3}$$

$$\forall i\ s.t.\ x_{ib} \in (-h, h)$$

where Y_{ibt} refers to the outcome of interest at clinic i at survey wave t assigned to a political border b. As before, $PML(N)\ Winner_{ijt}$ is an indicator variable that takes a value 1 if the politician for clinic i near a political border j belongs to the ruling party, Pakistan Muslim League (Nawaz Group). The control function $f(x_{ib})$ corresponds to an n^{th} order polynomial of the forcing variable x_{ij} which in this context, refers to the distance of a rural clinic to a border b. The forcing variable is positive for clinics that fall in constituencies with a sitting PML(N) politician, while it becomes negative in places where the politician belongs to a non-PML(N) party. I use a triangular kernel that weighs clinics that are closer the border more than clinics farther away. In particular, the weight drops to zero if the clinic is farther than 20 kilometers away from border b. Finally, γ_j refers to border fixed effects. I include them in all regressions that use this identification strategy. This allows the comparison of clinics that are close to each other, but on opposite sides of a political border.

Unlike Dell and Keele and Titiunik's work however, I cannot use a smooth function that gives me the effect of a treatment at one particular border. As seen from Figure H5, each clinic can be an arbitrary distance form several political borders. This creates the problem of multiple cut-offs in the running variable, which makes it difficult to ascertain which clinic should be kept for which particular border.

I develop a solution to this problem through the following procedure: first, I create copies of observations for each potential border the clinic can be referred to. So for instance, if a clinic in a treatment area can be arbitrarily close to clinics in four neighboring constituencies, I create four copes of this clinic with the corresponding value of distance to each border in turn. This inflates the number of observations I have tremendously. To account for this, I cluster all standard errors at the political constituency level, which accounts for correlation between observations by inflating the standard errors appropriately. This is more conservative than clustering errors at the clinic level, but necessary because the treatment is assigned at the politician level.

Table A2 presents summary statistics for these data. 19 percent of the observations in places close to the border have an absolute margin of victory less than five percent. For the analysis that uses spatial information on clinics, I define these clinics as being in a 'swing' constituency. I will show that most results from this exercise are concentrated in swing areas.

I always include border fixed effects, since this is required for identification to be achieved. However, unlike the close elections regression discontinuity, that reports results LATE to swing constituencies, the geographic RD's results are LATE to areas close to the border. To make them comparable to the close elections, I also present results for the second identification strategy by restricting the sample to 'swing' constituency. I define 'swing' constituencies as those whose absolute victory margin is less than 5. Though this can probably be done more flexibly, but data sparsity does not allow me to do this with much certainty.

B.1 Results

Table B1: Connections between Politicians and Doctors

	(1)	(2)
PML(N) Winner	0.046	0.796
	(0.253)	(0.484)
Mean Dep Variable	0.170	0.087
# Constituencies	100	31
# Observations	1094	275
Fixed Effects	Border	Border
Model	Geo	Geo
Sample	Full	Swing

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. In column (1) I run model 3 on the geographic RD dataset, and find that the point estimate remains very close to zero, hinting at no correlation in the overall sample. This is consistent with the naive specification. In column (2), I restrict the sample only to swing areas, as defined by an absolute margin of victory less than 5, and run the geographic RD model again. Though the result is not statistically significant, the point estimate is very close to the point estimate returned from the close elections specification in Table 2 column (4).

Table B2: Doctor Attendance

	(1)	(2)
PML(N) Winner	0.106	-0.879***
	(0.170)	(0.267)
Mean Dep Variable	0.475	0.555
# Constituencies	122	36
# Observations	3130	659
Fixed Effects	Border	Border
Model	Geo	Geo
Sample	Full	Swing

Notes: *Level of significance*:$*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. Column (1) runs OLS on the full sample and finds no effect of a PML(N) legislator on attendance, but restricting the data to swing constituencies produces strong impacts of PML(N) incumbents on doctor attendance. We see that the probability of finding a doctor in PML(N) areas goes does by 88 percent compared to minority party areas in Column (2).

Table B3: Doctor Tenure

	(1)	(2)
Panel A: Dependent Variable - Doctor Tenure Overall (in months)		
PML(N) Winner	-3.536	58.314
	(35.183)	(60.862)
Mean Dependant Variable	84.553	55.383
# Constituencies	97	30
# Observations	1042	269
Fixed Effects	Border	Border
Model	Geo	Geo
Sample	Full	Swing
Panel B: Dependent Variable - Doctor Tenure at Clinic (in months)		
PML(N) Winner	12.614	129.790**
	(28.683)	(53.898)
Mean Dependant Variable	33.780	30.638
# Constituencies	91	30
Fixed Effects	Border	Border
Model	Geo	Geo
Sample	Full	Swing

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. Panel A: In columns (1) and (2), I find that PML(N) winner does not cause an increase in overall tenure. Panel B: In column (1) and (2), I run the geographic RD model and find that doctors indeed have higher tenure at clinics, but only in swing areas.

Table B4: Doctor Attendance by Survey Wave

	All (1)	Wave 1 (2)	Wave 2 (3)	Wave 3 (4)
PML(N) Winner	-0.879***	-0.515	-0.314	-2.032***
	(0.267)	(0.671)	(0.888)	(0.711)
Mean Dep Variable	0.555	0.571	0.533	0.561
# Constituencies	36	33	33	32
# Observations	659	231	214	214
Fixed Effects	Tehsil	Tehsil	Tehsil	Tehsil
Model	Geo	Geo	Geo	Geo
Sample	Full	Full	Swing	Swing

Notes: *Level of significance*:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the constituency level reported in parentheses. All dependent variables are logged. Survey Wave 1 was conducted in November 2011, Wave 2 in June 2012 and Wave 3 was done in October 2012. General Elections were held on Feb 18, 2008 and May 11, 2013.

Table B5: Placebo Regression with Geographic RD

	(1) Registered Voters	(2) Voter Turnout	(3) Number of Candidates	(4) Party Herfindahl	(5) Distance to Headquarter
PML(N) Winner	0.054	-0.044	0.277	0.051	-0.697
	(0.109)	(0.047)	(1.614)	(0.042)	(4.281)
Constant	11.861***	0.551***	7.192***	0.357***	41.333***
	(0.075)	(0.032)	(1.104)	(0.029)	(3.053)
# Constituencies	99	100	100	99	119
# Observations	132	132	132	131	4494

Notes: *Level of significance*:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

C Robustness Check with Randomization Inference

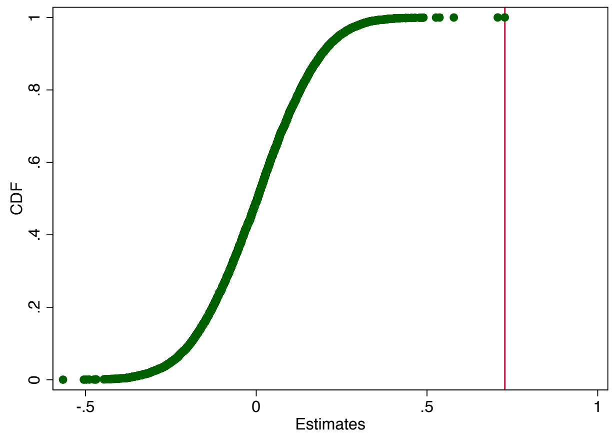

Figure C1: Randomization Inference: Doctor Connections with Politicians

Notes: Each of the 10,000 dots in this figure is a coefficient of interest (x-axis) from a regression of doctor connections on the close elections regression discontinuity model, where the vector of the treatment indicator variables is randomly assigned at the constituency level 10,000 times. The y-axis presents the cumulative distribution of these simulated treatment effects. The dot intersected with the vertical red line represents the actual coefficient.

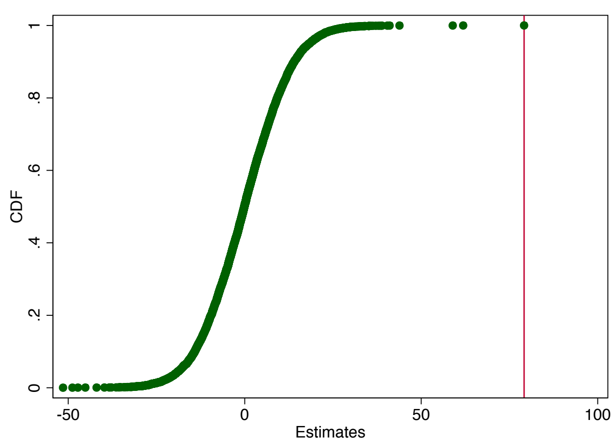

Figure C2: Randomization Inference: Doctor Tenure at Clinic

Notes: Each of the 10,000 dots in this figure is a coefficient of interest (x-axis) from a regression of doctor tenure at clinic on the close elections regression discontinuity model, where the vector of the treatment indicator variables is randomly assigned at the constituency level 10,000 times. The y-axis presents the cumulative distribution of these simulated treatment effects. The dot intersected with the vertical red line represents the actual coefficient.

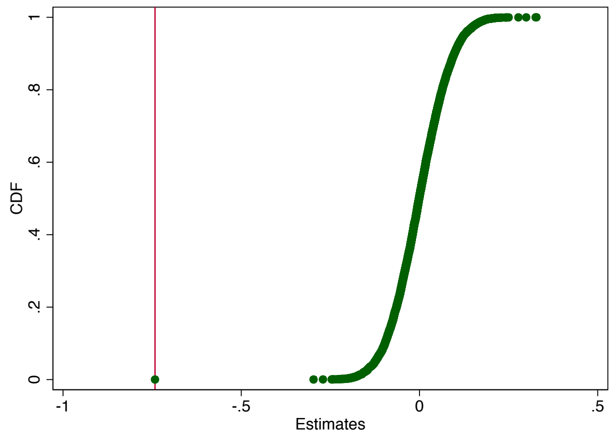

Figure C3: Randomization Inference: Doctor Attendance

Notes: Each of the 10,000 dots in this figure is a coefficient of interest (x-axis) from a regression of doctor attendance on the close elections regression discontinuity model, where the vector of the treatment indicator variables is randomly assigned at the constituency level 10,000 times. The y-axis presents the cumulative distribution of these simulated treatment effects. The dot intersected with the vertical red line represents the actual coefficient.

D Robustness to alternate specifications

Table D1: Doctor Connections

	(1) Quartic	(2) Cubic	(3) Quadratic	(4) Linear
Bandwidth = +/- 0.50				
PML(N) Winner	0.728**	0.733**	0.385	0.002
	(0.359)	(0.328)	(0.242)	(0.196)
# Constituencies	78	78	78	78
# Observations	226	226	226	226
Bandwidth = +/- 0.20				
PML(N) Winner	0.940*	0.755*	0.266	0.225
	(0.528)	(0.394)	(0.257)	(0.283)
# Constituencies	60	60	60	60
# Observations	181	181	181	181
Bandwidth = +/- 0.10				
PML(N) Winner	.	.	1.051***	1.118***
	.	.	(0.127)	(0.038)
# Constituencies	36	36	36	36
# Observations	116	116	116	116
Fixed Effects	Tehsil	Tehsil	Tehsil	Tehsil

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

Table D2: Doctor Tenure at Clinic

	(1) Quartic	(2) Cubic	(3) Quadratic	(4) Linear
Bandwidth = +/- 0.50				
PML(N) Winner	79.147***	66.728**	0.677	2.095
	(23.234)	(27.245)	(31.865)	(14.506)
# Constituencies	70	70	70	70
# Observations	200	200	200	200
Bandwidth = +/- 0.20				
PML(N) Winner	90.666***	83.639***	84.247***	15.634
	(22.394)	(26.599)	(25.367)	(19.429)
# Constituencies	56	56	56	56
# Observations	165	165	165	165
Fixed Effects	Tehsil	Tehsil	Tehsil	Tehsil

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

Table D3: Doctor Attendance

	(1) Quartic	(2) Cubic	(3) Quadratic	(4) Linear
Bandwidth = +/- 0.50				
PML(N) Winner	-0.742***	-0.328	-0.115	-0.262*
	(0.214)	(0.201)	(0.171)	(0.134)
# Constituencies	93	93	93	93
# Observations	658	658	658	658
Bandwidth = +/- 0.20				
PML(N) Winner	-1.256***	-1.286***	-0.595**	-0.280
	(0.398)	(0.332)	(0.247)	(0.246)
# Constituencies	69	69	69	69
# Observations	518	518	518	518
Bandwidth = +/- 0.10				
PML(N) Winner	-2.104***	-0.750***	-1.593***	-0.935***
	(0.292)	(0.211)	(0.338)	(0.235)
# Constituencies	42	42	42	42
# Observations	321	321	321	321
Fixed Effects	Tehsil	Tehsil	Tehsil	Tehsil

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

E 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 E1 describes the breakdown of our sample.

Table E1: 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		

F Hiring Process for Doctors

There are two different hiring processes for the Doctors (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.

G Matching Clinics to Political Constituencies

Matching clinics to political constituencies is not straightforward. I adapt this note from Callen et al. (2013), where we followed a two pronged strategy to place the clinics in their relevant electoral constituencies. The two identification strategies require data to be set up in different ways. As a results there is a difference between the two strategies that I discuss below.

G.1 For Close Elections Regression Discontinuity

During the second round of our survey onwards, 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 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 the technique described below to break the tie between the remaining few clinics.

G.2 For Geographic Regression Discontinuity

Since this geographic regression discontinuity relies on spatial information, information, clinics needed to be assigned to political constituencies based purely on the spatial information at hand. For the clinics, 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[39]. 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.

G.3 Coding Check

Survey coding achieved in the first strategy provides a higher benchmark in accuracy because we were able to achieve triangulation through multiple means. We notice that in the sample under consideration in this paper, about thirty five percent of the clinics are not coded for the same constituency. This would be a cause for concern if the misclassification was correlated with the treatments.

In Table G1, I check if the treatment in both identification strategies is predicting the difference in coding between the two identification strategies. I find that that this is not the case, which provides evidence to the fact that the potential miscoding in the geographic RD design is not correlated systematically with the treatment.

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

Table G1: Coding Check

	(1)	(2)	(3)	(4)
PML(N) Winner	-0.060	-0.191	0.004	0.194
	(0.283)	(0.259)	(0.231)	(0.242)
Constant	0.464**	0.206	0.564***	0.586***
	(0.201)	(0.210)	(0.172)	(0.140)
# Constituencies	93	93	122	36
# Observations	657	657	3130	659
Fixed Effects	-	Tehsil	Border	Border
Sample	Full	Full	Full	Swing
Model	Close	Close	Geo	Geo

Notes: *Level of significance*:*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors clustered at the constituency level reported in parentheses.

H Additional Tables and Figures

FAFEN @_FAFEN 21 Apr
Police constable gets PML-N panaflexes printed in Chunian, #Kasur (NA-141) #ECP #Election2013

FAFEN @_FAFEN 21 Apr
#PMLN panaflex seen on Govt Higher Secondary School for Boys near Saddar Police Station in Muridke, #Sheikhupura (NA-131) #ECP

FAFEN @_FAFEN 28 Apr
Tehsildar seen using govt vehicle on Thana Mor Kamalia to canvass for his wife, an indp candidate,Toba Tek Singh (NA-94) #ECP @Maria_Memon

FAFEN @_FAFEN 2 May
Patwari seen conducting #PMLN candidate's election campaign in Rojhan, #Rajanpur (NA-175) #ECP #Election2013

FAFEN @_FAFEN 28 Apr
Govt. High School Garh teacher seen campaigning for #PMLN in Garh, Tandlianwala, #Faisalabad (NA-78) #ECP

FAFEN @_FAFEN 24 Apr
#PTI banner seen on TMA Office near Hafizabad Distributary, #Hafizabad (NA-102) #ECP #Election2013

FAFEN @_FAFEN 20 Apr
#PMLN hoarding seen on wall of Rural Health Center in Jalalpur Bhattian, Pindi Bhattian, #Hafizabad (NA-103) #ECP #Pakistan

FAFEN @_FAFEN 5 May
Patwari campaigns for #PMLN candidate in Basti Chiina, #Bhakkar (NA-74) #ECP #Election2013

FAFEN @_FAFEN 5 May
#PMLN holds rally in Government Girls Primary School in Rachara, Daska, #Sialkot (NA-113) #ECP #Election2013

FAFEN @_FAFEN 22 Apr
Govt Boys Elementary School Mangari teacher observed campaigning for #PMLN in Nadala, Shakargarh, #Narowal (NA-116) #ECP #Pakistan

FAFEN @_FAFEN 16 Apr
A revenue department registry clerk seen campaigning at Circular Road near Chan Peer Darbar for #PMLN candidate, Narowal (NA-117) #ECP

FAFEN @_FAFEN 1 May
Government teacher takes part in #PTI campaign in Muhalla Tilo Pura, Mailsi, #Vehari (NA-170) #ECP #Election2013

FAFEN @_FAFEN 2 May
Education officer seeking votes for #PMLN candidate in Jand, #Attock (NA-58) #ECP #Election2013

FAFEN @_FAFEN 11 Apr
School headmaster delivers speech during independent candidate's rally at Vanjari, Issakhel, Mianwali (NA-71) #ECP

Figure H1: Selected Tweets from Free and Fair Elections Network before 2013 Elections

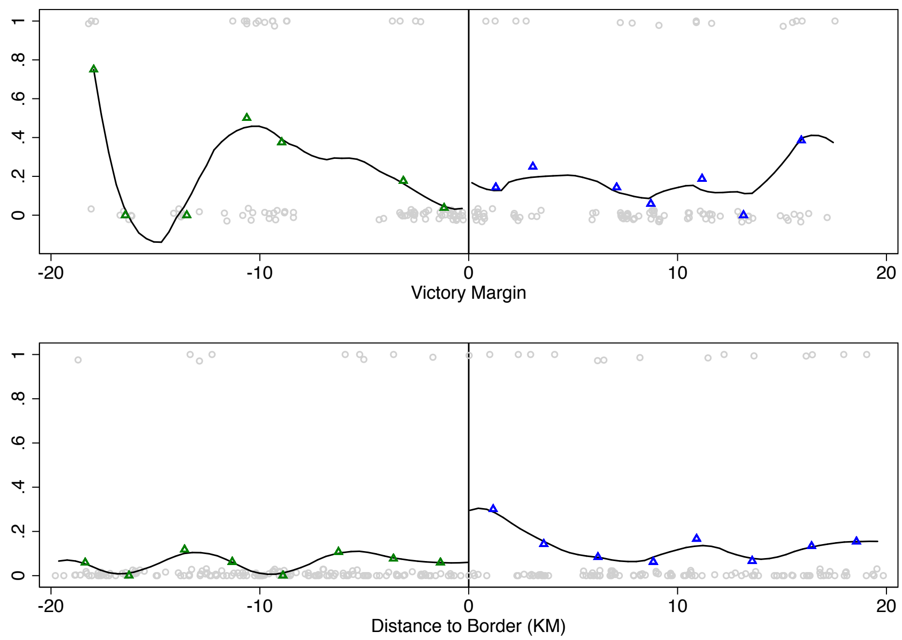

Figure H2: Doctor Connections with Politician

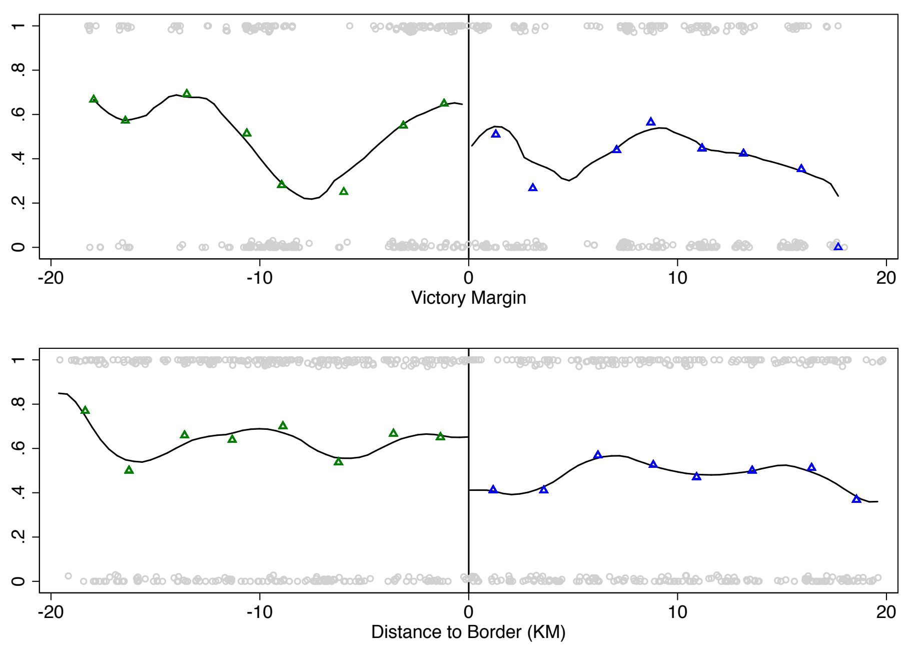

Figure H3: Doctor Presence

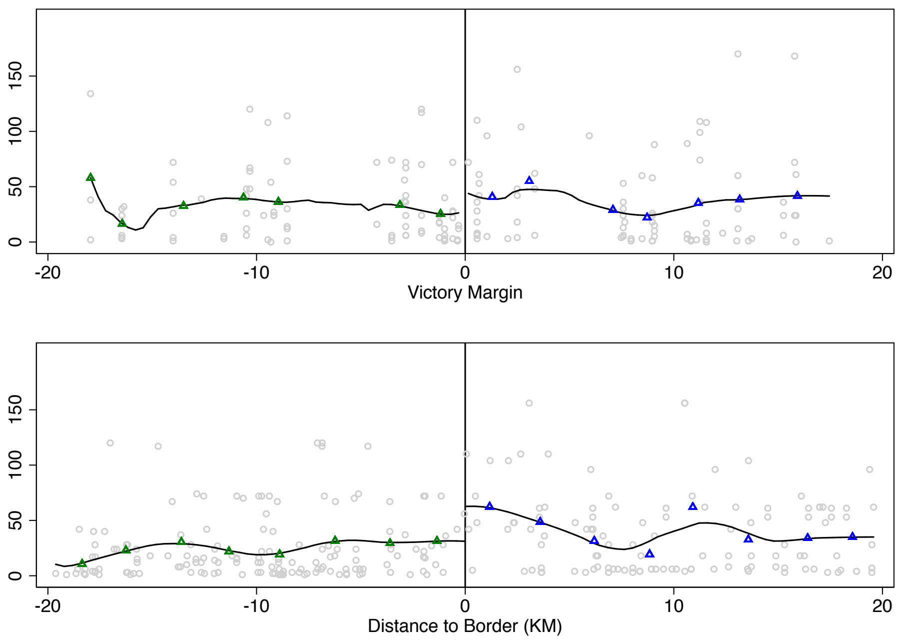

Figure H4: Doctor Tenure at Clinic

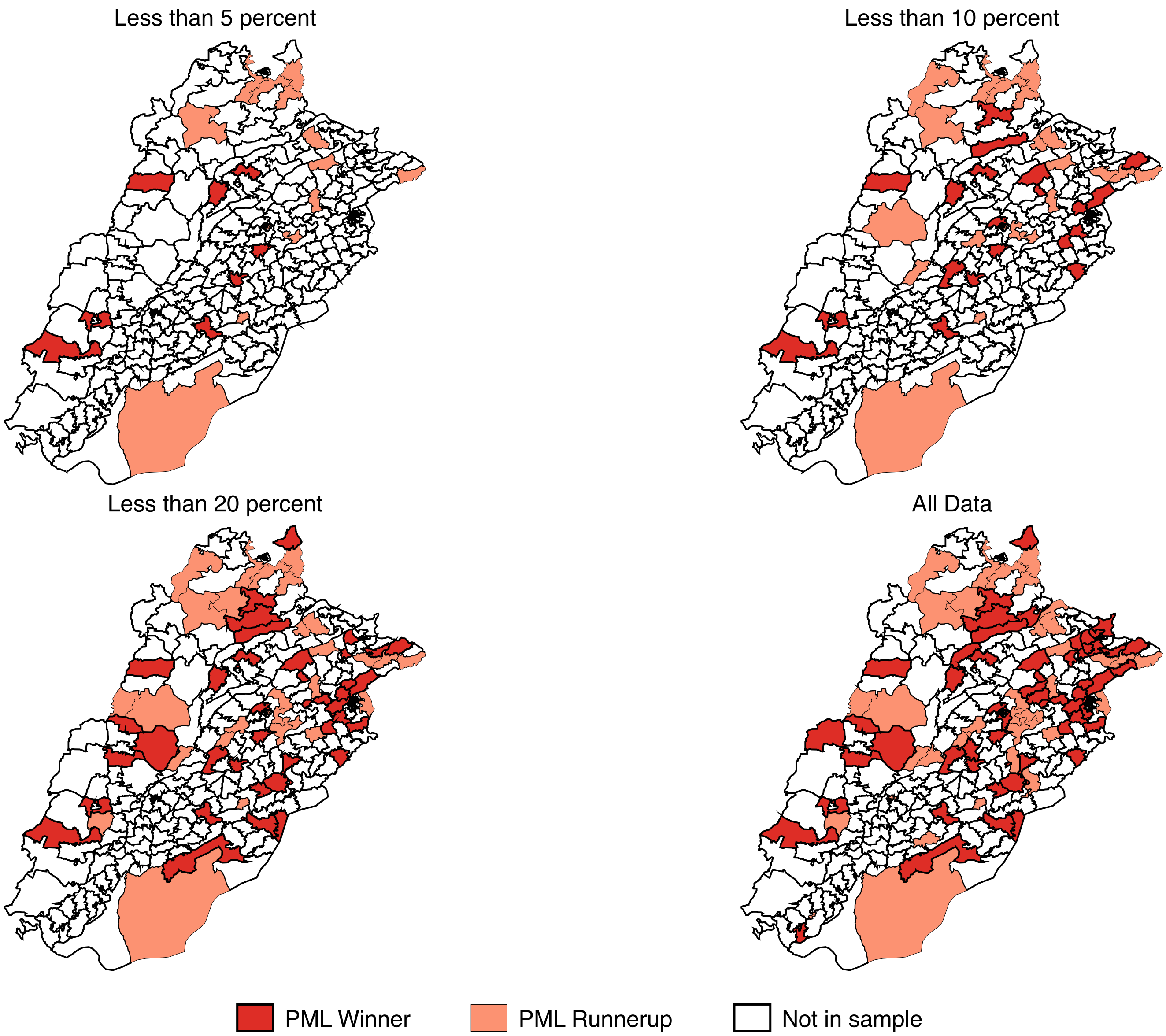

Figure H5: Constituency Sample by Margin of Victory