NBER WORKING PAPER SERIES

PERSONALITIES AND PUBLIC SECTOR PERFORMANCE: EVIDENCE FROM A HEALTH EXPERIMENT IN PAKISTAN

Michael Callen
Saad Gulzar
Ali Hasanain
Yasir Khan
Arman Rezaee

Working Paper 21180
http://www.nber.org/papers/w21180

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge MA 02138
May 2015, Revised April 2018

We thank Farasat Iqbal (Punjab Health Sector Reforms Project) for championing and implementing the project and Asim Fayaz and Zubair Bhatti (World Bank) for designing the smartphone monitoring program. Support is provided by the International Growth Centre (IGC) state capabilities program, the IGC Pakistan country office, and the University of California Office of the President Lab Fees Research Program Grant #235855. Callen was supported by grant #FA9550-09-1- 0314 from the Air Force Office of Scientific Research. We thank Tahir Andrabi, Eli Berman, Ali Cheema, Julie Cullen, Clark Gibson, Naved Hamid, Gordon Hanson, Asim Khwaja, Jennifer Lerner, Jane Mansbridge, Edward Miguel, Craig McIntosh, Ijaz Nabi, Rohini Pande, ChristopherWoodruff, and seminar participants at UC Berkeley, UC Los Angeles Anderson, UC San Diego, Paris School of Economics, New York University, University of Washington, Harvard Kennedy School, and participants at the IGC Political Economy Group, Development and Conflict Research (DACOR), Pacific Development (PacDev), New England Universities Development Consortium (NEUDC), Southern California Conference in Applied Microeconomics (SoCCAM), Bay Area Behavioral and Experimental Economics Workshop (BABEEW), Symposium on Economic Experiments in Developing Countries (SEEDEEC), and the Bureau for Research and Economic Analysis of Development (BREAD) conferences for insightful comments. Excellent research assistance was provided by Muhammad Zia Mehmood. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Personalities and Public Sector Performance: Evidence from a Health Experiment in Pakistan
Michael Callen, Saad Gulzar, Ali Hasanain, Yasir Khan, and Arman Rezaee
NBER Working Paper No. 21180
May 2015, Revised April 2018
JEL No. C93,D02,D73,H11,O31

ABSTRACT

This paper provides evidence that the personalities of policymakers matter for policy. Three results support the relevance of personalities for policy. First, doctors with higher Big Five and Perry Public Sector Motivation scores attend work more and falsify inspection reports less. Second, health inspectors who score higher on these measures exhibit larger treatment responses to increased monitoring. Last, senior health officials with higher personality scores respond more to data on staff absence by compelling better subsequent attendance. These results suggest that interpersonal differences matter are consequential for state performance.

Michael Callen
Rady School of Management
University of California, San Diego
Wells Fargo Hall, Room 4W104
9500 Gilman Drive #0553
La Jolla, CA 92093-0553
and NBER
mjcallen@ucsd.edu

Saad Gulzar
Stanford University
616 Serra Street
Encina Hall West, Room 100
Stanford, CA 94305-6044
gulzar@stanford.edu

Ali Hasanain
Lahore University of Management Sciences
Sector U, DHA
Lahore 54792
Pakistan
ali.hasanain@gmail.com

Yasir Khan
University of California, Berkeley
Haas School of Business
yasir.khan@berkeley.edu

Arman Rezaee
University of California, Davis
1149 Social Sciences & Humanities Building
One Shields Avenue
Davis, CA 95616
abrezaee@ucdavis.edu

1 Introduction

Governments are the primary provider of services for the poor in developing countries. Yet, government employees, from front-line providers such as teachers and doctors to senior officials, commonly face weak incentives to perform (World Bank, 2004; Reinikka and Svensson, 2004; Chaudhury et al., 2006; Bandiera et al., 2009; Wild et al., 2012). A principal focus of many reforms aimed at improving service delivery is, therefore, to strengthen incentives.[1] Evidence supports the view that, in addition to incentives, personality traits play a key role in determining performance (Borghans et al., 2008; Almlund et al., 2011; Heckman, 2011), can be changed (Kautz et al., 2014; Blattman et al., 2015), and that better recruitment policy can improve the personality profile of individuals selecting into public service (Dal Bó et al., 2013; Ashraf et al., 2014).[2] This suggests the possibility of strengthening services in developing countries through the separate avenue of personality traits.[3] This paper examines whether such non-cognitive traits matter for public service delivery outcomes.

We consider three questions in the context of a large-scale field experiment designed to improve health worker performance in Punjab, Pakistan.[4] First, do personality measures predict performance under weak status quo incentives? Second, do these measures predict

[1] Olken and Pande (2012) provide an overview of incentive reforms designed to reduce corruption and improve public sector performance more generally.

[2] Guided by insights from the field of industrial and organizational (I-O) psychology, firms, militaries, and governments in developed countries have long used psychometric measures to inform hiring, training, and promotion decisions. In a widely-cited meta-analysis of 85 years of data, for example, Schmidt and Hunter (1998) find that conscientiousness tests such as those in this paper not only predict job performance but do so while being much less correlated with general mental aptitude than years of education or job knowledge tests. Many others have stressed the predictive validity of these non-cognitive traits (Kaplan and Saccuzzo, 1997; Bowles et al., 2001; Heckman et al., 2006; Borghans et al., 2008; Groth-Marnat, 2009; Gatewood et al., 2010; Bazerman and Moore, 2012).

[3] Rasul and Rogger (2014) provide evidence that management practices are also an important determinant of public sector performance. In Nigeria, they find a strong positive relationship between a measure of managerial autonomy for bureaucrats and project completion, suggesting an additional means of improving service delivery beyond standard incentives.

[4] According to 2008 population estimates, Punjab is the ninth largest sub-national unit in the world with approximately 85 million citizens, of which 70 percent are rural. According to a 2011 report, the Punjab Department of Health provides outpatient services 90 percent of this total population per year, making it one of the largest health systems in existence. Despite the far reach of this system, Punjab performs poorly on major health indicators, with an infant mortality rate of 88 per 1000 live births, for example (National Institute of Population Studies, 2013).

responses to a reform that changes incentives? Third, do these measures predict who will respond to salient information on subordinate absence? We answer each of these questions in the affirmative, thus demonstrating the strength of the relationship between the personalities of officials in government and public sector performance.

The behavior of government bureaucrats is shaped by many forces beyond their control, including political considerations, institutional incentives, and so on. This may be acutely true in low capacity settings. Our findings indicate that these forces do not have complete primacy; the specific identity of individuals in government matters. Indeed, it appears to matter a tremendous amount. The people who comprise government play a fundamental role in shaping its performance. Politics and institutions are likely much less mutable than are the people who work in government. We therefore view the core contribution of this paper as providing a broad and substantial empirical endorsement of the value of studying government personnel for development economics (Finan et al., 2015).

Returning to our specific research questions, we find that the Big Five and Perry Public Service Motivation (PSM) measures systematically predict doctor and, to a lesser extent, inspector performance.[5] Doctors who score one standard deviation higher on the measured Big Five trait of conscientiousness, for example, are 5.8 percentage points more likely to be present at work during an unannounced visit. Similarly, health inspectors that score one standard deviation higher on the measured PSM trait of commitment to policymaking are five percentage points less likely to be found colluding with doctors to falsify inspection reports. In addition, health inspectors that score one standard deviation better on a proxy measure of the tendency to procrastinate are six percentage points more likely to complete each of their assigned inspections in a two month period.[6] Overall, we find significant positive

[5]The Big Five personality traits, according to the Five Factor Model of personalities, are five separate dimensions of human personality that were designed to be descriptive and non-overlapping. These traits are agreeableness, emotional stability, extroversion, conscientiousness, and openness. The PSM measure is argued to capture attributes of individual personality relevant to the desire to provide public service. PSM has six traits—attraction to policymaking, commitment to policymaking, social justice, civic duty, compassion, and self-sacrifice.

[6]We obtain a proxy measure of an inspector's tendency to procrastinate by examining the degree to which the inspector tends to get his monthly quota of inspections done later in the month. Our approach is similar

correlations for four of eleven measured doctor personality traits and one of two personality trait summary indices (Big Five) and doctor attendance, and seven of the remaining eight coefficients are also positive.[7] A similar, though weaker, pattern holds with health inspectors, which we discuss in detail below.

Importantly, these personality measures also predict performance better than other measured covariates, such as work experience and travel distance from a doctor's health clinic to home. We conduct this analysis using the least absolute shrinkage and selection operator (LASSO) estimator. One advantage of this estimator is that it identifies the subset of regressors that are most predictive. For doctors, we find that the Big Five index remains predictive of attendance when the cross-validated error is minimized, while other measured covariates do not. The same is true with the PSM index.

To provide evidence on the second question, we designed and implemented a smartphone technology that verifies whether officials are performing regular facility inspections across Punjab. We evaluated this using a randomized control trial spanning the province.[8] We find that a one standard deviation increase in our measured aggregate Big Five index for a government inspector is associated with a 35 percentage point differential increase in inspections in response to treatment.[9]

On the final question, a one standard deviation increase above the mean in our measured aggregate Big Five index of a senior health official is associated with an additional 40 percentage point reduction in doctor absence at a facility managed by the official when the

to that of Shapiro (2005) and Kuhn (2013), who use the steepness of the biweekly consumption profile to measure time preferences.

[7]Throughout the paper, we will scale our personality measures such that higher values are normatively better from the perspective of worker performance. We will report results both on individual traits and on summary indices of the Big Five and Public Sector Motivation traits. We discuss the rationale for this approach in Section 3.1.1 below.

[8]Considering the distribution of personality types of agents most affected by an intervention can also help us understand what treatment effects might look like in other settings. On an intuitive level, if a bureaucracy is staffed with workers whose personalities are well-suited to the job, increasing incentives to perform may make very little difference. Conversely, if workers are highly incompatible with their jobs, reforms may induce little additional effort. In line with this intuition, we find suggestive evidence that treatment effects from the monitoring technology are localized to the middle of the personality distribution.

[9]When compared to other measured inspector covariates in a single model, we find the Big Five index predicts as well as if the inspector has received a higher education degree.

facility's performance is experimentally flagged for the official's attention.[10] These officials oversee health systems responsible for several million citizens. The magnitude of our result suggests that improvements at this level of the bureaucracy might be particularly impactful.

The relationship between personality traits and policy outcomes in our data supports the recent focus on the selection and motivation of policy actors (Dal Bó et al., 2013; Ashraf et al., 2014, Forthcoming; Finan et al., 2015; Deserranno, 2016), the relationship between personalities and performance in other domains (Barrick and Mount, 1991; Salgado, 1997; Nyhus and Pons, 2005; Heckman et al., 2006; Ramey et al., Forthcoming), and the potential malleability of personality traits (Kautz et al., 2014; Blattman et al., 2015). On selection into public service, Ashraf et al. (Forthcoming) find that both financial and non-financial incentives are more effective for more intrinsically motivated public health workers in Zambia and Ashraf et al. (2014), in the same context, find that health workers recruited by making career incentives salient perform better on the job than those recruited by making social incentives salient, despite being no less pro-social. Dal Bó et al. (2013) find that increasing wages substantially improves the pool of applicants to public jobs, as measured by IQ, Big Five, and Perry Public Sector Motivation.[11] The literature in psychology and in economics also consistently points to a relationship between personality measures and economic success. For example, Heckman et al. (2006) find that measures of locus of control

[10]Both the results relating to the second and the third question are based on comparisons of treatment effects across different subgroups and so are not, themselves, experimentally identified (Deaton, 2010). However, because personality is not randomly assigned, we can only argue that personalities strongly predict the types of individuals who will respond to changes in incentives. Relatedly, because we could potentially consider a number of different dimensions of heterogeneity, our statistical tests may not be of proper size (Miguel et al., 2014). We argue this should not be a major concern for three reasons. First, we designed the study expressly to understand the relevance of personality for performance. Other than checking staff attendance, we only collected data on the personalities and political connections of doctors, a dimension of heterogeneity we analyze in Callen et al. (2016). As evidence of this, we added an extra survey wave in which we tracked down doctors that we never found present in a clinic and in which we only measured personality traits at considerable effort and expense. Second, we composed a pre-analysis plan for this project in March of 2012, prior to the collection of any data on personalities. Finally, our results are similarly strong even after we account for multiple hypothesis testing through both the use of indices and also through controlling for the False Discovery and Family-Wise Error Rates across hypotheses. This is described in Section 3.4.

[11]Our results directly complement this paper as we find that workers with higher scores on the Big Five and Public Sector Motivation measures work more often and more effectively in a similar context with weak extrinsic incentives. Taken together, this suggests that increasing wages can improve service delivery by causing more effective workers to select into public service.

and self-esteem (traits related to emotional stability, one of the Big Five personality traits) from adolescence predict adult earnings to the same degree as cognitive ability. Similarly, Kautz et al. (2014) summarize a body of research finding that non-cognitive characteristics are often as predictive as cognitive skills in predicting economic success. Nyhus and Pons (2005) find using Dutch household data that wages are correlated with two of the Big Five personality traits, emotional stability and conscientiousness.[12] Other meta-analyses find conscientiousness to be consistently predictive of earnings (Barrick and Mount, 1991; Salgado, 1997). For instance, Hogan and Holland (2003) find in a meta-analysis that all five Big Five measures positively predict performance on specific job criteria, and that the predictions become stronger as the job criteria become more specific.[13] Regarding whether traits are fixed, Kautz et al. (2014), in a comprehensive review of the literature, argue that the evidence so consistently supports malleability that non-cognitive attributes should be called "skills", rather than "traits", partly to re-orient policy toward the value of investing in these dimensions of human capital.[14]

These three literatures, combined with the positive relationship between better traits and better performance in our data, suggest three ways that taking non-cognitive attributes into consideration might improve service delivery. First, the finding that the psychological profile of applicants to public jobs can be affected by the recruitment process suggests delivery out-

[12]These two traits are also the most consistently predictive of performance in our data.

[13]There is also more general evidence that the traits of senior executives are important in determining the performance of the entities that they manage. At the firm level, Johnson et al. (1985) find that shareholder wealth is positively correlated with measures of a firm's executive's 'talents' and 'decision-making responsibility.' Bertrand and Schoar (2003) find that a significant extent of the heterogeneity in investment, financial, and organizational practices of firms can be explained by the presence of manager fixed effects. Malmendier et al. (2011) find that overconfidence affects management decisions. At the cross-national level, Jones and Olken (2005) find, using deaths of leaders as exogenous variation, that leaders matter for a country's growth, especially when constraints on the executive are weak.

[14]Similarly, Roberts et al. (2006) examine 92 studies for patterns in the mean-level of Big Five personality traits. The authors find that people increase in measures of social dominance (a facet of extroversion), conscientiousness, and emotional stability as they age, especially over ages 20 to 40. Blattman et al. (2015) find in an experiment that providing Cognitive Behavioral Therapy (CBT) to high-risk Liberian men caused their conscientiousness scores and other measures of self-control to improve after just eight weeks. It is important to note that the psychological literature is in agreement, however, that these measured personality traits are more than situational specific, and thus are worthwhile to use for explanatory purposes as we do in this paper (Roberts, 2009).

comes can be improved via selection. Second, given broad evidence that traits are malleable, delivery could be improved by measures that strengthen non-cognitive attributes. Third, psychometric measures might be useful as diagnostics in hiring or promotion decisions.[15] The degree of correlation between personality measures, doctor attendance, health inspections, and the responsiveness of senior officials complements these literatures by showing that public sector employees with greater levels of specific non-cognitive skills deliver better public service outcomes.

While our data allow us to make some progress on relating personalities to performance, they also face some limitations. First, because our sample includes officials in positions of power, obtaining measures of cognitive ability was thought to be potentially demeaning. We therefore are unable to directly compare the relevance of cognitive and non-cognitive attributes for service delivery. Second, as in much of the literature, no component of the personality traits we measure is exogenously determined, limiting our ability to identify the causal relationship between personalities and performance. To address this, in our information experiment with senior officials, we aimed to manipulate a factor affecting performance—information about the performance of their subordinates—that most plausibly should be mediated through the mechanism of personalities.

The paper proceeds as follows: Section 2 provides the institutional details necessary to understand our results. Section 3 outlines our research design and reports results. Section 4 concludes.

2 Public Health Services in Punjab

This section describes the main institutional details relevant to our experiment and our empirical results.

In Punjab, the provision of health care services is managed by the Department of Health.

[15] Klinger et al. (2013) discuss the merits and disadvantages of using psychometrics to screen for loan provision. A major concern, which applies equally in the public sector, is the potential for strategic misrepresentation of personality type.

Authority in the department is highly centralized in the upper echelons of the bureaucratic hierarchy. Senior actors described in this section play a central role in determining the quality of delivery. They are also responsible for a substantial number of facilities spread, in many cases, across vast geographic distances. This presents a major challenge for monitoring that we aim to address with our smartphone monitoring system.

The main performance outcomes in this paper are measured at primary front-line public health clinics, called Basic Health Units (BHUs).[16] BHUs are designed to be the first stop for rural patients seeking medical treatment in government facilities, providing mainly primary services, including out-patient services, neo-natal and reproductive health care, and vaccinations against diseases. Hereafter in this paper, we use the word 'clinic' interchangeably to describe BHUs. There are 2,496 BHUs in Punjab.[17] Almost all BHUs are located in rural and peri-urban areas. 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 and patients seen in these clinics are required to pay a nominal fee of around $0.01 USD per visit.

Do Clinics Matter for Health Outcomes? A key question is whether clinics matter for health outcomes, given low levels of health worker attendance and other administrative issues. The data we can assemble to address this question suggests that they do. Merging the 2006 Demographic and Health Survey (DHS) in Pakistan with BHU locations using GPS coordinates, we find that, for households in the bottom quarter of wealth, distance to the nearest BHU is positively correlated with male child mortality and negatively correlated with children being vaccinated and with mothers' use of prenatal and antenatal care and

[16] There are five major types of facilities: (i) Basic Health Unit (BHU); (ii) Rural Health Center (RHC); (iii) Tehsil Headquarter Hospital (THQ); (iv) District Headquarter Hospital (DHQ); and (v) Teaching Hospital. In Punjab, a tehsil is the largest administrative sub-division of a district. There are 121 tehsils across 37 districts.

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

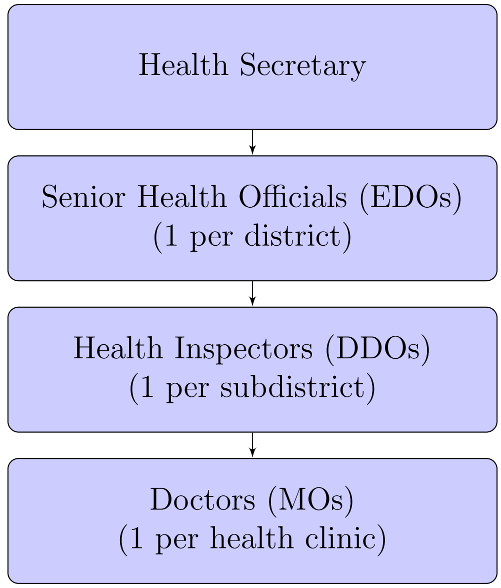


Figure 1: Health Sector Administration in Punjab

save delivery toolkits.[18]

2.1 Health Sector Administration

Figure 1 depicts a simplified version of the health administration hierarchy in Punjab. District governments are responsible for managing local health facilities. Each District Department of Health is headed by an Executive District Officer (EDO) who reports both to the official in charge of the district and to two provincial health officials.[19] EDOs are directly supported by several Deputy District Officers (DDOs). DDOs primarily inspect and manage health facilities.[20] DDOs are required to inspect every clinic in their jurisdiction at least once a month and record information collected during the visit on a standard form. DDOs have the authority to punish a clinic's absent staff by issuing a formal reprimand, suspend-

[18]Results available upon request. While a newer wave of the DHS is available for Pakistan, GPS coordinates of household clusters are not available for this wave. We expect correlations from 2006 to still be relevant as nearly all current BHUs were built through one large project in the 1990s.

[19]The senior official in charge of the district is the District Coordinating Officer (DCO). The provincial health officials are the Director General of Health Services and the Secretary of the Department of Health.

[20]While inspections are the primary official functions of the DDO, our time use data indicate that, on average, DDOs spend 38.9 percent of their time on inspections and management, with the remainder of their time principally spent managing immunization drives. For full details please see Callen et al. (2016).

ing staff, and/or withholding pay (in the case of contract staff). Each Medical Officer is similarly responsible for their own clinic, with proportional duties. Throughout the paper, we will refer to Executive District Officers as senior health officials, Deputy District Officers as inspectors, and Medical Officers as doctors, focusing on their role rather than their title.

As is true in many developing countries, low health worker attendance is a major issue in Punjab. From unannounced visits to clinics in 2011, we find that only 56 percent of clinics were inspected in the prior two months, and that doctors were only present 43 percent of the time when one was posted.[21] This points to a lack of enforcement that allows health inspectors and doctors to shirk. In the next section, we provide results related to the role of personality traits in the performance of senior officials, inspectors, and doctors.

3 Results

In this section, we present three sets of results, each corresponding to one of the three questions laid out in the introduction. First, we study correlations between the measured personality traits of doctors and health inspectors, their job performance (attendance and inspections respectively), and their propensity to collude with one another. Second, we use these measures to predict health inspectors' response to an experimental intervention which increases the probability of detecting shirking. Finally, we examine whether traits identify which senior health officials react to information about the absence of their subordinates. This analysis relies on manipulating the information provided to senior officials about the absence of their subordinates.

[21] Doctors were not posted at 35 percent of clinics, which means unconditional doctor presence was only 32 percent.

3.1 Do personality measures predict performance under status quo incentives?

We first examine whether personality measures predict bureaucratic performance under status quo incentives, for doctors and then for health inspectors. We measured personality for doctors in Punjab posted to a representative sample of 850 of the 2,496 rural health clinics in the province. Of the 850 facilities in this sample, 306 facilities had no doctor posted. We omit these clinics from our analysis of doctor performance. To reach the remaining doctors, we interviewed doctors in two unannounced independent inspections, and then followed up with pre-scheduled interviews, facilitated by the department of health. Doctors were strongly encouraged to attend the pre-scheduled interviews by the department of health. This process resulted in interviews of 389 out of 544 posted doctors, or 72 percent of our sample population.

We recognize that these doctors may be potentially unrepresentative of the overall sample of posted doctors. However, we believe that this select sample is highly relevant for two reasons. First, there are very likely a number of ghost workers—names on government payrolls that do not correspond to an actual person, allowing other corrupt actors to capture their salary. In this setting, there is no way for us to know how many of the doctors we did not reach actually exist. Given the substantial lengths we went to, including involving the active collaboration of the Department of Health in scheduling interviews, it is possible that many of them are indeed ghost workers and so are not part of the relevant sample of interest. Second, our pre-scheduled interviews were facilitated by doctors' supervisors via multiple phone calls and clear orders. If a doctor is not at work when we visit twice independently and refuses direct orders from their superior, clearly the doctor is underperforming. We are less interested in understanding how the individual characteristics of such intractably resistant individuals relate to performance.

We also measured personality for the universe of health inspectors and senior health officials in Punjab, or a total of 102 inspectors and 33 senior health officials. We interviewed inspectors and officials through pre-arranged office visits.

For all 850 clinics in our sample, we also measured attendance during unannounced visits in November 2011, June 2012, and October 2012.

3.1.1 Measuring Personality

The personality measurement batteries in this paper are from personality psychology and are used broadly, including recently in economics. We use two measures: the Big Five personality traits and the Perry Public Service Motivation (PSM) traits.

Developed by psychologists in the 1980s, the Five Factor Model is now one of the most widely used personality taxonomies in the field.[22] We measure the Big Five traits using a 60 question survey developed specifically in Urdu and validated for use in Pakistan by the National Institute of Psychology at Quaid-i-Azam University, Islamabad. Each of the 60 questions offers the respondent a statement such as "I see myself as someone who does a thorough job" and asks them to agree or disagree with the statement on a five point Likert scale (Disagree strongly, Disagree a little, Neutral, Agree a little, or Agree strongly).[23]

In addition to measuring Big Five traits separately as the mean response to twelve questions (where disagree strongly is assigned a 1, disagree a little a 2, etc.), all traits are normalized into z-scores and averaged to form a single Big Five index.[24] This approach is consistent with research in psychology that finds high degrees of of correlation between the five personality traits in many different studies and suggests that the traits can be collapsed into a General Factor of Personality, which can be interpreted "as a basic personality disposition that integrates the most general non-cognitive dimensions of personality. It is associated with social desirability, emotionality, motivation, well-being, satisfaction with life, and self-esteem. It also may have deep biological roots, evolutionary, genetic, and neuro-

[22] See John et al. (2008) for a summary of the measures and its history. Borghans et al. (2008) provide a summary of empirical results in psychology and economics.

[23] John et al. (2008) provide the mapping between questions and traits.

[24] The results presented in the following sections are robust to a 'naive' personality index in which each of the 60 questions is individually normalized and then one average z-score is formed. These results are available on request.

physiological" Musek (2007, pg. 1213).[25] We also document a high degree of correlation between Big Five traits in four different populations in Pakistan in Appendix Figure A.4.[26]

The Perry Public Service Motivation (PSM) battery is designed to measure intrinsic motivation for public service. Also developed in the 1980s, it comprises a total of 40 questions measuring six traits—attraction to policymaking, commitment to policymaking, social justice, civic duty, compassion, and self-sacrifice.[27] We reproduce both the Big Five and PSM batteries we used in the appendix.[28]

Table 2 reports summary statistics for these measures separately for doctors and health inspectors in treatment and control districts in our randomized control evaluation of a new monitoring technology.[29] There is substantial variation in personality traits across individuals consistent with the original intention of the battery: to capture substantial and important differences in personality types.[30] It is this heterogeneity that allows for the possibility of linking differences in personality to variation in performance.

We capture these measures after treatment is administered. This raises the possibility that treatment could impact traits, confounding our analysis. However, if treatment impacted traits then there would be differences between treatment and control workers in personality measures. We find no evidenced that treatment affected personality traits. This increases our confidence that they are stable over the horizon of the study. This is consistent with previously cited literature that suggests malleability over the course of years, not

[25]See Digman (1997) and Van der Linden et al. (2010) for two additional meta-analyses with similar results.

[26]These populations include (i) public sector polio vaccinators in Punjab ($N = 420$); (ii) residents of slums near Islamabad, Peshawar, and Dera Ghazi Khan, often care migrants from areas close to Pakistan's border with Afghanistan ($N = 1152$); (iii) all politicians from 240 electoral constituencies of Haripur and Abbotabad districts located in the province of Khyber-Pakhtunkhwa who contested the first village council elections in 2015 ($N = 3628$); and (iv) students at the Lahore University of Management Science, an elite private sector university in Punjab ($N = 227$).

[27]Perry and Wise (1990) and Perry (1996) introduce the battery and Petrovsky (2009) provides a summary of studies using this measure.

[28]Though the survey included is for doctors (Medical Officers), we used the same instrument for health inspectors and senior health officials. We include both the Urdu version that was fielded, as well as a translation of the instrument to English for reference.

[29]We describe the experiment in Subsection 3.1.4 below. The full distributions for these measures are reported in Table A.1. Summary statistics for senior health officials are reported in Table A.2.

[30]Borghans et al. (2008) explain the development of the Big Five.

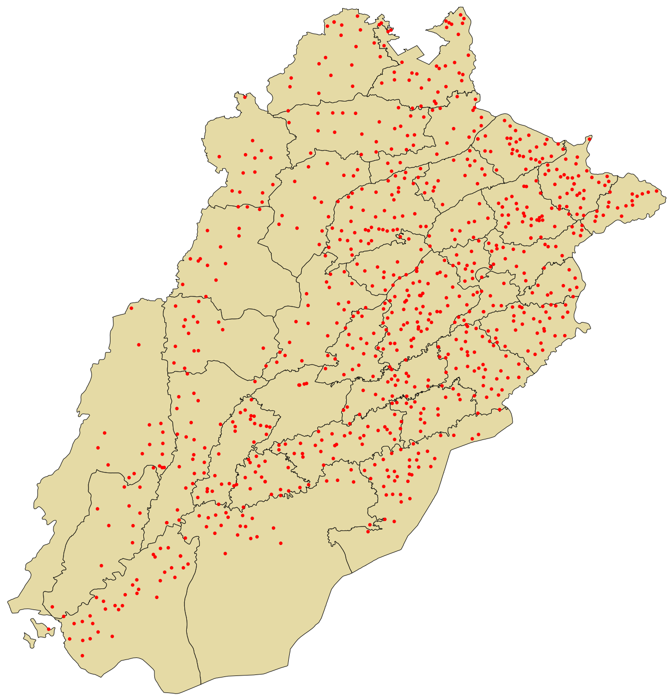


Figure 2: Locations of Clinics (Basic Health Units) in the Experimental Sample

months, or given intense cognitive-behavioral therapy (Kautz et al., 2014; Blattman et al., 2015).

3.1.2 Measuring Doctor Performance

To obtain measures of performance, we collected primary data on a representative sample of 850 of the 2,496 clinics or Basic Health Units in Punjab. Clinics were selected randomly using an Equal Probability of Selection design, stratified on district and distance between the district headquarters and the clinic. Our estimates of absence are, therefore, self-weighting and require no sampling correction. All districts in Punjab except Khanewal—the technology pilot district—are represented in our data. Figure 2 provides a map of clinics in our experimental sample along with the district boundaries in Punjab.

Information on staff absence, health inspections, and facility usage was collected through three independent and unannounced inspections of these clinics. We visited each facility three times: November 2011, June 2012, and October 2012. Our survey team interviewed and physically verified the presence of the Medical Officer, or doctor, and verified the last health inspection that occurred through written records stored at the facility.[31]

We have two measures of doctor job performance: (i) whether doctors were present during our unannounced visits, and (ii) a proxy measure of collusion between doctors and health inspectors to falsify reports. We define collusion as a dummy variable coded as one when the doctor is absent during both of our post-treatment unannounced visits and is marked present during every single health inspection during the treatment period.[32]. We find doctors to be present during forty three percent of the unannounced visits and predict collusion with health inspectors thirteen percent of the time. These baseline performance measures for doctors are reported in Table A.1.

3.1.3 Personality and Doctor Performance

Figure 3, Panel A shows that doctors that score one standard deviation above the mean on the Big Five measure of conscientiousness are about five percentage points more likely to be present at work during an unannounced visit. Similarly, two measures of PSM, civic duty and self-sacrifice, are also significantly predictive, and the aggregate PSM index is nearly significantly predictive at 95%. Finally, all but one coefficient are positively correlated

[31] In addition, the attendance of Dispensers, Health/Medical Technicians, Lady Health Visitors, Midwives, and School Health and Nutrition Specialists were also recorded. Survey teams were trained at regional hubs (four in total) by senior enumerator trainers and our team members. Following these trainings, the teams made visits to clinics in their assigned districts and remained in regular contact with their team leaders and our research team. Surveys took three weeks to field for each wave. The attendance sheet for the staff was filled out at the end of the interviews and in private. Inspectors record visits by signing paper registers maintained at the health facility. We measure whether an inspection occurred by interviewing facility staff and verifying the register record. Data collection and entry followed back-checks and other validation processes consistent with academic best practice.

[32] The median number of health inspections for each facility in our treatment sample is 12, with a max of 50. The collusion we have in mind occurs when a health inspector calls a doctor before an inspection to alert him to be in attendance. Then, after the health inspector records his presence, the doctor is under very little pressure to attend until he gets another similar phone call from the inspector. Of course, such patterns in the data could arise by chance, though the chance decreases with the number of inspections. As such, we have run all of our collusion analysis using weighted least squares and we find results very similar to those OLS results presented below. Results provided upon request. The strong correlation we find between these measures and personality types also suggests that the proxy is successfully capturing malfeasance. An immediate problem with this proxy is that it partly reflects attendance. We deal with this by also reporting p-values adjusted to reflect multiple hypotheses.

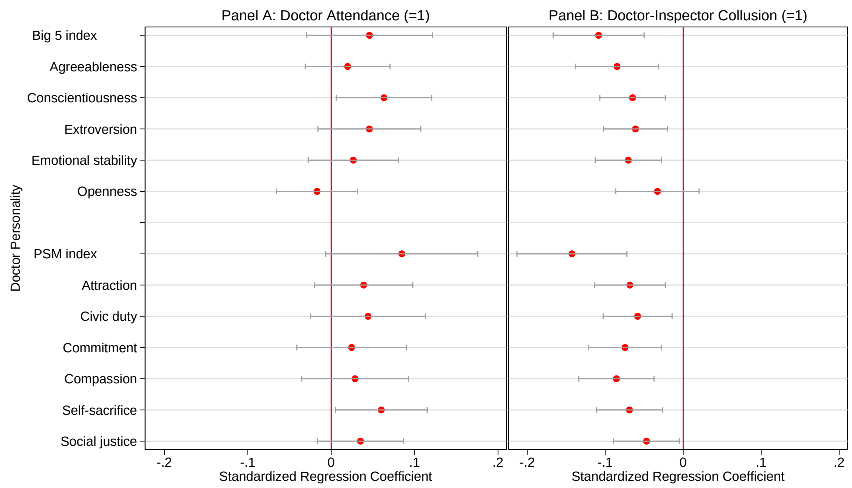


Figure 3: Personality and Performance: Doctors

Notes: Each regression coefficient reported comes from a separate regression of the performance measure, Doctor Attendance in Panel A and Doctor-Inspector Collusion in Panel B, on the indicated doctor personality measure. Error bars represent 95 percent confidence intervals, with standard errors clustered at the clinic level. All regressions include tehsil (sub-district) and survey wave fixed effects. In all cases, personality measures are normalized to have mean zero and standard deviation of one in the sample, and thus the regression coefficients reported can be interpreted as the impact of a one standard deviation increase in a given personality trait or aggregate measure. The sample is restricted to control district clinics for which doctor personality data are available and a doctor is posted. Regressions corresponding to the figure are reported in Appendix Tables A.3 and A.4.

with doctor attendance. In Panel B, we find that doctor personality measures are even stronger predictors of collusion between health inspectors and doctors. Doctors who score one standard deviation higher on measured civic duty, for example, are about 6 percentage points more likely to be identified as potentially colluding. Both the Big Five and PSM indices and ten out of eleven Big Five and PSM traits are highly predictive of collusion, with negative signs.[33]

We draw two lessons from this exercise. First, in Appendix Table A.5, we find that personality is a stronger predictor for doctors than three other plausibly important observables—doctor tenure in the department of health, doctor tenure at the specific health clinic at which the doctor worked at the time of the survey, and the distance from this clinic to the doctor's home in Pakistan (in KM). Though we have only a limited number of covariates for this exercise, they are potentially correlated with a wide number of factors relevant to

[33]See Appendix Tables A.3 and A.4 for point-estimates.

the relationship between personality and performance. Overall tenure, for example, will be correlated with age, experience, and the number of relationships with others in the health department. Tenure at a specific facility will be correlated with how much influence a doctor has in the Department of Health as transfers are frequent and often undesirable. Distance to home might proxy for the desirability of a posting as in interviews doctors frequently expressed a strong desire to work near their home and family.

We also more thoroughly investigate the power of personality traits and other doctor characteristics in predicting attendance through the use of a LASSO estimator in Section 3.1.9 below.

Second, the degree of the estimated coefficients is meaningful. While ideally we would have measures of health outcomes to correlate with doctor performance, we are able to correlate this performance with the number of out-patients seen at a clinic in a given month. We document a strong positive correlation between doctor presence at their clinic during one of our unannounced visits and reported out-patients seen at that clinic in Appendix Table A.6.

3.1.4 Monitoring Intervention

We collected personality data during a larger experimental policy reform that considered audits by government monitors as a solution to the problem of bureaucratic absence. The "Monitoring the Monitors" program replaced the traditional paper-based monitoring system for clinic utilization, resource availability, and worker absence with an android-based smartphone application. In the new system, data generated by health inspections are transmitted to a central database using General Packet Radio Service (GPRS). Data are then aggregated and summary statistics, charts, and graphs are presented in a format designed in collaboration with senior health officials to effectively communicate information on health facility performance. These data are also: (i) geo-tagged, time-stamped, and complemented with facility staff photos to check for reliability; and (ii) available in real time to district and provincial officials through an online dashboard. The objective of this monitoring system is to make the activities of health inspectors available to their senior officials in real time. Figure 4 shows one view of the online dashboard.[34]

We can think of this monitoring system as increasing the probability that a health inspector will be caught if he is failing to do his inspections. Prior to Monitoring the Monitors, and in control districts, the paper-based monitoring system severely limits a senior officials ability to monitor inspectors. In treatment districts, on the other hand, reports are immediately and automatically sent up the chain of command, and the required geo-tags, time stamps, and photos serve as instant verification that the inspector and all reported staff are present at the clinic being inspected.[35] We present a theoretical framework to help understand the potential impacts of this discrete increase in this probability on health workers' decision to work or shirk in Appendix Section A.1.

3.1.5 Measuring the Tendency to Procrastinate

A nascent literature uses intertemporal consumption and effort profiles to measure time preference and time inconsistency.[36] Inspectors in Punjab are required to inspect every facility in their jurisdiction once a month. The intertemporal inspection allocations captured by our smartphone monitoring system reveal patterns indicating a tendency to procrastinate for a majority of our inspectors.

Panel A of Figure 5 depicts the average number of inspections on each day of the month conditional on the number of facilities in each inspector's jurisdiction. On the first day of the month, inspectors perform an average of about 0.31 inspections. After the first ten

[34] Application development started in August 2011. After developing the application and linking it to a beta version of the online dashboard, the system was piloted in the district of Khanewal. We remove Khanewal district from the experimental sample. Health administration staff were provided with smartphones and trained to use the application.

[35] See Callen et al. (2016) for the core results from the broad Monitoring the Monitors experiment.

[36] Augenblick et al. (Forthcoming) elicit time preferences based on the intertemporal allocation of non-monetary tasks in the lab. Shapiro (2005) and Kuhn (2013) provide evidence that the intra-month consumption profile of food stamp recipients reflects dynamically-inconsistent planning and better fits a quasi-hyperbolic model than a standard exponential discounting model.

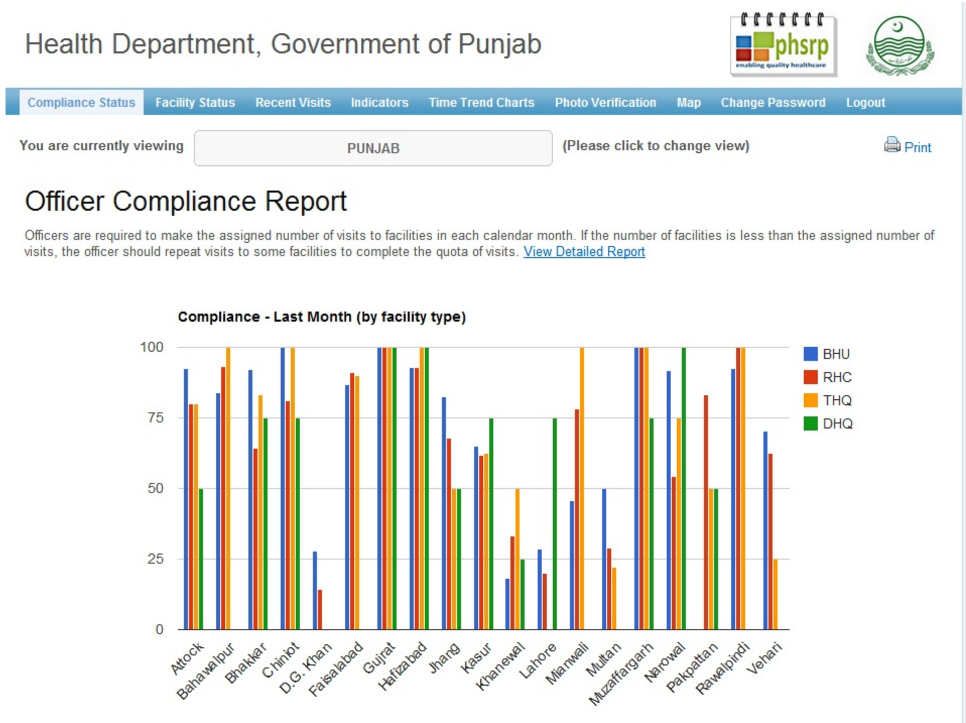


Figure 4: Online Dashboard - Summary of Inspection Compliance by District

days of the month, average inspections on a given day are roughly 0.8. The time profile of inspections over a month has a positive slope. Several months of data allow estimation of the slope of the intertemporal profile of inspections, providing a proxy measure of each inspector's tendency to procrastinate. We estimate

$$Inspections_{d,m} = \alpha + \eta \; Day \; of \; Month_{d,m} + \delta_m + \epsilon_{d,m} \tag{1}$$

where $inspections_{d,m}$ is the number of inspections on a given day d in a month m, δ_m are fixed effects for each month, and $Day \; of \; Month$ runs from one to 28 depending on the calendar day of the month.[37] Inspectors with a positive η estimate do fewer inspections at

[37]The effective deadline for inspections is the 28th of the month as senior officials and inspectors meet during the final days of the month to review the month's inspections. We only include months for which we have complete information for a health inspector and drop holidays. We retain data for 36 health inspectors and have an average of 8.75 months of inspection-level data per inspector. The median number of inspections in a month is 25 and inspectors are responsible for between 4 and 46 facilities with a median of fifteen. Two factors limit our sample. First, we only have daily inspection data for treatment districts, which include roughly 50 health inspectors. Of these inspectors, we drop fourteen who transferred into treatment districts

Panel A: Inspections by Day of Month — Panel B: Histogram of Slope Parameters

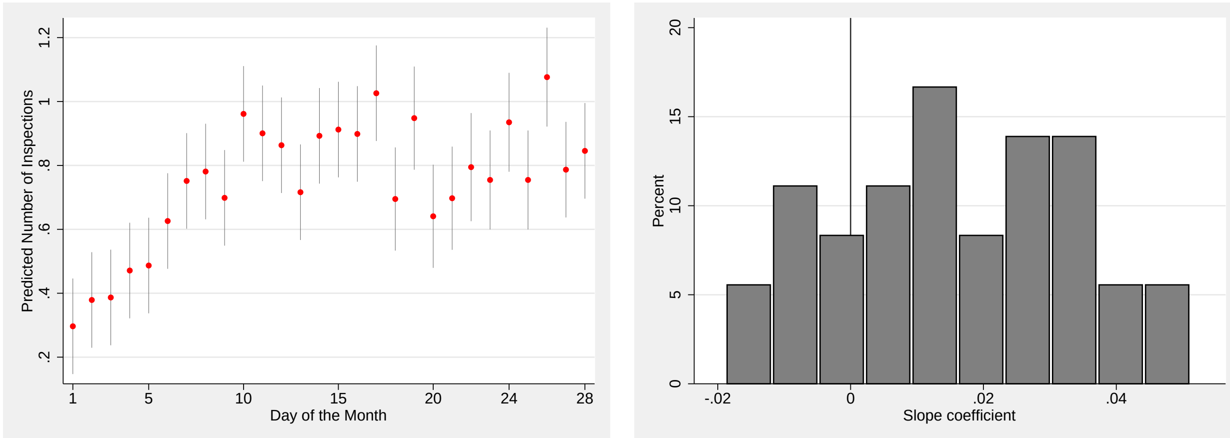


Figure 5: The Temporal Allocation of Inspections

Notes: Panel A plots the predicted number of inspections from a regression of inspections on dummies for each day of the month, and for each month, as well as a control for the number of facilities in the inspector's jurisdiction. Panel B is a histogram of slope parameters obtained from estimating Equation (1) separately for each of the 36 inspectors in our sample.

the beginning of the month and more at the end as they approach the deadline for their quota, suggesting a tendency to procrastinate.

Panel B of Figure 5 provides a histogram of the estimates of η for 36 inspectors. 29 of these 36 inspectors have positive slope coefficients. The average slope coefficient is 0.014, which indicates that over the course of the month the number of inspections per day increases by about 0.4.

3.1.6 Measuring Inspector Performance

We have two measures of job performance for health inspectors: (i) a dummy equal to one if the facility records an inspection in the two months prior to an unannounced visit; and (ii) the same proxy measure of collusion between doctors and health inspectors to falsify reports as described in Section 3.1.2. These measures were obtained during the same three independent and unannounced inspections of health clinics described in Section 3.1.2. Baseline performance measures for health inspectors are reported in Table A.1.

taking over the phone of the previous inspector. Transfer records do not indicate the date of transfer, making it impossible to identify the period of smartphone data that correctly corresponds to these 14 inspectors.

3.1.7 Procrastination and Inspector Performance

As with our personality measures, we can correlate our proxy measure of the tendency to procrastinate with health inspector performance. In Table 1, we present results of a regression of health inspections on our estimated time slope coefficient. We see that health inspectors with larger time slope coefficients (reflecting a larger tendency to procrastinate) conduct fewer inspections, once you limit the sample to those inspectors with at least nine facilities in their jurisdiction (the 10th percentile in terms of health facilities per district across the sample). Specifically, we see that a one standard deviation increase in the procrastination measure is associated with a 6.7 percentage point decrease in the probability that an inspection was carried out in the last two months at a health clinic. This relationship may reflect a limitation on the number of inspections that can be carried out in a fixed period of time. Those who delay all of their inspections until the end of the month are not able to complete their monthly assignment.

3.1.8 Personality and Inspector Performance

We examine how much the personalities of health inspectors predict their job performance in control districts (i.e., those under status quo incentives) in Figure 6. In Panel A, we consider the relation between personalities and whether an inspection was carried out in the last two months. In Panel B, we see that PSM traits are associated with less collusion, enough to distinguish the coefficient on the aggregate index from zero. In this case, health inspectors that score one standard deviation higher on aggregate PSM are about seven percentage

Table 1: Procrastination and Inspector Performance

	Health Inspection in Last Two Months (=1)				
	(1)	(2)	(3)	(4)	(5)
Time Slope Coef. (Standardized)	-0.001	-0.060*	-0.067*	-0.079**	-0.060*
	(0.041)	(0.024)	(0.027)	(0.027)	(0.022)
Mean of dependent variable	0.708	0.695	0.723	0.723	0.723
# Observations	456	420	357	357	357
# Tehsils	32	28	25	25	25
R-Squared	0.221	0.242	0.241	0.249	0.256
Inspector Jurisdiction Size Percentile:	0	10	25	25	25
Controls for Big Five Traits	NO	NO	NO	YES	NO
Controls for PSM Traits	NO	NO	NO	NO	YES

Notes: This table reports on the correlation between an inspectors tendency to procrastinate and their inspection performance. Column 1 provides estimates from an OLS regression of a dummy equal to one if a facility was inspected in the last two months on the time slope coefficient. The time slope coefficient is estimated for each inspector using a regression of the number of inspections done on a given day of the month on a day of the month variable, with month fixed effects. We then standardize the variable across inspectors. Higher time slope coefficients indicate a larger tendency to procrastinate. Standard errors clustered at the tehsil (sub-district) level—the jurisdiction of a given inspector—are reported in parentheses. All regressions include district and survey wave fixed effects. The sample is limited to health inspectors in treatment districts for which we have daily inspection data. The 10th percentile # Health Clinics in an inspectors tehsil corresponds to nine clinics, the 25th percentile to 12 clinics. The median number of health clinics in a tehsil is 19 and the max is 46. Controls for Big Five Traits include agreeableness, conscientiousness, extroversion, emotional stability, and openness. Controls for PSM traits include attraction to policymaking, commitment to policymaking, social justice, civic duty, compassion, and self-sacrifice. *Levels of Significance:* *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

points less likely to be identified as potentially colluding.[38,39]

In Appendix Table A.11, we examine how health inspector personality predicts job performance relative to six other plausibly important observables—age, whether the inspector has completed higher education, the inspector's tenure in the department of health, the inspector's tenure as an inspector, the distance from the inspector's office to his hometown (in

[38]See Appendix Tables A.7 and A.8 for complete details on the results summarized in Figure 6. The estimates in Figure 6 indicate a negative relationship between both conscientiousness and emotional stability and the number of inspections. These coefficients both reflect $p < 0.10$ and suggest that better traits are associated with worse performance. These coefficients are estimated only on the subsample of 298 clinics in control districts which have a doctor posted. In Appendix Tables A.9 and A.10, we find no evidence of a correlation on the full sample of 424 control facilities, indicating that inspectors with better traits are more likely to have inspected facilities *without* doctors posted. There is therefore some weak evidence that better inspectors substitute away from better facilities with a doctor posted toward more rural facilities without a doctor.

[39]Since our collusion outcome is defined at the doctor-inspector level, we can also examine how doctor and inspector traits simultaneously predict collusion; i.e., whether good doctors and inspectors are substitutes or compliments or neither for performance. While we have no theory for how traits should interact, we find no evidence that they do. That is that individual traits remain predictive and their interaction is not in all cases. Results available upon request.

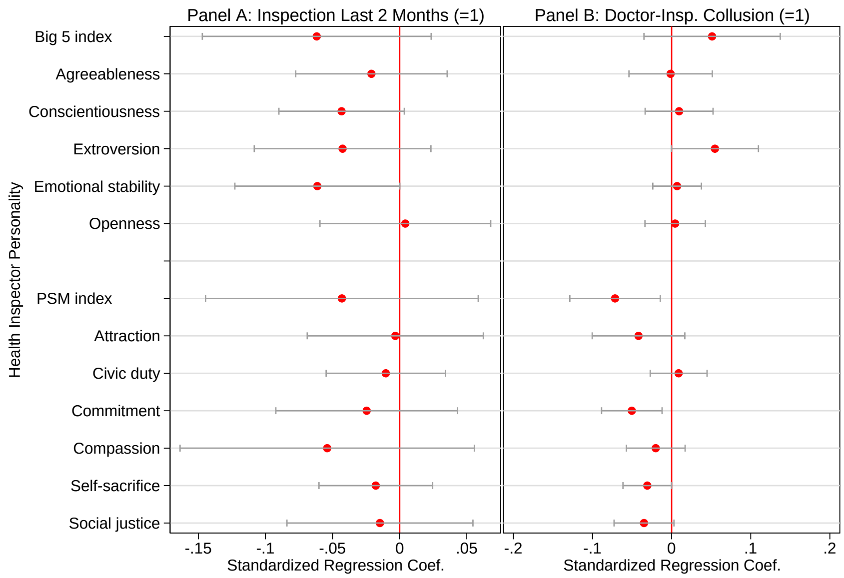


Figure 6: Personality and Performance: Health Inspectors

Notes: Each regression coefficient reported comes from a separate regression of the displayed performance measure on the indicated standardized health inspector personality measure. Error bars represent 95 percent confidence intervals. Standard errors are clustered at the clinic level. All regressions include tehsil (sub-district) and survey wave fixed effects. In all cases, personality measures are normalized to have mean zero and standard deviation of one in the sample, and thus the regression coefficients reported can be interpreted as the impact of a one standard deviation increase in a given personality trait or aggregate measure. The sample is restricted to control district clinics for which doctor personality data are available and a doctor is posted. Appendix Tables A.7 and A.8 provide corresponding regression tables.

KM), and a dummy for whether the inspector reports liking his current post. We do not find that any of these six observables are systematically better predictors than personality. In fact, the PSM index is clearly the strongest predictor in this exercise.

We also more thoroughly investigate the power of personality traits and other health inspector characteristics in predicting performance through the use of a LASSO estimator in the following Section.

3.1.9 How well does personality predict relative to other traits?

If one's goal is simply to predict doctor and inspector performance using measurable, fixed characteristics, and if measuring each characteristic is costly, we might ask whether (i) personality traits are the best predictors for the job, and, regardless, (ii) how much we might gain by combining personality and other characteristics in one model. We address both of these questions simultaneously using the least absolute shrinkage and selection operator (LASSO) estimator (Tibshirani, 1996). This method minimizes the sum of squares subject to the sum of absolute value of the standardized coefficients being less than a chosen value (λ). In equation form, this is

$$(\hat{\alpha}, \hat{\beta}) = \arg\min \sum_{i=1}^{N} (y_i - \alpha - \sum_j \beta_j x_{ij})^2 \qquad \text{subject to} \sum_j |\beta_j| \leq \lambda. \tag{2}$$

In this equation, λ is called the tuning paramater. It leads to trimming of estimated coefficients, and it often leads to coefficients of zero, and hence allows for variable selection. To select the proper tuning parameter, we implement k-fold cross-validation and select the λ that minimizes mean cross-validated error (that is the λ that leads to coefficients on average that do the best job across many simulations at predicting in a 10% sample of our data after the model is fit in 90%).

We present the results of this analysis in Appendix Figures A.5, A.6, for doctors, and Appendix Figures A.7, and A.8 for health inspectors. For doctors, we see that the Big Five index coefficient remains positive and near to that from our OLS estimates at the value of λ that minimizes the cross-validated error, while our other covariates' coefficients drop to zero. The same is true with the PSM index. This suggests not only that these personality measures better predict doctor attendance than experience and distance to home but that there is no gain to prediction, in the mean squared error sense, from these additional covariates. We see a consistent story when we look at the Big Five and PSM traits individually, with conscientiousness being most predictive of the Big Five traits and civic duty and self sacrifice of the PSM traits.

Consistent with health inspector personality measures being less predictive of inspections, we find that, at the λ that minimizes the cross-validated error in each of the sets of models, all or nearly all covariates remain non-zero and have meaningful coefficients. In other words, for health inspectors personality characteristics are not clearly better at predicting inspections than other characteristics, but to best predict inspections we should use a combination of personality and other characteristics. While less stark than the doctor predictions, these nonetheless support the importance of personality traits in understanding the performance of health inspectors.

3.2 Do personality measures predict responses to a reform that changes incentives?

We now consider whether personality traits, including the tendency to procrastinate, predict health inspectors' response to a reform that increased incentives to complete inspections.

3.2.1 Evaluating the Smartphone Monitoring

Our experimental sample comprises all health facilities in the district of Punjab, which has a population of at least 85 million citizens. Tens of millions of public sector health users therefore were potentially affected by the program. As described above, we monitored a subsample of 850 clinics, drawn to be representative of facilities in the province, using independent and unannounced inspections.[40] We randomly implemented the program in 18 of the 35 districts in our experimental sample. In assigning treatment, we stratified on baseline attendance and the number of clinics in a district to ensure a roughly even number of treatments and controls. Figure 7 depicts control and treatment districts.[41]

[40] These are the same clinics and inspections from the correlations presented in the previous section.

[41] Treatment is randomized at the district level. The intervention channels information about inspections to district health officials; a design randomizing treatment at an administrative unit beneath the district, say the tehsil, would very like result in treatment affecting control units. The Department of Health also viewed sub-district randomization as not administratively feasible. Cluster randomization also allays some concerns about externalities generated by interactions between inspectors in the same district. All inspectors in a district are required to attend monthly meetings. While they typically have frequent interactions within districts, these relations are almost non-existent across districts.

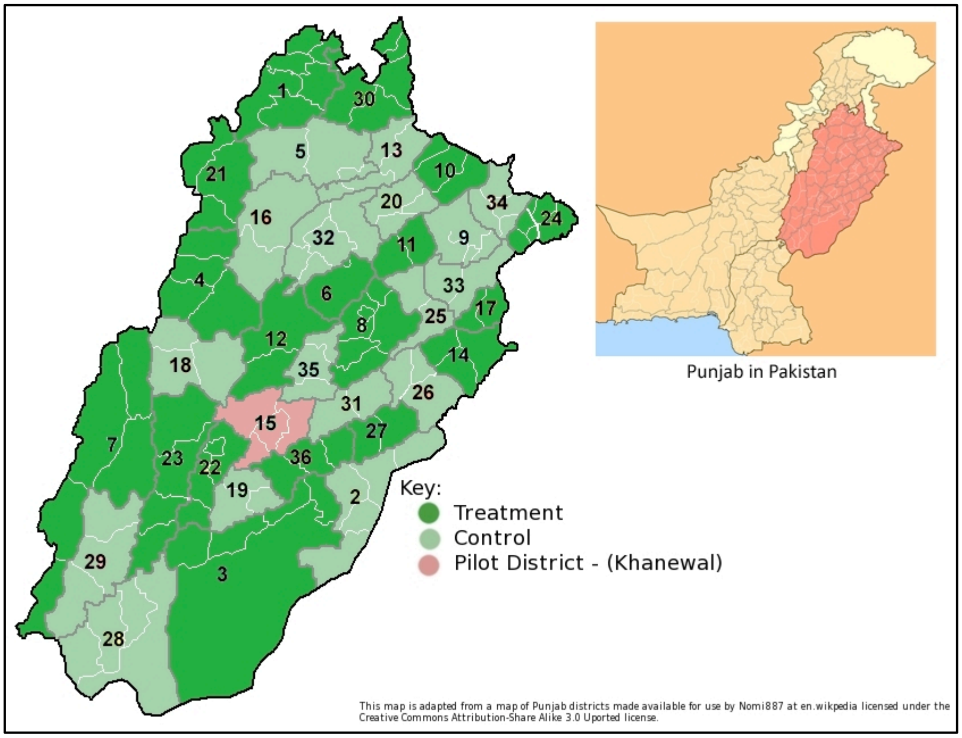


Figure 7: Treatment and Control Districts

3.2.2 Personality and Treatment Response

We investigate whether impacts of the monitoring program are heterogeneous by the personality type of the inspector. Table 2 presents personality measures by treatment status for doctors and health inspectors. There is one significant difference in the balance table—treated health inspectors have slightly lower civic duty scores than those in control groups on average. This is plausibly due to sampling fluctuation as it is a fairly small difference and the only one among the 27 differences estimated.

We consider the effects of an increase in health inspector monitoring on their performance by inspector personality. Results are presented in Table 3.[42] We estimate regressions using

[42]Our other previous measure of performance, collusion between inspectors and doctors, cannot be studied in this context because the construction of collusion relies on data from our treatment districts' smartphone app. We have no information on health inspector-reported doctor attendance in the control districts of the Monitoring the Monitors experiment.

Table 2: Treatment Balance on Doctor and Health Inspector Personality

	Big Five Personality Traits							
	Doctor Personality Traits				Inspector Personality Traits			
	Treatment	Control	Difference	P-value	Treatment	Control	Difference	P-value
Big Five Index	-0.058	0.042	-0.100	0.295	-0.017	0.018	-0.035	0.801
	[0.713]	[0.820]	(0.095)		[0.637	[0.738]	(0.138)	
Agreeableness	3.498	3.577	-0.079	0.309	3.783	3.666	0.117	0.253
	[0.622]	[0.678]	(0.077)		[0.477]	[0.537]	(0.102)	
Conscientiousness	3.958	3.996	-0.037	0.605	4.159	4.113	0.046	0.646
	[0.548]	[0.570]	(0.072)		[0.452]	[0.531]	(0.099)	
Extroversion	3.624	3.686	-0.062	0.277	3.703	3.724	-0.021	0.830
	[0.464]	[0.501]	(0.057)		[0.525]	[0.459]	(0.099)	
Emotional Stability	-2.647	-2.536	-0.111	0.180	-2.461	-2.343	-0.119	0.322
	[0.641]	[0.702]	(0.082)		[0.571]	[0.618]	(0.119)	
Openness	2.926	2.932	-0.006	0.907	3.020	3.123	-0.103	0.218
	[0.372]	[0.451]	(0.050)		[0.471]	[0.353]	(0.083)	
	Perry Public Sector Motivation							
	Doctor Personality Traits				Inspector Personality Traits			
	Treatment	Control	Difference	P-value	Treatment	Control	Difference	P-value
PSM Index	-0.017	-0.018	0.001	0.989	-0.061	0.064	-0.125	0.309
	[0.695]	[0.691]	(0.079)		[0.621]	[0.610]	(0.122)	
Attraction	3.481	3.442	0.039	0.581	3.552	3.585	-0.033	0.764
	[0.630]	[0.610]	(0.070)		[0.532]	[0.575]	(0.110)	
Civic duty	4.182	4.184	-0.002	0.969	4.255	4.421	-0.165	0.051
	[0.594]	[0.526]	(0.059)		[0.415]	[0.432]	(0.084)	
Commitment	3.773	3.774	-0.001	0.982	3.915	3.956	-0.040	0.628
	[0.511]	[0.463]	(0.050)		[0.458]	[0.379]	(0.083)	
Compassion	3.493	3.546	-0.053	0.432	3.743	3.663	0.080	0.400
	[0.515]	[0.516]	(0.067)		[0.475]	[0.484]	(0.095)	
Self Sacrifice	4.065	4.080	-0.015	0.820	4.316	4.392	-0.077	0.409
	[0.563]	[0.574]	(0.065)		[0.482]	[0.450]	(0.092)	
Social Justice	3.950	3.906	0.044	0.464	4.098	4.196	-0.098	0.284
	[0.571]	[0.619]	(0.060)		[0.490]	[0.427]	(0.091)	
# Health Workers	242	147			52	50		

Notes: Variable standard deviations reported in brackets. Standard errors clustered at the district level reported in parentheses. The doctor sample is limited to clinics where a doctor is posted at baseline. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Actual observations for each regression vary by a small amount based on no responses.

the difference-in-difference specification

$$Y_{dit} = \beta_0 + \beta_1 Trait_{di} + \beta_2 Treatment_{dit} + \beta_3 Treatment_{dit} \cdot Trait_i + \delta_t + \lambda_i + \varepsilon_{dit} \quad (3)$$

where Y_{dit} is a dummy equal to one if a facility records an inspection in the prior two months, $Treatment_{dit}$ is a variable equal to one for treated districts during the post-treatment periods (waves two and three), where i refers to the clinic, d refers to the district, and t to the survey wave, and $Trait_i$ is a personality trait of the inspector overseeing facility i. δ_t and λ_i are

Table 3: Testing for Heterogeneous Impacts of Monitoring by Personality Type

	Health Inspection in Last Two Months (=1)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PANEL A: Big Five Personality Traits									
Monitoring (=1)		0.178	0.022	-0.006	0.010	0.003	0.030	-0.033	0.023
		(0.154)	(0.129)	(0.114)	(0.109)	(0.115)	(0.124)	(0.118)	(0.129)
Monitoring x Big Five Index				0.351**					
				(0.133)					
Monitoring x Agreeableness					0.170*				
					(0.094)				
Monitoring x Conscientiousness						0.186*			
						(0.102)			
Monitoring x Extroversion							0.116		
							(0.098)		
Monitoring x Emotional Stability								0.210**	
								(0.083)	
Monitoring x Openness									0.195
									(0.126)
Mean of dependent variable		0.641	0.655	0.655	0.655	0.655	0.655	0.655	0.655
# Observations		1332	1146	1146	1146	1146	1146	1146	1146
# Clinics		645	548	548	548	548	548	548	548
R-Squared		0.048	0.048	0.069	0.069	0.062	0.053	0.064	0.063
P-value		0.256	0.867	0.013	0.078	0.078	0.245	0.017	0.133
Adjusted P-value				0.083	0.214	0.214	0.274	0.101	0.249
PANEL B: Public Service Motivation									
Monitoring (=1)	0.178	0.022	0.023	0.026	0.039	0.024	0.012	0.041	0.021
	(0.154)	(0.129)	(0.120)	(0.111)	(0.127)	(0.111)	(0.119)	(0.130)	(0.122)
Monitoring x PSM Index			0.202						
			(0.140)						
Monitoring x Attraction				0.211**					
				(0.078)					
Monitoring x Civic Duty					-0.029				
					(0.066)				
Monitoring x Commitment						0.103			
						(0.082)			
Monitoring x Compassion							0.184		
							(0.115)		
Monitoring x Self Sacrifice								0.016	
								(0.090)	
Monitoring x Social Justice									0.014
									(0.102)
Mean of dependent variable	0.641	0.655	0.648	0.648	0.648	0.648	0.648	0.648	0.648
# Observations	1332	1146	1165	1165	1165	1165	1165	1165	1165
# Clinics	645	548	556	556	556	556	556	556	556
R-Squared	0.048	0.048	0.057	0.076	0.051	0.062	0.062	0.054	0.053
P-value	0.256	0.867	0.159	0.011	0.661	0.218	0.119	0.863	0.892
Adjusted P-value			0.250	0.101	0.508	0.274	0.249	0.508	0.508

Notes: This table reports heterogeneous impacts of our smartphone monitoring treatment by personality type. Column (1) reports average treatment effects on treatment and control district clinics. Columns (2) - (10) are limited to clinics in tehsils for which health inspector personality data is available. The difference in observations between Panels A and B is due to one inspector answering the PSM but not the Big Five survey. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across inspectors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. P-values reported are from a two-sided hypothesis test that the null effect is zero. Adjusted P-values are corrected for multiple hypothesis testing. One correction is done across the Big Five and PSM indices P-values using the Family-Wise Error Rate procedure. A second is done across the eleven Big Five and PSM traits using False Discover Rate procedure. Both procedures are reported in Anderson (2008). *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

survey wave and clinic fixed effects, respectively. We cluster all standard errors at the district level.

For health inspectors, there are heterogeneous effects of our experiment on the rate of health inspections. Health inspectors with a Big Five index one standard deviation above the mean, for example, exhibit a 35 percentage point higher treatment effect in terms of health inspections. With an unconditional mean inspection rate of 66 percent, inspectors with a z-score one standard deviation above the mean come very close to completing all of their inspections as a result of treatment. We decompose this effect in columns (5)-(9) and find that that it is being driven most strongly by emotional stability—the trait of being able to capably respond to new stressors and demands. Besides openness, all Big Five traits have positive and large coefficients. We also see some positive and similarly large effects of the PSM index, attraction, and compassion within the PSM traits, though only attraction is significant.[43]

Figure 8 presents nonparametric treatment effects of health inspector Big Five index across the distribution of inspectors according to the Big Five index. We can see that the effect in Table 3 is primarily being driven by those health inspectors in the middle of the Big Five distribution. This fits the extended model presented in Appendix Section A.1 in which it is plausible that the effects of this intervention are localized to those inspectors in the middle of the distribution. See Appendix Figures A.9 and A.10 for nonparametric treatment effects trait-by-trait. While the location of the treatment effect peaks varies by trait, the overall shape is similar for specific traits.[44]

There are two more points to make about these experimental results. First, as you can see

[43]Note that to test for robustness in our effects to the small number of district clusters in our analysis, we have conducted Fisher exact tests (randomization inference) for all heterogeneous treatment results as a separate exercise to adjusting for multiple hypothesis testing. In all cases, the estimated p-value is as at least as significant as from un-adjusted OLS. We have also separated the differential effects into our two post-treatment survey waves and find that the results sustain over time for as long as we were able to follow health clinics (roughly one year after treatment began). This is important because in Callen et al. (2016), we document that the overall treatment effects on health inspections do in fact fade by the second survey wave. Results available upon request.

[44]Note that the point estimates in Figure 8 do not match those from Table 3. This is due to the fact that the regressions in the table include survey wave and clinic fixed effects.

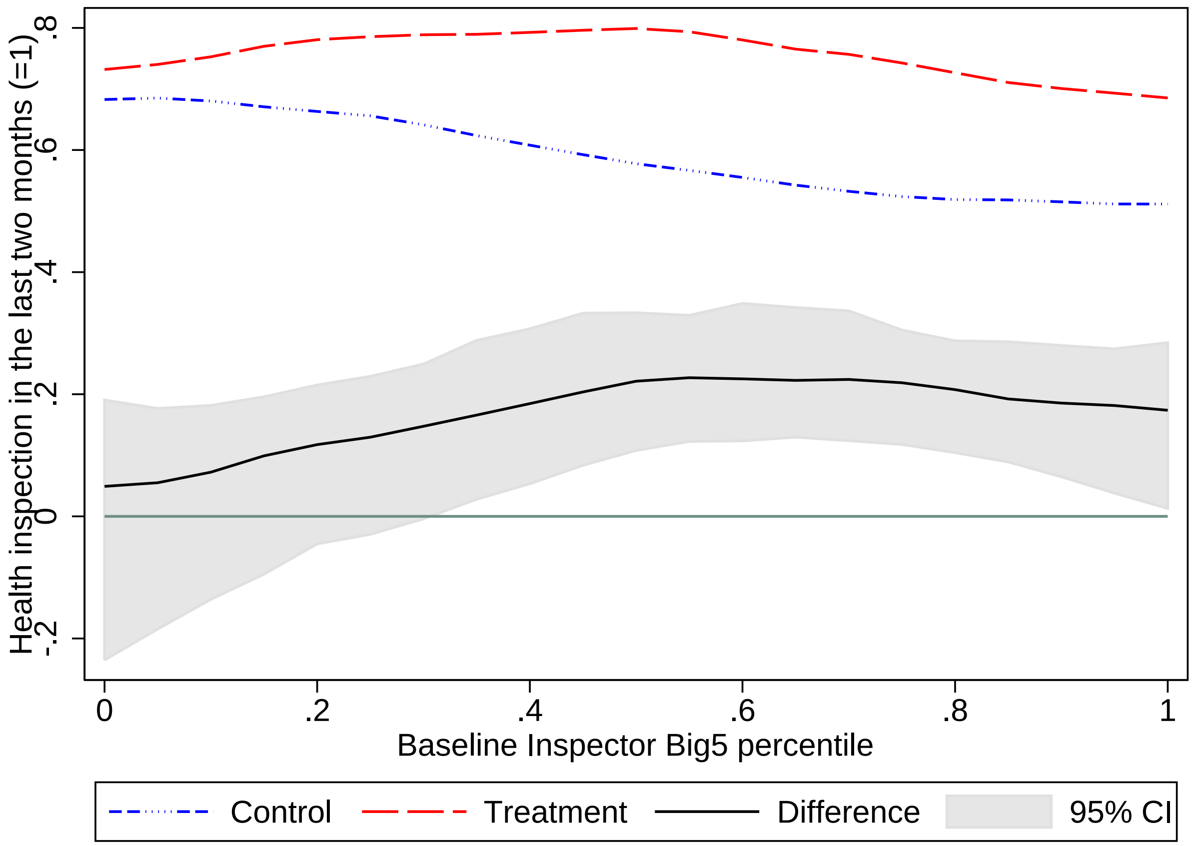


Figure 8: Nonparametric treatment effects

Notes: This figure plots a kernel-weighted local polynomial regression of whether a clinic had a health inspection in the last two months on every 5th percentile of baseline Big Five index separately for treatment and control districts, as well as the difference at each 5th percentile of baseline scores. The confidence intervals of the treatment effects are constructed by drawing 1,000 bootstrap samples of data that preserve the within-district correlation structure in the original data and plotting the 95 percent range for the treatment effect at each 5th percentile of baseline scores.

in Appendix Table A.13, personality does at least as much to predict the response to increased monitoring as all of the other covariates that we record for health inspectors. Completion of higher education is slightly higher and more significant predictor, but it predicts more-or-less separately from personality. Second, these correlations are of a meaningful magnitude. Increased inspections may not lead to an overall increase in doctor attendance, but they generate information that is helpful in the case that a health inspector or more likely a senior health official *is* interested in enforcing attendance. We will see this directly in the next subsection.

3.3 Do personality measures predict who will respond to salient information on subordinate absence?

In this section, we examine whether personality identifies the senior health officials who will react to information about the absence of their subordinates. To do this we study the response of senior officials, as measured by doctor absenteeism in clinics under their supervision, to a second policy intervention in which we manipulated the presentation of information to these officials.

3.3.1 Information Experiment

The Monitoring the Monitors system aggregates data from health inspections and presents them to senior health officials in each district of Punjab on an online dashboard. This dashboard is only visible to these senior health officials as well as to the Secretary of Health for Punjab and the Director General of Health for Punjab. Figure 9 provides an example of a dashboard view visible to senior health officials.

To test whether senior health officials react to information about the absence of their subordinates, we directly manipulated the data on the dashboard to make certain facilities with high staff absence salient. This was achieved by highlighting in red, or "flagging" reports by inspectors that found three or more staff absent at a clinic.[45] This cutoff of three or more staff absences was set by our research team and was not communicated to any of the doctors, health inspectors, or senior health officials. We selected this cut-off based on the distribution of staff absence from baseline data. The peak of the distribution lies at two or three absent staff, suggesting that a cut-off at the center of this peak would yield the highest power to detect an effect of flagging in red.

Though the cutoff was purposefully arbitrary, our motivation for making absence data salient was not. Senior health officials in Punjab are in charge of health service provision

[45]In Callen et al. (2016), we examine at length whether this manipulation affects subsequent doctor absence, finding consistent evidence that flagging facilities leads to decreased subsequent doctor absence.

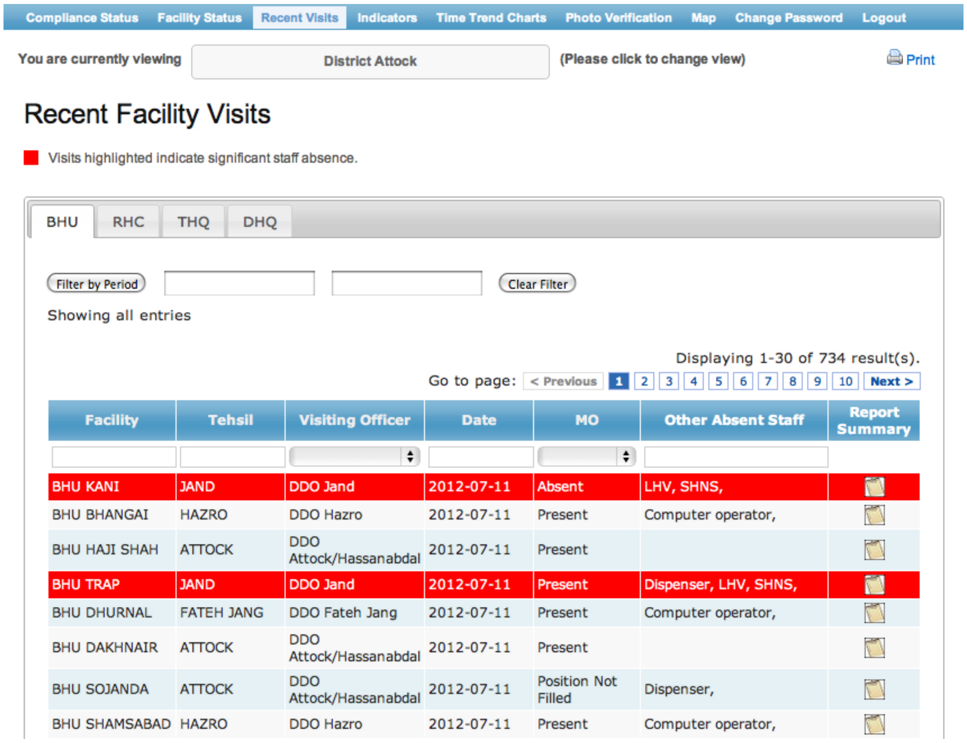


Figure 9: Highlighting Underperforming Facilities to Test Mechanisms

in their district. These officials are constantly receiving information from facilities, staff, and citizens. Given the volume of information available to these officials, we designed the intervention to test whether making information salient could catalyze action by senior health officers.

3.3.2 Personality Predicts Response to Information

Appendix Table A.2 presents summary statistics for senior health officials in Punjab, which are similar in magnitude to summary statistics of both doctors and health inspectors. We examine whether manipulating attendance information affects subsequent doctor absence with the following specification

$$Absent\ Survey_{it} = \psi_0 + \psi_1 Trait_i + \psi_2 Flagged_{it-1} + \psi_3 Trait_i * Flagged_{it-1} + \delta_t + \eta_{it} \quad (4)$$

where $Absent\ Survey_{jt}$ is equal to one if the doctor posted to facility i was absent during our unannounced visit in wave t, $Flagged_{it-1}$ is a dummy equal to one if the facility was flagged in red on the dashboard prior to survey wave t, $Trait_i$ is a personality measure for the senior official in charge of facility i, and δ_t are survey wave fixed effects.

Facilities are flagged only if three or more staff members are absent. Consequently, if we restrict our sample to only facilities where, in the month prior to our unannounced visit, only two or three staff were absent, we can estimate the effect of flagging on a sample where the only difference might plausibly be whether the facility was flagged.[46]

Table 4 reports results from this test, limiting the sample to facilities with two or three staff absent during an inspection. Facilities flagged for absence to a senior official with a Big Five index one standard deviation above the mean subsequently experience an increase in doctor attendance that is 40 percentage points greater than a facility flagged to a senior official at the mean Big Five index.[47]

There are several ways through which the above effect may have operated. For instance, the health officials could have taken formal action against delinquent workers, or they could simply have censured the officers informally. While we are unable to discern this effect given our data, anecdotally, we have learned that the second channel is more likely to work, given limited powers for hiring and firing people.

Appendix Table A.16 provides suggestive evidence that senior health officials with higher personality types stepped up the share of their time spent monitoring health facilities in

[46]In Appendix Table A.14 we verify the drop in absence for people who score higher on the Big Five index is limited to right around the discontinuity, with a waning, though significant, effect in a slightly larger window.

[47]Note that in Table 4 we cannot reject the null hypothesis that the interaction term on the Big Five index is different than the uninteracted flagging effect. In Appendix Tables A.15, we show that when senior health officials' are split into quartiles by Big Five index, we can significantly reject that those in the bottom and top quartile have the same flagging effect (with a substantial differential effect). We define the window during which a clinic can be flagged in red prior to one of our unannounced visits as 15 to 45 days before our visit. Senior health officials only looked at the web dashboard every week or two, so we would not expect an immediate response from flagging. However, if the window is made too long, virtually every facility will become flagged and we will lose variation. The p-values of the significance of the coefficient on the Big Five index and PSM index for a wide range of windows are reported in Appendix Figures A.11 and A.12. These figures also indicate that we have not selected the window most favorable for our result.

Table 4: Tests of Heterogeneity in the Information Treatment by Senior Official Personality

	Doctor Present (=1)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PANEL A: Big Five Personality Traits									
Clinic Flagged as Underperforming on Dashboard		-0.161*	-0.146	0.159	0.140	0.144	0.132	0.154	0.163
		(0.095)	(0.103)	(0.098)	(0.103)	(0.100)	(0.105)	(0.100)	(0.110)
Flagged x Big Five Index				0.402**					
				(0.200)					
Flagged x Agreeableness					0.086				
					(0.144)				
Flagged x Conscientiousness						0.172*			
						(0.097)			
Flagged x Extroversion							0.097		
							(0.096)		
Flagged x Emotional Stability								0.185*	
								(0.105)	
Flagged x Openness									0.051
									(0.106)
Mean of dependent variable		0.563	0.520	0.520	0.520	0.520	0.520	0.520	0.520
# Observations		142	123	123	123	123	123	123	123
# Clinics		122	106	106	106	106	106	106	106
R-Squared		0.226	0.204	0.231	0.206	0.227	0.211	0.219	0.205
P-value		0.092	0.160	0.047	0.551	0.078	0.313	0.081	0.630
Adjusted P-value				0.000	1.000	0.747	0.781	0.747	1.000
PANEL B: Public Service Motivation									
Clinic Flagged as Underperforming on Dashboard	-0.161*	-0.146	0.165	0.146	0.155	0.254**	0.153	0.146	0.201*
	(0.095)	(0.103)	(0.105)	(0.103)	(0.104)	(0.121)	(0.110)	(0.103)	(0.108)
Flagged x PSM Index			0.124						
			(0.169)						
Flagged x Attraction				0.072					
				(0.102)					
Flagged x Civic Duty					0.027				
					(0.089)				
Flagged x Commitment						0.231			
						(0.148)			
Flagged x Compassion							-0.028		
							(0.114)		
Flagged x Self Sacrifice								-0.032	
								(0.100)	
Flagged x Social Justice									0.139
									(0.097)
Mean of dependent variable	0.563	0.520	0.520	0.520	0.520	0.520	0.520	0.520	0.520
# Observations	142	123	123	123	123	123	123	123	123
# Clinics	122	106	106	106	106	106	106	106	106
R-Squared	0.226	0.204	0.208	0.207	0.204	0.217	0.204	0.204	0.219
P-value	0.092	0.160	0.464	0.481	0.761	0.123	0.809	0.749	0.155
Adjusted P-value			1.000	1.000	1.000	0.747	1.000	1.000	0.747

Notes: This table tests for heterogeneity in the impact of providing information about clinic staff absence to senior officials by the personality types of the senior officials. Clinics were flagged in red on an online dashboard if three or more of the seven staff were absent in one or more health inspections of the clinic fifteen to forty-five days prior to an unannounced visit by our survey enumerators. All columns restrict the sample to those clinics where only two or three staff were absent (up to seven staff can be marked absent). In addition, the sample is limited to Monitoring the Monitor treatment districts due to the necessity of the web dashboard for flagging clinics. Column (1) reports un-interacted impacts of flagging. Columns (2) - (10) are further limited to clinics in districts for which senior health official personality data is available. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across inspectors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Standard errors clustered at the clinic level reported in parentheses. All regressions include district and survey wave fixed effects and condition on a doctor being posted. P-values reported are from a two-sided hypothesis test that the null effect is zero. Adjusted P-values are corrected for multiple hypothesis testing. One correction is done across the Big Five and PSM indices P-values using the Family-Wise Error Rate procedure. A second is done across the eleven Big Five and PSM traits using False Discover Rate procedure. Both procedures are reported in Anderson (2008). *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

response to dashboard flags. You can see senior health officials with a one standard deviation higher Big Five index increased the share of their time spent monitoring health facilities by 3.1 percentage points for each facility that was flagged in their district in the window prior to our collection of their time use information (wave three). The mean number of flags per district in this time-frame was 7.88, which translates to large increases in time spent monitoring by better personality types in response to flags. Although, this evidence is at best suggestive because it is based on seventeen observations.[48]

The worry with the above results is that senior health officials might be substituting other work with increased monitoring of health facilities. The data suggest that senior health officials may have decreased their share of time spent on the lunch prayer break, on work related to monthly polio vaccination drives, and on 'other work' in response to flags. Unfortunately, these effects are not significant individually.[49]

As with the correlational and experimental results above, we show that personality is a better predictor of the response to information than other important covariates for senior health officials. See Appendix Table A.17 for these results.

The results presented in this section provide another validation of personality measures in predicting performance, this time in the case of senior health officials. Personality measures predict which senior health officials will react to information about the absence of their subordinates with large magnitudes. Simply flagging high absence clinics in red essentially eliminates doctor absence in clinics overseen by senior health officials one standard deviation above the mean in terms of their Big Five index. These results also speak to potential mechanisms. It seems plausible that the same information treatment provided to individu-

[48]Time use information was collected through a written module provided in the same visit in which personality measures were collected in which officials were asked to account for all work activities in each half-hour block between 8:30am and 8:30pm from the last two regular work days. Officials could choose from fourteen categories, including Monitoring Visits to the BHUs, Management of BHUs done in the office, Meetings with BHU staff in office, Monitoring visits to RHCs, Management of RHCs done in the office, Monitoring visits to THQ & DHQ, Management of THQ & DHQ done in the office, Lunch/Prayer break, Tea Break, Meeting with General Public, Meeting with other Govt. Official, EPI and Polio, Other Official activities, and Other.

[49]Category-by-category time use tables available by request.

als in highly comparable positions results in different real world impacts because different personality types take different action in response to information.

3.4 Summary of Results and Multiple Hypothesis Testing

Consistent with a growing emphasis in economics on accounting for potential overrejection of the null hypothesis of no effect that may result from multiple inference, we present multiple inference adjusted p-values for all of our primary analysis (Anderson, 2008; Bidwell et al., 2016; Casey et al., 2012). This primary analysis measures the association between two different personality measures and six objective performance measures for public health workers at three different levels of the bureaucracy in Punjab, Pakistan. As explained in Section 3.1.1, we primarily consider a single index each as the measures of the Big Five and Perry Public Service Motivation personality traits. Creating an index to collapse multiple hypothesis tests into one is a common means of accounting for multiple inference (Kling et al., 2007). However, as we are still testing two null hypotheses for each of our performance measures—that the Big Five index is not associated with differential performance and that the PSM index is not—we adjust p-values across these two indices for each outcome.[50]

Specifically, for correlations between personality measures and doctor and inspector performance under status quo incentives, we apply false discovery rate (FDR) adjustments at the personality measure level. When testing for heterogeneous treatment effects, we apply family wise error rate (FWER) corrections at the personality measure level. In both cases we use the procedure outlined in Anderson (2008). While our preference would be to follow Anderson in applying the more conservative FWER corrections for all of our non-exploratory analysis, the FWER correction requires drawing placebo treatment assignments which is not possible for the status quo correlations. Thus we use the FDR correction.

[50]Note that we are correcting for multiple inference across personality measures within an outcome rather than across outcomes within a measure, as is more traditional in the literature. This is for two reasons: (i) it is consistent with how we are interpreting our analysis outcome-by-outcome, and (ii) it is consistent with the fact that each index is already accounting for multiple inference across traits. We have computed adjusted p-values correcting across outcomes rather than personality measures and find results that are less conservative (all p-values are smaller). Results available upon request.

Table 5: Results Summary

Alternative Hypothesis:	Personality Predicts Performance				Personality Predicts Monitoring Treatment Heterogeneity	Personality Predicts Information Treatment Heterogeneity
Public Actor:	Doctor		Inspector			Administrator
Performance Measure:	Attendance	Collusion	Inspections	Collusion	Inspections	Doctor Attendance
Panel A: Un-adjusted P-Values						
Big 5 Index	+ (0.22)	- (0.00)	- (0.16)	+ (0.25)	+ (0.01)	+ (0.05)
Agreeableness	+ (0.73)	- (0.00)	- (0.47)	- (0.96)	+ (0.08)	+ (0.55)
Conscientiousness	+ (0.03)	- (0.01)	- (0.08)	+ (0.67)	+ (0.08)	+ (0.08)
Extroversion	+ (0.07)	- (0.01)	- (0.21)	+ (0.06)	+ (0.24)	+ (0.31)
Emotional Stability	+ (0.22)	- (0.00)	- (0.06)	+ (0.66)	+ (0.02)	+ (0.08)
Openness	- (0.52)	- (0.62)	+ (0.90)	+ (0.82)	+ (0.13)	+ (0.63)
PSM Index	+ (0.03)	- (0.00)	- (0.41)	- (0.02)	+ (0.16)	+ (0.46)
Attraction	+ (0.24)	- (0.02)	- (0.92)	- (0.17)	+ (0.01)	+ (0.48)
Civic Duty	+ (0.02)	- (0.02)	- (0.65)	+ (0.63)	+ (0.66)	+ (0.76)
Commitment	+ (0.21)	- (0.00)	- (0.48)	- (0.01)	+ (0.22)	+ (0.12)
Compassion	+ (0.70)	- (0.00)	- (0.34)	- (0.30)	+ (0.12)	- (0.81)
Self Sacrifice	+ (0.03)	- (0.00)	- (0.41)	- (0.06)	+ (0.86)	- (0.75)
Social Justice	+ (0.20)	- (0.02)	- (0.68)	- (0.08)	+ (0.89)	+ (0.16)
Panel B: P-Values Adjusted for Multiple Hypothesis Testing						
Big 5 Index	+ (0.12)	- (0.00)	- (0.48)	+ (0.14)	+ (0.08)	+ (0.00)
Agreeableness	+ (0.50)	- (0.01)	- (1.00)	- (1.00)	+ (0.21)	+ (1.00)
Conscientiousness	+ (0.12)	- (0.01)	- (0.73)	+ (0.80)	+ (0.21)	+ (0.75)
Extroversion	+ (0.15)	- (0.01)	- (1.00)	+ (0.23)	+ (0.27)	+ (0.78)
Emotional Stability	+ (0.27)	- (0.01)	- (0.73)	+ (0.80)	+ (0.10)	+ (0.75)
Openness	- (0.50)	- (0.06)	+ (1.00)	+ (0.97)	+ (0.25)	+ (1.00)
PSM Index	+ (0.07)	- (0.00)	- (0.48)	- (0.04)	+ (0.25)	+ (1.00)
Attraction	+ (0.27)	- (0.01)	- (1.00)	- (0.31)	+ (0.10)	+ (1.00)
Civic Duty	+ (0.12)	- (0.01)	- (1.00)	+ (0.80)	+ (0.51)	+ (1.00)
Commitment	+ (0.27)	- (0.01)	- (1.00)	- (0.17)	+ (0.27)	+ (0.75)
Compassion	+ (0.50)	- (0.01)	- (1.00)	- (0.53)	+ (0.25)	- (1.00)
Self Sacrifice	+ (0.12)	- (0.01)	- (1.00)	- (0.23)	+ (0.51)	- (1.00)
Social Justice	+ (0.27)	- (0.01)	- (1.00)	- (0.24)	+ (0.51)	+ (0.75)

Notes: This table provides a summary of coefficient direction and P-values (in parentheses) for the primary hypothesis tested in each of the regressions available in Figures 3 and 6 and Tables 3 and 4.Coefficient directions are indicated by either + (positive) or - (negative). P-values are in parentheses. Un-adjusted P-values reported are from a two-sided hypothesis test that the null effect is zero. Adjusted P-values are corrected for multiple hypothesis testing. One correction is done across the Big Five and PSM indices P-values using the Family-Wise Error Rate procedure. A second is done across the eleven Big Five and PSM traits using False Discover Rate procedure. Both procedures are reported in Anderson (2008).

For our exploratory, trait-by-trait analysis, we apply false discovery rate (FDR) adjustments at the personality trait level, adjusting for each of the eleven tests (pooling Big Five and PSM traits) we are conducting for each outcome. This is consistent with Anderson (2008), Bidwell et al. (2016), and Casey et al. (2012).

Table 5 presents a summary of p-values for rejecting the null hypothesis for each of our primary results with and without multiple inference corrections. Focusing on the indices, we reject the null of no association between personality and performance for six of twelve tests at the five percent level before we adjust for multiple inference. After adjusting, we reject the null for four of twelve tests at the five percent level and for six of twelve tests at the ten percent level. That is to say that adjusting our p-values causes two cases in which a coefficient previously significant at five percent slips to ten percent. We take this as encouraging for our argument that personality measures predict performance.

Adjusting for multiple inference has more of an impact on our exploratory, trait-by-trait analysis. We reject the null hypothesis of no effect for twenty six of 66 tests at the ten percent level or below with unadjusted p-values. Once we adjust them for multiple inference, we reject the null only thirteen times at the ten percent level or below, and eleven of these thirteen are for one outcome—doctor collusion. Note however that an additional eleven adjusted p-values are between 0.1 and .25. Given how conservative these adjustments are (they are more conservative than adjusting across outcomes within each trait or than adjusting within each personality measure separately, and we are using two-sided tests when one-sided could be more appropriate), we take these results to be a strong caveat against interpreting trait-by-trait results but one that does not change the underlying picture.

4 Conclusion

Governments, like any organization, are made of people with potentially stark personality differences. We find that measurable dimensions of personality are useful in predicting performance, how public sector workers respond to changes in incentives, and how senior policy officials react to information about the performance of their subordinates.

These findings suggest several policy levers to improve the quality of service delivery. First, recruitment policy will have effects through the personalities of personnel attracted to the job (Dal Bó et al., 2013; Ashraf et al., 2014, Forthcoming; Finan et al., 2015; Deserranno, 2016). Second, a growing body of research suggests that personality traits are malleable (Kautz et al., 2014). This suggests a role for training, potentially aimed at strengthening non-cognitive traits (Blattman et al., 2015). Third, political economy broadly views bureaucrats as agents carrying out the policy directives of politicians, supervisors, or some other principal (Huber and Shipan, 2008; Gulzar and Pasquale, 2017). We find that how they respond to changes in incentives can be predicted by measurable personality differences. Indeed, there is now work showing that measurable differences in preferences between individuals can be constructively incorporated into the design of incentives (Andreoni et al., 2016), as the principal-agent literature has previously speculated (Prendergast, 1999). Collectively, this points to benefits from understanding interpersonal differences when designing incentives. Last, there is now growing interest in whether and how providing information to policymakers can change their actions and improve policy. We demonstrate with an information experiment that increased information about subordinate performance can improve outcomes even with existing incentive structures, and that policy-makers with different personality profiles respond differently to this information. Collectively, this suggests that understanding interpersonal differences in the bureaucracy can do a lot to improve policies aimed at making it more effective.

References

Almlund, Mathilde, Angela Lee Duckworth, James J Heckman, and Tim D Kautz, "Personality psychology and economics," Technical Report, National Bureau of Economic Research 2011.

Anderson, Michael L, "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American statistical Association*, 2008, *103* (484).

Andreoni, James, Michael Callen, Karrar Hussain, Yasir Khan, and Charles Sprenger, "Using Preference Estimates to Customize Incentives: An Application to Polio Vaccination Drives in Pakistan," 2016.

Ashraf, Nava, Oriana Bandiera, and B. Kelsey Jack, "No margin, no mission? A Field Experiment on Incentives for Public Service Delivery," *Journal of Public Economics*, Forthcoming, *8834*.

_ , _ , and Scott S Lee, "Do-gooders and go-getters: career incentives, selection, and performance in public service delivery," 2014.

Augenblick, Ned, Muriel Niederle, and Charles Sprenger, "Working Over Time: Dynamic Inconsistency in Real Effort Tasks," *The Quarterly Journal of Economics*, Forthcoming.

Bandiera, Oriana, Andrea Prat, and Tommaso Valletti, "Active and Passive Waste in Government Spending: Evidence from a Policy Experiment," *American Economic Review*, 2009, *99* (4), 1278–1308.

Barrick, Murray R. and Michael K. Mount, "The Big Five Personality Dimensions and Job Performance: A Meta-Analysis," *Personnel Psychology*, 1991, *44* (1), 1–26.

Bazerman, Max and Don A Moore, *Judgment in Managerial Decision Making, 8th Edition*, Wiley & Sons, 2012.

Benabou, Roland and Jean Tirole, "Intrinsic and extrinsic motivation," *The Review of Economic Studies*, 2003, *70* (3), 489–520.

Bertrand, Marianne and Antoinette Schoar, "Managing with Style: The Effect of Managers on Firm Policies," *Quarterly Journal of Economics*, 2003, *CXVIII*, 1169–1208.

Besley, Timothy and Maitreesh Ghatak, "Competition and incentives with motivated agents," *American Economic Review*, 2005, *95* (3), 616–636.

Bidwell, Kelly, Katherine Casey, and Rachel Glennerster, "Debates: Voting and Expenditure Responses to Political Communication," 2016.

Blattman, Christopher, Julian C. Jamison, and Margaret Sheridan, "Reducing crime and violence: Experimental evidence on adult noncognitive investments in Liberia," 2015. Working paper.

Borghans, Lex, Angela Lee Duckworth, James J. Heckman, and Bas ter Weel, "The Economics and Psychology of Personality Traits," *The Journal of Human Resources*, 2008, *XLIII* (4), 973–1059.

Bowles, Samuel, Herbert Gintis, and Melissa Osborne, "The determinants of earnings: A behavioral approach," *Journal of Economic Literature*, 2001, pp. 1137–1176.

Callen, Michael, Saad Gulzar, Ali Hasanain, and Yasir Khan, "The Political Economy of Public Sector Absence: Experimental Evidence from Pakistan," 2016. NBER Working Paper No. 22340.

Casey, Katherine, Rachel Glennerster, and Edward Miguel, "RESHAPING INSTITUTIONS: EVIDENCE ON AID IMPACTS USING A PREANALYSIS PLAN," *The Quarterly Journal of Economics*, 2012, *1755*, 1812.

Chaudhury, Nazmul, Jeffrey Hammer, Michael Kremer, Karthik Muralidharan, and F Halsey Rogers, "Missing in action: teacher and health worker absence in developing countries," *The Journal of Economic Perspectives*, 2006, *20* (1), 91–116.

Dal Bó, Ernesto, Frederico Finan, and Martín A. Rossi, "Strengthening State Capabilities: The Role of Financial Strengthening State Capabilities: The Role of Financial Incentives in the Call to Public Service," *Quarterly Journal of Economics*, 2013, *forthcoming.*

Deaton, Angus, "Instruments, Randomization, and Learning about Development," *Journal of Economic Literature*, 2010, *48* (2), 424–55.

der Linden, Dimitri Van, Jan te Nijenhuis, and Arnold B Bakker, "The general factor of personality: A meta-analysis of Big Five intercorrelations and a criterion-related validity study," *Journal of research in personality*, 2010, *44* (3), 315–327.

Deserranno, Erika, "Financial Incentives as Signals: Experimental Evidence from the Recruitment of Village Promoters in Uganda," 2016.

Digman, John M, "Higher-order factors of the Big Five.," *Journal of personality and social psychology*, 1997, *73* (6), 1246.

Finan, Frederico, Benjamin A Olken, and Rohini Pande, "The personnel economics of the state," Technical Report, National Bureau of Economic Research 2015.

Gatewood, Robert, Hubert Feild, and Murray Barrick, *Human resource selection*, Cengage Learning, 2010.

Groth-Marnat, Gary, *Handbook of psychological assessment*, John Wiley & Sons, 2009.

Gulzar, Saad and Ben Pasquale, "Politicians, Bureaucrats, and Development: Evidence from India," *American Political Science Review*, 2017.

Heckman, James J., "Integrating Personality Psychology into Economics," 2011, (NBER WP #17378).

— **, Jora Stixrud, and Sergio Urzua**, "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 2006, *24* (3), 411–482.

Hogan, Joyce and Brent Holland, "Using Theory to Evaluate Personality and Job-Performance Relations: A Socioanalytic Perspective," *Journal of Applied Psychology*, 2003, *88* (1), 100–112.

Huber, John and Charles Shipan, "Politics, Delegation, and Bureaucracy," in "The Oxford Handbook of Political Economy," Oxford University Press, 2008.

John, Oliver P., Laura P. Naumann, and Christopher J. Soto, "Paradigm shift to the integrative Big Five trait taxonomy: History, measurement, and conceptual issues," in "Handbook of personality: Theory and research," The Guilford Press, 2008, chapter 4.

Johnson, W. Bruce, Robert Magee, Nandu Nagarajan, and Harry Newman, "An Analysis of the Stock Price Reaction to Sudden Executive Deaths," *Journal of Accounting and Economics*, 1985, *7*, 151–174.

Jones, Benjamin F. and Benjamin A. Olken, "Do Leaders Matter? National Leadership and Growth Since World War II," *Quarterly Journal of Economics*, 2005, *120* (3), 835–864.

Kaplan, Robert M. and Dennis P. Saccuzzo, *Psychological Testing: Principles, Applications, and Issues*, Pacific Grove, Calif.: Brooks/Cole Pub. Co., 1997.

Kautz, Tim D, James J. Heckman, Ron Diris, Bas ter Weel, and Lex Borghans, "Fostering and Measuring Skills: Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success," 2014, (NBER WP #20749).

Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz, "Experimental analysis of neighborhood effects," *Econometrica*, 2007, *75* (1), 83–119.

Klinger, Bailey, Asim Ijaz Khwaja, and Carlos del Carpio, *Enterprising Psychometrics and Poverty Reduction*, Springer, 2013.

Kuhn, Michael A, "Curing the Calorie Crunch: The Effect of EBT on Household Present-Bias," 2013.

Malmendier, Ulrike, Geoffrey Tate, and Jon Yan, "Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies," *The Journal of Finance*, 2011, *66* (5), 1687–1733.

Miguel, Edward, C Camerer, K Casey, J Cohen, KM Esterling, A Gerber, R Glennerster, DP Green, M Humphreys, G Imbens et al., "Promoting transparency in social science research," *Science*, 2014, *343* (6166), 30–31.

Musek, Janek, "A general factor of personality: Evidence for the Big One in the five-factor model," *Journal of Research in Personality*, 2007, *41* (6), 1213–1233.

National Institute of Population Studies, *Pakistan Demographic and Health Survey 2012-13*, National Institute of Population Studies, 2013.

Nyhus, Ellen K. and Empar Pons, "The Effects of Personality on Earnings," *Journal of Economic Psychology*, 2005, *26* (3), 363–384.

Olken, Benjamin A. and Rohini Pande, "Corruption in Developing Countries," *Annual Review of Economics*, 2012, *4*, 479–509.

Perry, James L., "Measuring Public Service Motivation: An Assessment of Construct Reliability and Validity," *Journal of Public Administration Research and Theory*, 1996, *6* (1), 5–22.

_ **and Lois Recascino Wise**, "The Motivational Bases of Public Service," *Public Administration Review*, 1990, *50*, 367–73.

Petrovsky, Nicolai, "Does Public Service Motivation Predict Higher Public Service Performance? A Research Synthesis," 2009.

Prendergast, Canice, "The Provision of Incentives in Firms," *Journal of Economic Literature*, 1999, *1*, 7–63.

Ramey, Adam, Jonathan Klingler, and Gary Hollibaugh, *More Than a Feeling: Personality, Polarization, and the Transformation of the US Congress*, University of Chicago Press, Forthcoming.

Rasul, Imran and Daniel Rogger, "Management of Bureaucrats and Public Service Delivery: Evidence from the Nigerian Civil Service," 2014.

Reinikka, Ritva and Jakob Svensson, "Local Capture: Evidence from a Central Government Transfer Program in Uganda," *The Quarterly Journal of Economics*, 2004, *119* (2), 679–705.

Roberts, Brent W., "Back to the Future: Personality and Assessment and Personality Development," *Journal of Research in Personality*, 2009, *43* (2), 137–145.

_ **, Kate E. Walton, and Wolfgang Viechtbauer**, "Patterns of Mean-Level Change in Personality Traits across the Life Course: A Meta-Analysis of Longitudinal Studies," *Psychological Bulletin*, 2006, *132* (1), 1–25.

Salgado, Jesus F., "The Five Factor Model of Personality and Job Performance in the The Five Factor Model of Personality and Job Performance in the European Community," *Journal of Applied Psychology*, 1997, *82* (1), 30–43.

Schmidt, Frank L and John E Hunter, "The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings.," *Psychological bulletin*, 1998, *124* (2), 262.

Shapiro, Jesse M, "Is there a daily discount rate? Evidence from the food stamp nutrition cycle," *Journal of Public Economics*, 2005, *89* (2), 303–325.

Tibshirani, Robert, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society. Series B (Methodological)*, 1996, pp. 267–288.

Wild, Lena, Vikki Chambers, Maia King, and Daniel Harris, "Common Constraints and Incentive Problems in Service Delivery," Technical Report, Overseas Development Institute 2012.

World Bank, *World Development Report 2004: Making Services Work for the Poor*, World Bank, 2004.

A Appendix - For Online Publication Only:

A.1 Theoretical Framework

In this section, we provide a framework to help us understand the first two questions considered in this paper—do personality measures (i) predict performance under status quo incentives and (ii) predict responses to a reform that changes incentives?[51]

Let our personality measures capture a worker's type, θ, with cumulative distribution $F(\theta)$. Let performance be the binary decision that a doctor or health inspector makes of whether to attend work. If a worker attends, he receives a fixed salary of W and incurs a cost of effort $\lambda(\theta)$. If a worker shirks, he exerts no effort and receives the fixed salary with probability $1-p$ and an arbitrarily small punishment c with probability p, as well as an outside option of Q.[52]

A.1.1 Personality Type and Performance

The marginal worker indifferent between working and shirking will satisfy

$$W - \lambda(\theta) = (1-p)W - pc + Q. \tag{5}$$

If work is less costly for better types ($\frac{\partial \lambda}{\partial \theta} < 0$), then all workers with θ greater than that of the marginal worker will choose to work. Equation 5 therefore gives that workers with better personality types are weakly more likely to attend work. This accords with Almlund et al. (2011), in which the authors define traits as features which allow individuals to produce more with a fixed amount of effort.[53]

[51] A number of papers incorporate personality traits into standard economic models such as the Roy Model (Almlund et al., 2011) or the principle-agent framework (Besley and Ghatak, 2005; Benabou and Tirole, 2003).

[52] We choose Q here to denote 'quack', the term in Pakistan for a private doctor. We use the 'he' pronoun because almost all government doctors and health inspectors are men.

[53] This might be because workers with better personality types are more efficient with their time or because the psychic costs required to achieve a given task are lower. Or, in a simple utility framework, we can think of θ as the ratio of the marginal utility from work to the marginal utility from leisure for a worker.

A.1.2 Personality Type and Responses to Changes to Incentives

We now turn to predictions regarding how changes to incentives affect the decision to work. Consider a worker of type θ_m who is just indifferent between working and shirking. To see what happens when the probability of detection p changes, note that

$$\theta^M = \lambda^{-1}(p(W+c) - Q) \tag{6}$$

$$\frac{\partial \theta^M}{\partial p} = \frac{1}{\lambda'(\lambda^{-1}(p(W+c) - Q)}. \tag{7}$$

Given our earlier assumption that $\frac{\partial \lambda}{\partial \theta} < 0$, and assuming that $p(W+c) > Q$, it must be that $\frac{\partial \theta^M}{\partial p} < 0$, or that the marginal worker's personality type decreases with an increase in detection probability.

We can see this in a simple picture in Figure A.1. Let θ^{M1} be the marginal worker before an increase in p and θ^{M2} the lower-type marginal worker afterwards. All workers with $\theta > \theta^{M1}$ continue to work and workers with types in the shaded area $\theta^{M1} > \theta > \theta^{M2}$ are induced to work by the increase in detection probability. The types induced to work are the highest (best) among those that shirk prior to the shift in p. Equation 5 therefore also describes how a personality type relates to a reform in incentives.[54]

Here we assume personality traits only affect the cost of effort in an otherwise simple indifference equation. It follows that better personality types are more likely to work ex-ante and that the better types among ex-ante shirkers will be more likely to respond to an increase in incentives. The decision to work is potentially much more complex. For example, personality traits that are useful in the public sector may also increase productivity

[54]Note that Figure A.1 allows us to make two additional points. The first is that the results in this paper, as with all results from randomized interventions, are Local Average Treatment Effects. That is, our intervention may induce some workers to work, but there are some workers that will always work and some that will never work regardless of the intervention. The second point is that the initial position of θ^{M1} matters significantly to the size of the impact of an increase in detection probability. This also highlights the importance of the shape of the distribution of personality types, as a very narrow distribution might see different effects than a uniform distribution from an increase in p. Both the initial position of θ^{M1} and the distribution of personality types can be estimated ex-ante, allowing for better targeted policies.

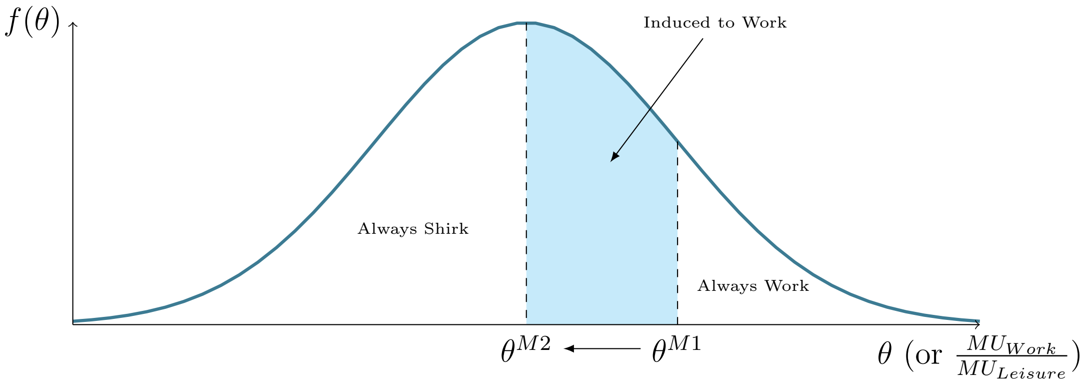


Figure A.1: Effect of an Increase in Detection Probability on the Decision to Work or Shirk

in the outside option (i.e., Q may also be a function of θ). More generally, θ might not only capture the single-dimensional productivity gains to personality traits. It may also capture heterogeneity in workers' outside options, in workers' cognitive ability, in workers' ability to mitigate political pressure from outside their office, and so on. We could deal with this in two ways. Most simply, we could redefine $\lambda(\theta)$ to include the all of these personality trait-dependent costs and benefits. Then the simple model would encapsulate a richer understanding of these costs and benefits of personality traits, but it would be unable to differentiate these costs and benefits. Second, we could enrich the model by, for example, modeling Q as a function of θ. Without additional and somewhat implausible assumptions, doing so immediately expands the set of predictions to the point where the model is no longer falsifiable. We will now demonstrate this.

A.1.3 Extending the Model

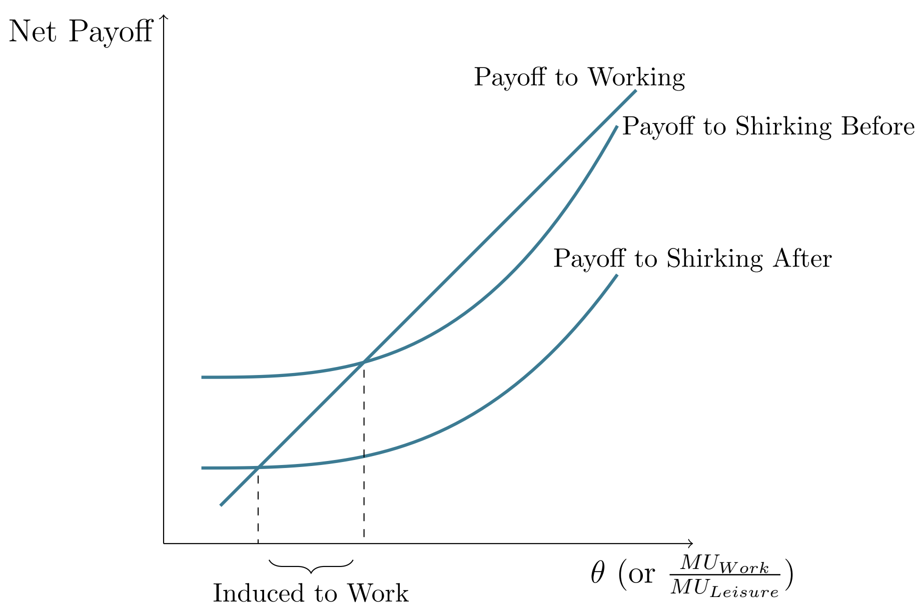
Let us extend the model to now assume that the outside option is a function of θ. Thus we have the following updated indifference condition:

$$W - \lambda(\theta) = (1 - p)W - pc + Q(\theta) \tag{8}$$

Though it is still straightforward to see here that an increase in p weakly increases the probability that a given worker will choose to work, it is not as straightforward, to determine either the status quo correlation between θ and performance or which types from the distribution of θ will respond to a given increase in p. To get traction on this, we will make two analogous assumptions. Assume that $\frac{\partial \lambda(\theta)}{\partial \theta} > 0, as before$, and that $\frac{\partial Q(\theta)}{\partial \theta} > 0$.

Given these assumptions, we can plot the net payoff to working versus the net payoff to shirking before and after an increase in p under various scenarios. Both Figure A.2 and A.3 show a case when the $\lambda(\theta)$ function is linear and the $Q(\theta)$ function is convex in θ.[55]

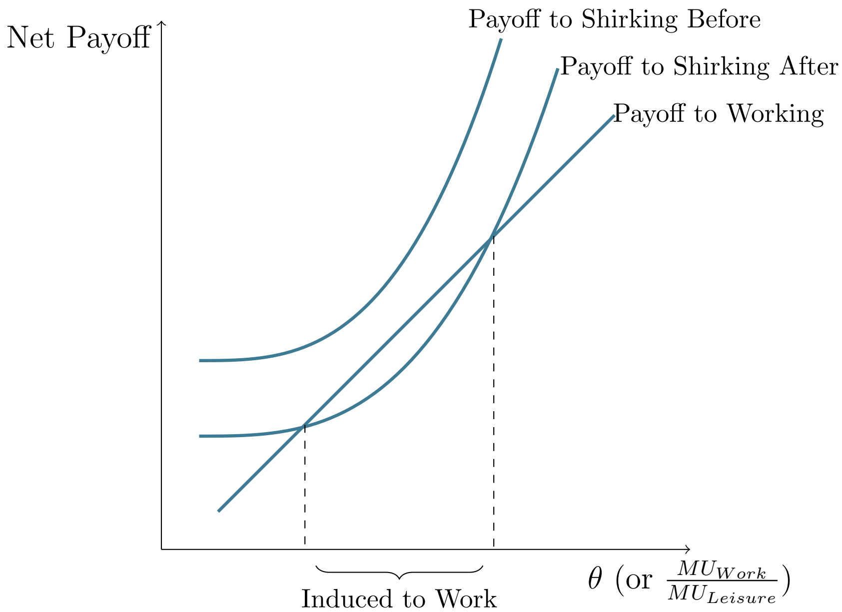
Figure A.2: Effect of an Increase in Detection Probability on the Decision to Work or Shirk



These figures allow us to make several important points. First, we can see that in both figures an increase in incentives to work induces a range of workers in the middle of the personality type distribution to work. Second, we can see that in the second figure, before an increase in p no one chooses to work. This highlights that the existence of a relationship between performance and personality type is subject to the outside option for

[55]Note that the case when both functions are linear is very unlikely to be accurate, while the case when both functions are strictly convex, while likely more accurate, does not lead to any additional intuition (both presented cases would hold so long as the $\lambda(\theta)$ function has less curvature than the $Q(\theta)$ function over the relevant range).

Figure A.3: Effect of an Increase in Detection Probability on the Decision to Work or Shirk



some personality types being sufficiently low. More generally, the difference between the two figures highlights the ambiguity in correlation between performance and personality type under a fixed p. In the first figure, all workers above a certain marginal worker will choose to work, with the marginal worker shifting to the left after p is increased. This would create a positive correlation between personality type and working under the status quo and a positive correlation between personality type and responding to an increase in p by switching from shirking to working. Where as in the second figure, the gains to the outside option for the highest personality types overcome the gains to those types for working even after p is increased sufficient to induce some personality types to work, causing the best personality types to join the worst personality types in shirking. This would lead to an ambiguous correlation between personality type and working.

A.2 Appendix Tables

Table A.1: Doctor and Health Inspector Personality Summary Statistics (Control Districts)

	Mean	SD	P10	P50	P90	Obs
PANEL A: Doctor Personality Summary Statistics						
Big Five Personality Traits						
Big Five Index	0.04	0.79	-0.99	0.05	1.14	192
Agreeableness	3.57	0.66	2.67	3.67	4.42	192
Conscientiousness	4.02	0.55	3.33	4	4.75	192
Extroversion	3.69	0.48	3.17	3.67	4.33	192
Emotional Stability	-2.54	0.70	-3.50	-2.50	-1.67	192
Openness	2.92	0.44	2.42	2.92	3.50	192
Public Service Motivation						
PSM Index	0.02	0.67	-0.83	-0.01	0.92	192
Attraction	3.46	0.60	2.60	3.40	4.20	192
Civic Duty	4.22	0.53	3.43	4.29	5	192
Commitment	3.79	0.45	3.29	3.86	4.29	192
Compassion	3.55	0.53	2.88	3.50	4.25	192
Self Sacrifice	4.09	0.60	3.38	4.12	4.88	192
Social Justice	3.96	0.59	3.20	4	4.60	192
Performance						
Present (=1)	0.43	0.50	0	0	1	637
PANEL B: Inspector Personality Summary Statistics						
Big Five Personality Traits						
Big Five Index	0.02	0.74	-1.25	0.10	1.04	49
Agreeableness	3.67	0.54	2.67	3.83	4.25	49
Conscientiousness	4.11	0.53	3.33	4.17	4.75	49
Extroversion	3.72	0.46	3.17	3.67	4.33	49
Emotional Stability	-2.34	0.62	-3.25	-2.25	-1.58	49
Openness	3.12	0.35	2.67	3.17	3.58	49
Public Service Motivation						
PSM Index	0.06	0.61	-0.75	0.11	0.67	50
Attraction	3.58	0.57	2.90	3.60	4.33	50
Civic duty	4.42	0.43	3.86	4.50	4.93	50
Commitment	3.96	0.38	3.43	3.86	4.46	50
Compassion	3.66	0.48	3.00	3.63	4.25	50
Self Sacrifice	4.39	0.45	3.87	4.50	4.94	50
Social Justice	4.20	0.43	3.60	4.20	4.90	50
Performance						
Inspected in the Last Two Months (=1)	0.56	0.50	0	1	1	558
PANEL C: Collusion						
Predicted Collusion (=1)	0.13	0.33	0	0	1	334

Notes: Sample for Panel A: doctors in control districts that completed the personalities survey module, given in waves 2 and 3 and during a special follow-up round. Sample for Panel B: health inspectors in control districts that completed the personalities survey module. Doctors and inspectors were only asked to complete the module once.The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Performance and collusion samples are clinic-wave observations in control districts across waves 1 through 3, where doctors are posted. Collusion is a dummy variable coded as 1 when a doctor is reported absent in both survey waves 2 and 3 but is reported as present by health inspectors during every visit between the launch of the program and present (up to 50 visits).

Table A.2: Senior Health Official Personality Summary Statistics (Control Districts)

	Mean	SD	P10	P50	P90	Obs
Big Five Personality Traits						
Big Five Index	0.07	0.74	-0.89	0.47	0.72	16
Agreeableness	3.75	0.59	3.17	3.88	4.33	16
Conscientiousness	4.10	0.51	3.42	4.25	4.67	16
Extroversion	3.80	0.34	3.42	3.83	4.25	16
Emotional Stability	-2.34	0.53	-3.17	-2.09	-1.75	16
Openness	3.07	0.36	2.73	2.88	3.58	16
Public Sector Motivation						
PSM Index	0.20	0.63	-0.64	0.06	1.00	16
Attraction	3.73	0.61	3.00	3.50	4.80	16
Civic Duty	4.54	0.39	3.86	4.57	5.00	16
Commitment	3.95	0.35	3.57	4.00	4.43	16
Compassion	3.80	0.45	3.25	3.62	4.50	16
Self Sacrifice	4.51	0.34	4.00	4.56	4.88	16
Social Justice	4.16	0.42	3.60	4.10	4.80	16

Notes: Sample: senior health officials in control districts that completed the personalities survey module, given during a single round after the final wave of clinic visits. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively.

Table A.3: Doctor Personality and Doctor Attendance

	Doctor Present (=1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: Big Five Personality Traits							
Big Five Index		0.042					
		(0.034)					
Agreeableness			0.008				
			(0.023)				
Conscientiousness				0.058**			
				(0.026)			
Extroversion					0.047*		
					(0.025)		
Emotional Stability						0.030	
						(0.024)	
Openness							-0.015
							(0.024)
Mean of dependent variable		0.493	0.493	0.493	0.493	0.493	0.493
# Observations		479	479	479	479	479	479
# Clinics		190	190	190	190	190	190
R-Squared		0.193	0.191	0.198	0.196	0.193	0.191
P-value		0.216	0.730	0.029	0.066	0.219	0.523
Adjusted P-value		0.122	0.500	0.124	0.153	0.269	0.500
PANEL B: Public Service Motivation							
PSM Index	0.080**						
	(0.037)						
Attraction		0.030					
		(0.026)					
Civic Duty			0.071**				
			(0.030)				
Commitment				0.033			
				(0.026)			
Compassion					0.011		
					(0.028)		
Self Sacrifice						0.056**	
						(0.025)	
Social Justice							0.028
							(0.022)
Mean of dependent variable	0.493	0.493	0.493	0.493	0.493	0.493	0.493
# Observations	479	479	479	479	479	479	479
# Clinics	190	190	190	190	190	190	190
R-Squared	0.198	0.193	0.201	0.193	0.191	0.199	0.193
P-value	0.033	0.242	0.019	0.213	0.696	0.030	0.201
Adjusted P-value	0.071	0.269	0.124	0.269	0.500	0.124	0.269

Notes: Standard errors clustered at the clinic level reported in parentheses. All regressions include tehsil (sub-district) and survey wave fixed effects. Sample: control district clinics for which doctor personality data is available and a doctor is posted. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across doctors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. P-values reported are from a two-sided hypothesis test that the null effect is zero. Adjusted P-values are corrected for multiple hypothesis testing. One correction is done across the Big Five and PSM indices P-values using the Family-Wise Error Rate procedure. A second is done across the eleven Big Five and PSM traits using False Discover Rate procedure. Both procedures are reported in Anderson (2008). *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A.4: Doctor Personality and Estimated Doctor-inspector Collusion

	Doctor-inspector Collusion (=1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: Big Five Personality Traits							
Big Five Index		-0.099***					
		(0.031)					
Agreeableness			-0.083***				
			(0.026)				
Conscientiousness				-0.059***			
				(0.021)			
Extroversion					-0.063***		
					(0.023)		
Emotional Stability						-0.063***	
						(0.022)	
Openness							-0.012
							(0.024)
Mean of dependent variable		0.103	0.103	0.103	0.103	0.103	0.103
# Observations		273	273	273	273	273	273
# Clinics		273	273	273	273	273	273
R-Squared		0.390	0.399	0.374	0.378	0.378	0.347
P-value		0.002	0.001	0.006	0.006	0.003	0.623
Adjusted P-value		0.002	0.011	0.011	0.011	0.011	0.061
PANEL B: Public Service Motivation							
PSM Index	-0.124***						
	(0.037)						
Attraction		-0.054**					
		(0.022)					
Civic Duty			-0.051**				
			(0.022)				
Commitment				-0.068***			
				(0.024)			
Compassion					-0.067***		
					(0.023)		
Self Sacrifice						-0.067***	
						(0.021)	
Social Justice							-0.049**
							(0.022)
Mean of dependent variable	0.103	0.103	0.103	0.103	0.103	0.103	0.103
# Observations	273	273	273	273	273	273	273
# Clinics	273	273	273	273	273	273	273
R-Squared	0.409	0.371	0.371	0.388	0.381	0.382	0.366
P-value	0.001	0.016	0.020	0.005	0.004	0.002	0.025
Adjusted P-value	0.002	0.011	0.011	0.011	0.011	0.011	0.011

Notes: Standard errors clustered at the clinic level reported in parentheses. All regressions include tehsil (sub-district) and survey wave fixed effects. Sample: treatment district clinics for which doctor personality data is available and a doctor is posted. All personality traits are normalized. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across doctors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Collusion is a dummy variable coded as 1 when a doctor is reported absent in both survey waves 2 and 3 but is reported as present by health inspectors during every visit between the launch of the program and present (up to 50 visits). P-values reported are from a two-sided hypothesis test that the null effect is zero. Adjusted P-values are corrected for multiple hypothesis testing. One correction is done across the Big Five and PSM indices P-values using the Family-Wise Error Rate procedure. A second is done across the eleven Big Five and PSM traits using False Discover Rate procedure. Both procedures are reported in Anderson (2008). *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A.5: Doctor Personality Measure Predictions Compared to Other Covariates

	(1)	(2)	(3)	(4)	(5)
	Doctor Present (=1)				
Distance to Hometown (KM)	-0.000		-0.000		-0.000
	(0.000)		(0.000)		(0.000)
Tenure in Department of Health (Years)	0.000		0.000		0.000
	(0.000)		(0.000)		(0.000)
Tenure at Clinic (Years)	-0.001		-0.001		-0.001
	(0.000)		(0.001)		(0.001)
Big Five Index		0.048	0.056		
		(0.032)	(0.031)		
PSM Index				0.091*	0.090**
				(0.035)	(0.035)
Mean of Dependent Variable	0.502	0.493	0.484	0.493	0.484
# Observations	514	479	471	479	471
# Clinics	212	190	187	190	187
R-Squared	0.049	0.054	0.062	0.063	0.068
	Doctor-inspector Collusion (=1)				
Distance to Hometown (KM)	-0.000		-0.000		0.000
	(0.000)		(0.000)		(0.000)
Tenure in Department of Health (Years)	0.000		0.000		0.000
	(0.000)		(0.000)		(0.000)
Tenure at Clinic (Years)	-0.000		-0.000		-0.000
	(0.000)		(0.000)		(0.000)
Big Five Index		-0.077**	-0.082**		
		(0.026)	(0.026)		
PSM Index				-0.119***	-0.123***
				(0.035)	(0.036)
Mean of Dependent Variable	0.112	0.103	0.100	0.103	0.100
# Observations	295	273	269	273	269
# Clinics	295	273	269	273	269
R-Squared	0.051	0.087	0.094	0.123	0.130

Notes: Standard errors clustered at the clinic level reported in parentheses. All regressions include tehsil (sub-district) and survey wave fixed effects. Sample: Clinics for which doctor personality data is available and a doctor is posted. Panel A is restricted to control clinics, Panel B to treatment. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across doctors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Collusion is a dummy variable coded as 1 when a doctor is reported absent in both survey waves 2 and 3 but is reported as present by health inspectors during every visit between the launch of the program and present (up to 50 visits). *Levels of Significance:* *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.6: Doctor Attendance and Health Service Provision (Control Districts)

	Number of Outpatients Seen
	(1)
Present (=1)	197.654***
	(51.926)
Mean of Dependent Variable	1071.240
# Observations	784
# Clinics	420
R-Squared	0.422

Notes: Standard errors clustered at the clinic level reported in parentheses. Regression includes tehsil (sub-district) and survey wave fixed effects. Sample is limited to clinics in control districts which keep records of outpatient visits (420 of 425). The number of outpatients seen is in the total for each month prior to our independent visits. Present is a dummy variable equal to one if the clinic's doctor was present during the same independent visits. *Levels of Significance:* $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Health Inspector Personality and Inspections

	Health Inspection in Last Two Months (=1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: Big Five Personality Traits							
Big Five Index		-0.062					
		(0.044)					
Agreeableness			-0.021				
			(0.029)				
Conscientiousness				-0.043*			
				(0.024)			
Extroversion					-0.043		
					(0.034)		
Emotional Stability						-0.061*	
						(0.031)	
Openness							0.004
							(0.032)
Mean of dependent variable		0.588	0.588	0.588	0.588	0.588	0.588
# Observations		454	454	454	454	454	454
# Tehsils		45	45	45	45	45	45
R-Squared		0.166	0.163	0.166	0.166	0.167	0.162
P-value		0.163	0.469	0.076	0.212	0.057	0.897
Adjusted P-value		0.482	1.000	0.726	1.000	0.726	1.000
PANEL B: Public Service Motivation							
PSM Index	-0.043						
	(0.052)						
Attraction		-0.003					
		(0.033)					
Civic Duty			-0.010				
			(0.023)				
Commitment				-0.025			
				(0.035)			
Compassion					-0.054		
					(0.056)		
Self Sacrifice						-0.018	
						(0.022)	
Social Justice							-0.015
							(0.035)
Mean of dependent variable	0.572	0.572	0.572	0.572	0.572	0.572	0.572
# Observations	467	467	467	467	467	467	467
# Tehsils	46	46	46	46	46	46	46
R-Squared	0.192	0.190	0.190	0.191	0.193	0.191	0.191
P-value	0.411	0.923	0.651	0.480	0.340	0.414	0.679
Adjusted P-value	0.482	1.000	1.000	1.000	1.000	1.000	1.000

Notes: Standard errors clustered at the health inspector level reported in parentheses. All regressions include district and survey wave fixed effects. Sample: control district clinics for which health inspector personality data is available and a doctor is posted. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across inspectors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. P-values reported are from a two-sided hypothesis test that the null effect is zero. Adjusted P-values are corrected for multiple hypothesis testing. One correction is done across the Big Five and PSM indices P-values using the Family-Wise Error Rate procedure. A second is done across the eleven Big Five and PSM traits using False Discover Rate procedure. Both procedures are reported in Anderson (2008). *Levels of Significance:* $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: Health Inspector Personality and Estimated Doctor-inspector Collusion

	Doctor-inspector Collusion (=1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: Big Five Personality Traits							
Big Five Index		0.051					
		(0.044)					
Agreeableness			-0.001				
			(0.027)				
Conscientiousness				0.009			
				(0.022)			
Extroversion					0.055*		
					(0.028)		
Emotional Stability						0.007	
						(0.016)	
Openness							0.004
							(0.019)
Mean of dependent variable		0.092	0.092	0.092	0.092	0.092	0.092
# Observations		292	292	292	292	292	292
# Tehsils		48	48	48	48	48	48
R-Squared		0.148	0.144	0.144	0.159	0.144	0.144
P-value		0.250	0.963	0.668	0.057	0.661	0.819
Adjusted P-value		0.143	1.000	0.802	0.234	0.802	0.968
PANEL B: Public Service Motivation							
PSM Index	-0.071**						
	(0.029)						
Attraction		-0.042					
		(0.030)					
Civic Duty			0.009				
			(0.018)				
Commitment				-0.050**			
				(0.019)			
Compassion					-0.020		
					(0.019)		
Self Sacrifice						-0.031*	
						(0.016)	
Social Justice							-0.035*
							(0.019)
Mean of dependent variable	0.095	0.095	0.095	0.095	0.095	0.095	0.095
# Observations	294	294	294	294	294	294	294
# Tehsils	49	49	49	49	49	49	49
R-Squared	0.160	0.153	0.149	0.167	0.151	0.155	0.157
P-value	0.018	0.168	0.630	0.013	0.295	0.056	0.077
Adjusted P-value	0.038	0.307	0.802	0.168	0.526	0.234	0.240

Notes: Standard errors clustered at the health inspector level reported in parentheses. All regressions include district and survey wave fixed effects. Sample: control district clinics for which health inspector personality data is available and a doctor is posted. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across inspectors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Collusion is a dummy variable coded as 1 when a doctor is reported absent in both survey waves 2 and 3 but is reported as present by health inspectors during every visit between the launch of the program and present (up to 50 visits). P-values reported are from a two-sided hypothesis test that the null effect is zero. Adjusted P-values are corrected for multiple hypothesis testing. One correction is done across the Big Five and PSM indices P-values using the Family-Wise Error Rate procedure. A second is done across the eleven Big Five and PSM traits using False Discover Rate procedure. Both procedures are reported in Anderson (2008). *Levels of Significance:* $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.9: Health Inspector Personality and Inspections—Full Sample

	Health Inspection in Last Two Months (=1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: Big Five Personality Traits							
Big 5 index		-0.020					
		(0.028)					
Agreeableness			0.010				
			(0.020)				
Conscientiousness				-0.017			
				(0.017)			
Extroversion					-0.034		
					(0.025)		
Emotional stability						-0.041	
						(0.032)	
Openness							0.038
							(0.026)
Mean of dependent variable		0.635	0.635	0.635	0.635	0.635	0.635
# Observations		860	860	860	860	860	860
# Tehsils		49	49	49	49	49	49
R-Squared		0.180	0.180	0.180	0.182	0.182	0.182
PANEL B: Public Service Motivation							
PSM index	-0.000						
	(0.041)						
Attraction		-0.005					
		(0.027)					
Civic duty			0.013				
			(0.020)				
Commitment				0.018			
				(0.025)			
Compassion					-0.027		
					(0.025)		
Self Sacrifice						0.008	
						(0.017)	
Social justice							-0.022
							(0.024)
Mean of dependent variable	0.619	0.619	0.619	0.619	0.619	0.619	0.619
# Observations	885	885	885	885	885	885	885
# Tehsils	50	50	50	50	50	50	50
R-Squared	0.206	0.206	0.207	0.207	0.208	0.207	0.207

Notes: Standard errors clustered at the health inspector level reported in parentheses. All regressions include district and survey wave fixed effects. Sample: control district clinics for which health inspector personality data is available, regardless of whether or not a doctor is posted. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across inspectors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A.10: Health Inspector Personality and Estimated Doctor-inspector Collusion—Full Sample

	Doctor-inspector Collusion (=1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: Big Five Personality Traits							
Big Five Index		0.102*					
		(0.050)					
Agreeableness			0.047				
			(0.032)				
Conscientiousness				0.051			
				(0.025)			
Extroversion					0.040		
					(0.037)		
Emotional Stability						0.020	
						(0.021)	
Openness							0.003
							(0.026)
Mean of Dependent Variable		0.194	0.194	0.194	0.194	0.194	0.194
# Observations		361	361	361	361	361	361
# Tehsils		51	51	51	51	51	51
R-Squared		0.183	0.179	0.181	0.178	0.175	0.174
PANEL B: Public Service Motivation							
PSM Index	-0.017						
	(0.045)						
Attraction		-0.026					
		(0.033)					
Civic Duty			0.040				
			(0.025)				
Commitment				-0.046*			
				(0.019)			
Compassion					-0.005		
					(0.023)		
Self Sacrifice						-0.005	
						(0.030)	
Social Justice							0.001
							(0.025)
Mean of Dependent Variable	0.196	0.196	0.196	0.196	0.196	0.196	0.196
# Observations	363	363	363	363	363	363	363
# Tehsils	52	52	52	52	52	52	52
R-Squared	0.174	0.175	0.179	0.182	0.174	0.174	0.174

Notes: Standard errors clustered at the health inspector level reported in parentheses. All regressions include district and survey wave fixed effects. Sample: control district clinics for which health inspector personality data is available, regardless of whether a doctor is posted. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across inspectors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Collusion is a dummy variable coded as 1 when a doctor is reported absent in both survey waves 2 and 3 but is reported as present by health inspectors during every visit between the launch of the program and present (up to 50 visits). *Levels of Significance:* *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.11: Health Inspector Personality Measure Predictions Compared to Other Covariates

	(1)	(2)	(3)	(4)	(5)
	Health Inspection in Last Two Months (=1)				
Age (Years)	-0.009		-0.005		-0.016
	(0.012)		(0.011)		(0.010)
Has Completed Higher Education (=1)	-0.016		-0.061		-0.058
	(0.072)		(0.082)		(0.079)
Tenure in Department of Health (Years)	-0.001		-0.003		0.004
	(0.012)		(0.012)		(0.011)
Tenure as Inspector (Years)	0.018		0.026*		0.036**
	(0.010)		(0.010)		(0.011)
Distance to Hometown (KM)	0.009		0.032		0.020
	(0.027)		(0.032)		(0.032)
Inspector Reports Liking Current Post (=1)	-0.016		-0.017		-0.014
	(0.014)		(0.022)		(0.019)
Big Five Index		-0.062	-0.105		
		(0.044)	(0.055)		
PSM Index				-0.043	-0.143*
				(0.052)	(0.070)
Mean of Dependent Variable	0.565	0.588	0.587	0.572	0.570
# Observations	469	454	441	467	454
# Tehsils	46	45	43	46	44
R-Squared	0.200	0.166	0.186	0.192	0.216
	Doctor-inspector Collusion (=1)				
Age (Years)	-0.004		-0.004		-0.011
	(0.011)		(0.010)		(0.010)
Has Completed Higher Education (=1)	-0.062		-0.052		-0.038
	(0.047)		(0.029)		(0.031)
Tenure in Department of Health (Years)	0.002		0.003		0.002
	(0.013)		(0.010)		(0.011)
Tenure as Inspector (Years)	-0.002		-0.001		-0.002
	(0.008)		(0.007)		(0.006)
Distance to Hometown (KM)	0.003*		0.023		0.024
	(0.001)		(0.012)		(0.013)
Inspector Reports Liking Current Post (=1)	0.001		0.008		0.005
	(0.009)		(0.010)		(0.009)
Big Five Index		0.051	0.055		
		(0.044)	(0.047)		
PSM Index				-0.071*	-0.113**
				(0.029)	(0.034)
Mean of Dependent Variable	0.096	0.092	0.092	0.095	0.095
# Observations	301	292	292	294	294
# Tehsils	50	48	48	49	49
R-Squared	0.154	0.148	0.172	0.160	0.195

Notes: Standard errors clustered at the health inspector level reported in parentheses. All regressions include district and survey wave fixed effects. Sample: Clinics for which doctor personality data is available and a doctor is posted. Panel A is restricted to control clinics, Panel B to treatment. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across doctors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. Collusion is a dummy variable coded as 1 when a doctor is reported absent in both survey waves 2 and 3 but is reported as present by health inspectors during every visit between the launch of the program and present (up to 50 visits). *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A.12: Personalities and Health Inspections—Experimental Evidence, Unconditional on Doctor Being Posted

	Health Inspection in Last Two Months (=1)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PANEL A: Big Five Personality Traits									
Monitoring (=1)		0.267**	0.141	0.127	0.166	0.134	0.144	0.106	0.143
		(0.129)	(0.118)	(0.107)	(0.103)	(0.105)	(0.117)	(0.111)	(0.115)
Monitoring x Big Five Index				0.233					
				(0.144)					
Monitoring x Agreeableness					0.102				
					(0.091)				
Monitoring x Conscientiousness						0.134			
						(0.100)			
Monitoring x Extroversion							0.042		
							(0.080)		
Monitoring x Emotional Stability								0.142	
								(0.087)	
Monitoring x Openness									0.165*
									(0.096)
Mean of Dependent Variable		0.651	0.672	0.672	0.672	0.672	0.672	0.672	0.672
# Observations		2175	1810	1810	1810	1810	1810	1810	1810
# Clinics		35	35	35	35	35	35	35	35
R-Squared		0.049	0.044	0.061	0.069	0.060	0.046	0.056	0.055
PANEL B: Public Service Motivation									
Monitoring (=1)	0.267**	0.152	0.141	0.148	0.143	0.137	0.150	0.158	0.138
	(0.129)	(0.116)	(0.111)	(0.108)	(0.115)	(0.105)	(0.113)	(0.123)	(0.111)
Monitoring x PSM Index			0.155						
			(0.153)						
Monitoring x Attraction				0.198**					
				(0.074)					
Monitoring x Civic Duty					-0.048				
					(0.070)				
Monitoring x Commitment						0.032			
						(0.078)			
Monitoring x Compassion							0.100		
							(0.093)		
Monitoring x Self Sacrifice								-0.034	
								(0.095)	
Monitoring x Social Justice									0.083
									(0.098)
Mean of Dependent Variable	0.651	0.664	0.664	0.664	0.664	0.664	0.664	0.664	0.664
# Observations	2175	1841	1841	1841	1841	1841	1841	1841	1841
# Clinics	35	35	35	35	35	35	35	35	35
R-Squared	0.049	0.045	0.053	0.066	0.046	0.057	0.049	0.046	0.052

Notes: Standard errors clustered at the district level reported in parentheses. All regressions include tehsil (sub-district) and survey wave fixed effects and are not conditional on a doctor being posted. Column (1) reports average treatment effects on treatment and control district clinics. Columns (2) - (10) are limited to clinics in tehsils for which health inspector personality data is available. The Big Five and PSM traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across inspectors. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A.13: Inspector Personality Measure Experimental Results Compared to Other Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
	Inspected in the Last Two Months (=1)					
Monitoring (=1)	0.178	1.015	-0.006	0.244	0.023	0.659
	(0.154)	(1.121)	(0.114)	(1.092)	(0.120)	(1.094)
Monitoring x Age (Years)		0.001		0.011		0.012
		(0.032)		(0.031)		(0.032)
Monitoring x Has Completed Higher Education (=1)		0.205		0.358*		0.296
		(0.147)		(0.148)		(0.155)
Monitoring x Tenure in Department of Health (Years)		-0.034		-0.027		-0.044
		(0.032)		(0.033)		(0.032)
Monitoring x Tenure as Inspector (Years)		0.028		0.019		0.023
		(0.024)		(0.024)		(0.029)
Monitoring x Distance to Hometown (KM)		0.047		0.085		0.086
		(0.027)		(0.050)		(0.049)
Monitoring x Inspector Reports Liking Current Post (=1)		-0.061		-0.058		-0.062
		(0.048)		(0.048)		(0.048)
Monitoring x Big Five Index			0.351*	0.277		
			(0.133)	(0.167)		
Monitoring x PSM Index					0.202	0.120
					(0.140)	(0.159)
Mean of dependent variable	0.641	0.644	0.655	0.504	0.648	0.503
# Observations	1332	1178	1146	1133	1165	1152
# Tehsils	35	33	34	33	34	33
R-Squared	0.048	0.095	0.069	0.103	0.057	0.098

Notes: Standard errors clustered at the district level reported in parentheses. All regressions include district and survey wave fixed effects. Sample: clinics for which health inspector personality data is available and a doctor is posted. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A.14: Differential Clinic Flagging Effects by Senior Health Official Personality, Robustness to Cutoff

	Doctor Present (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Big Five I ndex						
Clinic Flagged as Underperforming on Dashboard	0.100	0.094	0.099	0.086	0.146	0.159
	(0.067)	(0.067)	(0.073)	(0.072)	(0.103)	(0.098)
Flagged x Big Five Index		0.118		0.249*		0.402**
		(0.131)		(0.143)		(0.200)
Mean of Dependent Variable	0.521	0.521	0.528	0.528	0.480	0.480
# Observations	326	326	233	233	123	123
# Clinics	228	228	180	180	106	106
R-Squared	0.114	0.117	0.140	0.152	0.204	0.231
PANEL B: PSM Index						
Clinic Flagged as Underperforming on Dashboard	0.100	0.098	0.099	0.111	0.146	0.165
	(0.067)	(0.070)	(0.073)	(0.075)	(0.103)	(0.105)
Flagged x PSM Index		-0.016		0.082		0.124
		(0.108)		(0.117)		(0.169)
Mean of Dependent Variable	0.521	0.521	0.528	0.528	0.480	0.480
# Observations	326	326	233	233	123	123
# Clinics	228	228	180	180	106	106
R-Squared	0.114	0.114	0.140	0.142	0.204	0.208
Sample	Full	Full	Partial	Partial	Disc.	Disc.

Notes: Standard errors clustered at the clinic level reported in parentheses. All regressions include district and survey wave fixed effects and condition on a doctor being posted. Clinics were flagged in red on an online dashboard if three or more of the seven staff were absent in one or more health inspections of the clinic fifteen to forty-five days prior to an unannounced visit by our survey enumerators. The sample is limited to Monitoring the Monitor treatment districts due to the necessity of the web dashboard for flagging clinics. In addition, columns (3) and (4) restrict the sample to those clinics where only four or less staff were absent. We call this sample the "partial" sample. Columns (5) and (6) restrict the sample to those clinics where only two or three staff were absent. We call this sample the "discontinuity" sample. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. *Levels of Significance:* $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.15: Differential Clinic Flagging Effects by Senior Health Official Personality, Semi-parametric

	(1)	(2)
	Inspected in the Last Two Months (=1)	
Clinic Flagged as Underperforming on Dashboard	-0.143	0.074
	(0.193)	(0.170)
Flagged x Big Five Index Second Quartile (=1)	0.250	
	(0.251)	
Flagged x Big Five Index Third Quartile (=1)	0.396	
	(0.264)	
Flagged x Big Five Index Fourth Quartile (=1)	0.650**	
	(0.278)	
Flagged x PSM Index Second Quartile (=1)		0.497**
		(0.237)
Flagged x PSM Index Third Quartile (=1)		-0.068
		(0.239)
Flagged x PSM Index Fourth Quartile (=1)		0.308
		(0.261)
Mean of Dependent Variable	0.520	0.520
# Observations	123	123
# Clinics	106	106
R-Squared	0.244	0.225

Notes: Standard errors clustered at the clinic level reported in parentheses. All regressions include district and survey wave fixed effects and condition on a doctor being posted. Clinics were flagged in red on an online dashboard if three or more of the seven staff were absent in one or more health inspections of the clinic fifteen to forty-five days prior to an unannounced visit by our survey enumerators. The sample is limited to Monitoring the Monitor treatment districts due to the necessity of the web dashboard for flagging clinics. In addition, all columns restrict the sample to those clinics where only two or three staff were absent. *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A.16: Differential Senior Health Official Time Use by Personality

	Share of Time Senior Health Official Spent Monitoring Health Facilities						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Clinics Flagged as Underperforming on Dashboard	0.009	0.014***	0.011**	0.012**	0.010*	0.012*	0.008
	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
# Flagged x Big Five Index		0.031*					
		(0.016)					
# Flagged x Agreeableness			-0.000				
			(0.007)				
# Flagged x Conscientiousness				0.015*			
				(0.008)			
# Flagged x Extroversion					0.005		
					(0.007)		
# Flagged x Emotional Stability						0.011	
						(0.008)	
# Flagged x Openness							0.011
							(0.007)
Mean of the Dependent Variable	0.097	0.097	0.097	0.097	0.097	0.097	0.097
# Observations	17	17	17	17	17	17	17
R-Squared	0.124	0.361	0.160	0.413	0.156	0.188	0.289

Notes: Robust standard errors reported in parentheses. Sample limited to senior health officials in treatment districts. Clinics were flagged in red on an online dashboard if three or more of the seven staff were absent in one or more health inspections of the clinic fifteen to forty-five days prior to an unannounced visit by our survey enumerators. The sample is limited to Monitoring the Monitor treatment districts due to the necessity of the web dashboard for flagging clinics. The number flagged is the total number of clinics flagged in each district prior to our second endline (when we also collected senior health official personality and time use). Each regression also contains a control for the personality measure uninteracted. The Big Five traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less). All personality traits are then normalized across senior health officials. The Big Five Index is a z-score averages of the five Big Five traits. Time use information was collected through a written module provided in the same visit in which personality measures were collected in which officals were asked to account for all work activities in each half-hour block between 8:30am and 8:30pm from the last two regular work days. Officials could choose from fourteen categories, including Monitoring Visits to the BHUs, Management of BHUs done in the office, Meetings with BHU staff in office, Monitoring visits to RHCs, Management of RHCs done in the office, Monitoring visits to THQ & DHQ, Management of THQ & DHQ done in the office, Lunch/Prayer break, Tea Break, Meeting with General Public, Meeting with other Govt. Official, EPI and Polio, Other Official activities, and Other. *Levels of Significance:* *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.17: Differential Clinic Flagging Effects by Senior Health Official Personality Compared to Other Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
	Doctor Present (=1)					
Clinic Flagged as Underperforming on Dashboard	0.146	-1.528	0.159	0.800	0.165	1.917
	(0.103)	(2.640)	(0.098)	(2.564)	(0.105)	(3.613)
Flagged x Age (Years)		0.058		0.028		0.038
		(0.055)		(0.059)		(0.061)
Flagged x Has Completed Higher Education (=1)		0.326		0.241		0.215
		(0.290)		(0.248)		(0.314)
Flagged x Tenure in Department of Health (Years)		-0.058		-0.080		-0.120
		(0.084)		(0.079)		(0.072)
Flagged x Tenure as Official (Years)		-0.014		0.030		0.031
		(0.039)		(0.041)		(0.047)
Flagged x Distance to Hometown (KM)		0.011		-0.048		-0.039
		(0.030)		(0.034)		(0.037)
Flagged x Official Reports Liking Current Post (=1)		0.008		-0.002		-0.068
		(0.048)		(0.045)		(0.071)
Flagged x Big Five Index			0.402*	0.552*		
			(0.200)	(0.242)		
Flagged x PSM Index					0.124	0.452
					(0.169)	(0.347)
Mean of Dependent Variable	0.520	0.520	0.520	0.520	0.520	0.520
# Observations	123	123	123	123	123	123
# Clinics	106	106	106	106	106	106
R-Squared	0.204	0.225	0.231	0.245	0.208	0.235

Notes: Standard errors clustered at the clinic level reported in parentheses. All regressions include district and survey wave fixed effects and condition on a doctor being posted. Clinics were flagged in red on an online dashboard if three or more of the seven staff were absent in one or more health inspections of the clinic fifteen to forty-five days prior to an unannounced visit by our survey enumerators. The sample is limited to Monitoring the Monitor treatment districts due to the necessity of the web dashboard for flagging clinics. In addition, the sample is restructed to those clinics where only two or three staff were absent. We call this sample the "discontinuity" sample. The Big Five and PSM indices are z-score averages of the five and six traits within the Big Five and PSM respectively. *Levels of Significance:* $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

A.3 Appendix Figures

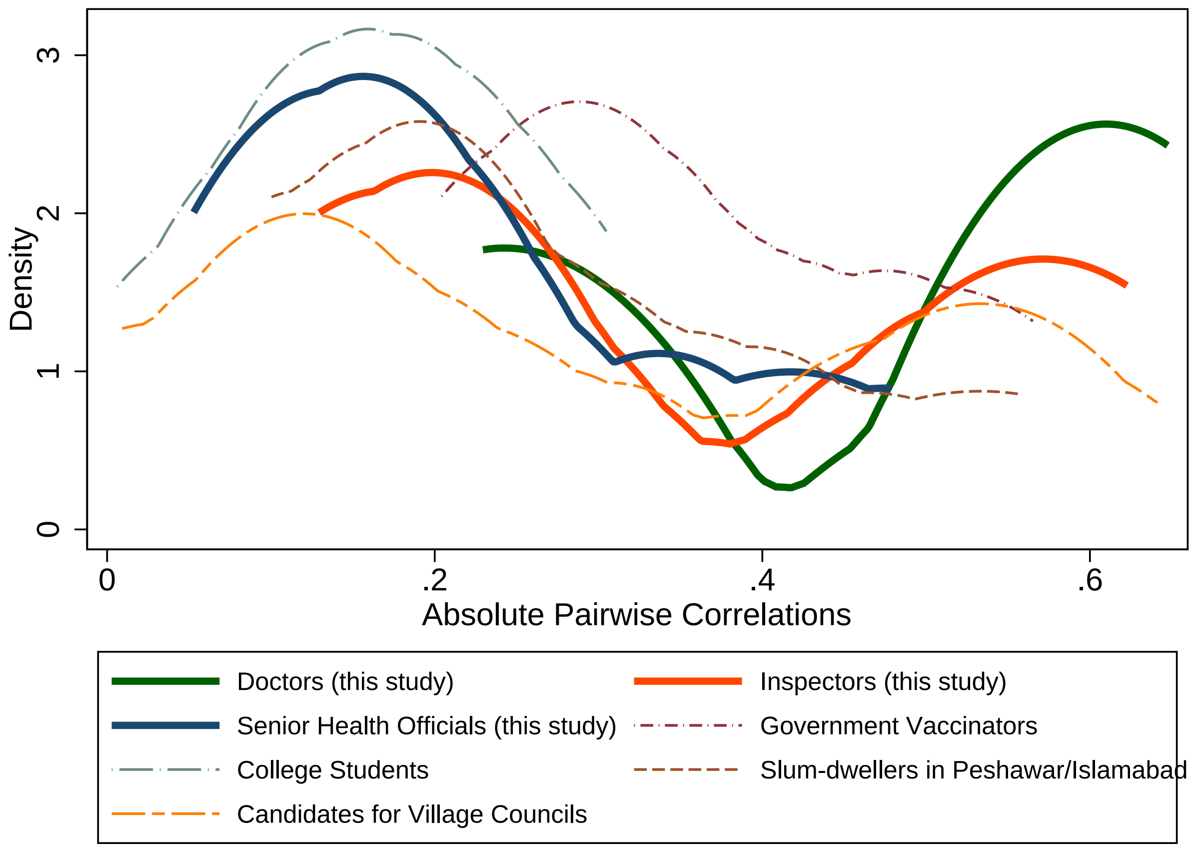


Figure A.4: Absolute Pairwise Correlations of Big Five Personality Traits in Different Samples

Notes: Displays smoothed density of ten absolute pairwise correlations between measures of each of the Big Five personality traits for seven samples. The first three samples are those of doctors, inspectors, and senior health officials in this study. Additional samples: (i) public sector polio vaccinators in Punjab ($N = 420$); (ii) residents of slums near Islamabad, Peshawar, and Dera Ghazi Khan, often care migrants from areas close to Pakistan's border with Afghanistan ($N = 1152$); (iii) all politicians from 240 electoral constituencies of Haripur and Abbotabad districts located in the province of Khyber-Pakhtunkhwa who contested the first village council elections in 2015 ($N = 3628$); and (iv) students at the Lahore University of Management Science, an elite private sector university in Punjab ($N = 227$). These samples are obtained from collaborators who have used the same locally sourced version of the Big Five personality test as this study. The Big Five traits are each mean responses to statements that represent the trait on a five point Likert scale, in which 1 corresponds to disagree strongly, 2 to disagree a little, 3 to neutral, 4 to agree a little, and 5 to agree strongly. Likert responses are given the same direction (5 always being more agreeable, for example, never less).

Panel A Panel B

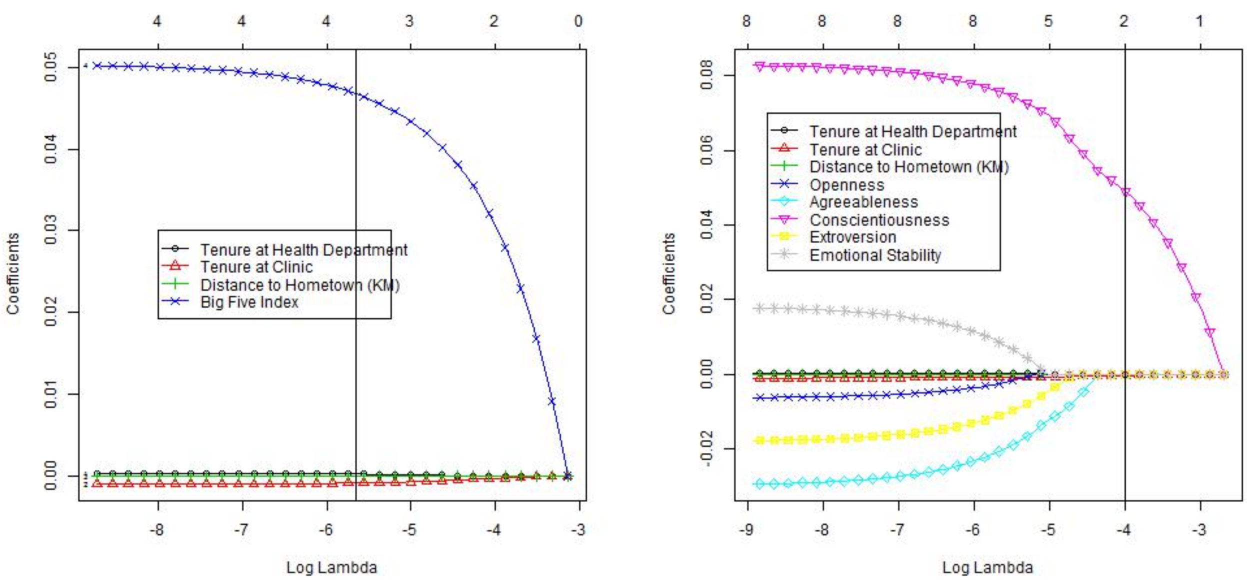


Figure A.5: LASSO model coefficients predicting doctor attendance—Big Five

Notes: Plots coefficient values from a LASSO model with doctor attendance as the outcome against possible values of λ in the model. Panel A plots coefficients for the following covariates: doctor Big Five Index, years of tenure at the health department, years of tenure at the specific health clinic, and distance of the health clinic to the doctor's hometown in KM. Panel B replaces the Big Five Index with each of the Big Five traits individually. The vertical lines ares at the value of Log λ that minimizes the mean cross-validation error given the set of covariates. The upper X-axis reports the number of non-zero coefficients in the model at each value of Log λ.

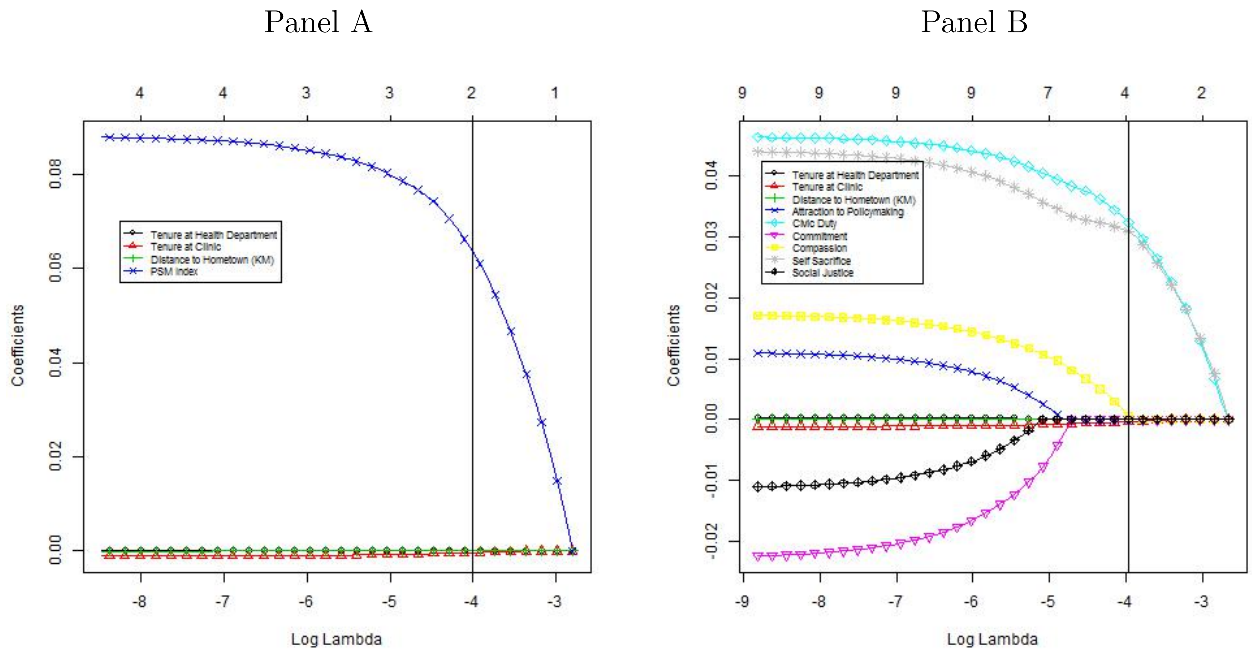


Figure A.6: LASSO model coefficients predicting doctor attendance—PSM

Notes: Plots coefficient values from a LASSO model with doctor attendance as the outcome against possible values of λ in the model. Panel A plots coefficients for the following covariates: doctor PSM Index, years of tenure at the health department, years of tenure at the specific health clinic, and distance of the health clinic to the doctor's hometown in KM. Panel B replaces the PSM Index with each of the PSM traits individually. The vertical lines ares at the value of Log λ that minimizes the mean cross-validation error given the set of covariates. The upper X-axis reports the number of non-zero coefficients in the model at each value of Log λ.

Panel A Panel B

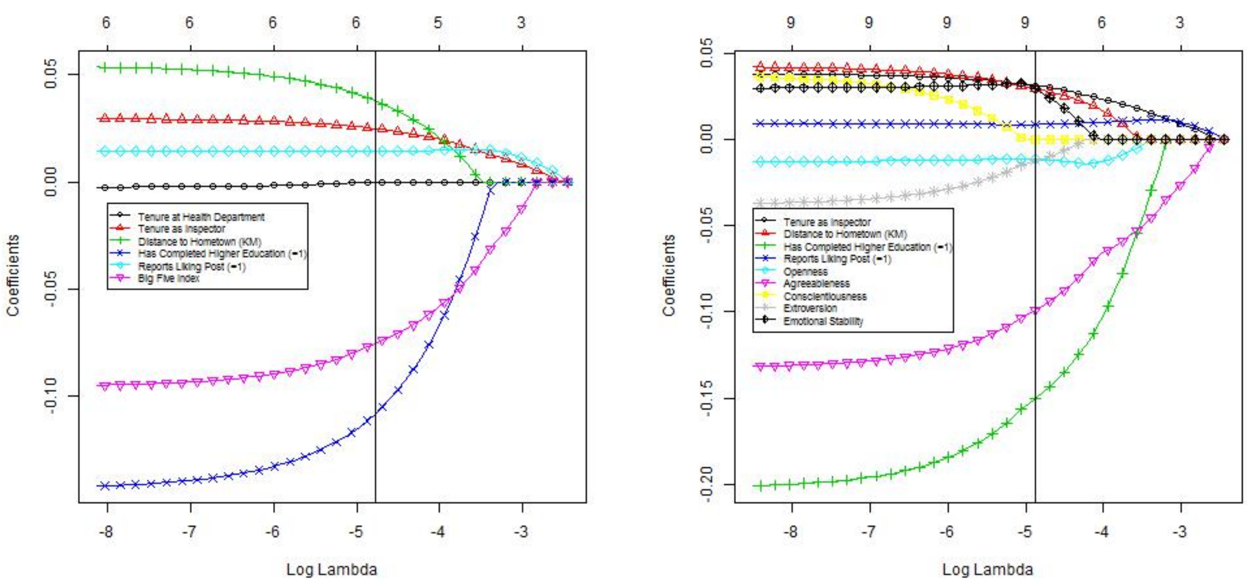


Figure A.7: LASSO model coefficients predicting health inspections—Big Five

Notes: Plots coefficient values from a LASSO model with health inspections as the outcome against possible values of λ in the model. Panel A plots coefficients for the following covariates: health inspector Big Five Index, years of tenure at the health department, years of tenure as an inspector, distance of the inspectors office to his hometown in KM, and dummies for whether the health inspector has completed higher education and reports liking his current post. Panel B replaces the Big Five Index with each of the Big Five traits individually. The vertical lines ares at the value of Log λ that minimizes the mean cross-validation error given the set of covariates. The upper X-axis reports the number of non-zero coefficients in the model at each value of Log λ.

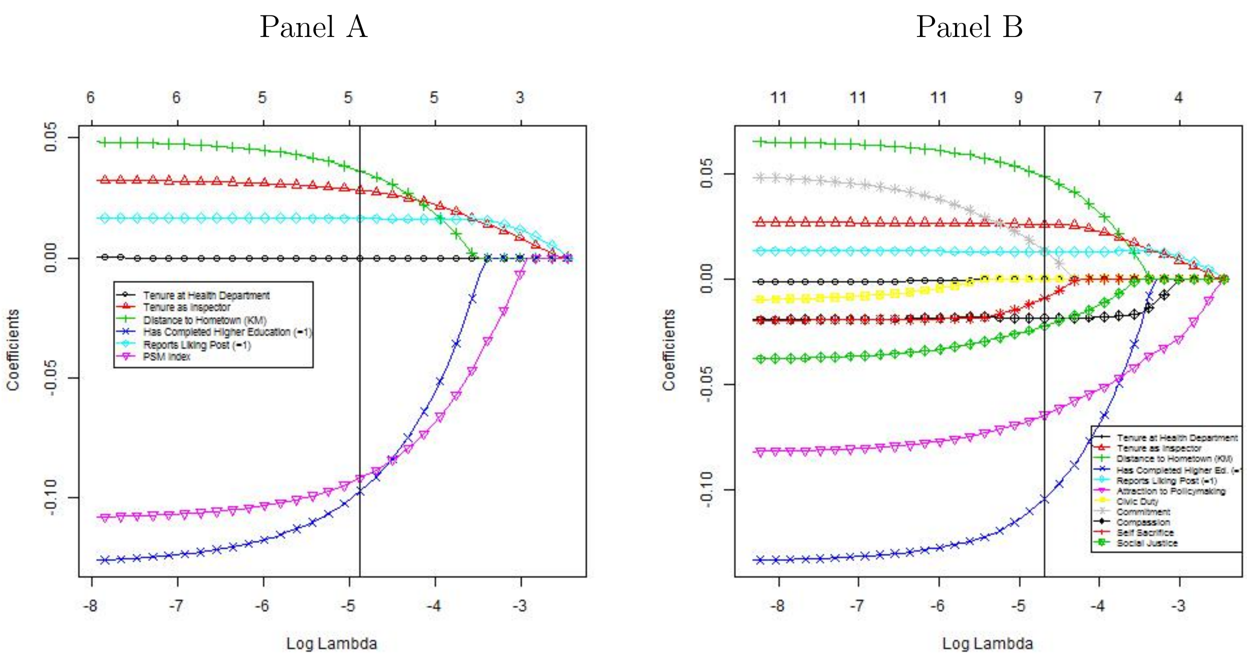


Figure A.8: LASSO model coefficients predicting health inspections—PSM

Notes: Plots coefficient values from a LASSO model with health inspections as the outcome against possible values of λ in the model. Panel A plots coefficients for the following covariates: health inspector PSM Index, years of tenure at the health department, years of tenure as an inspector, distance of the inspectors office to his hometown in KM, and dummies for whether the health inspector has completed higher education and reports liking his current post. Panel B replaces the PSM Index with each of thePSM traits individually. The vertical lines ares at the value of Log λ that minimizes the mean cross-validation error given the set of covariates. The upper X-axis reports the number of non-zero coefficients in the model at each value of Log λ.

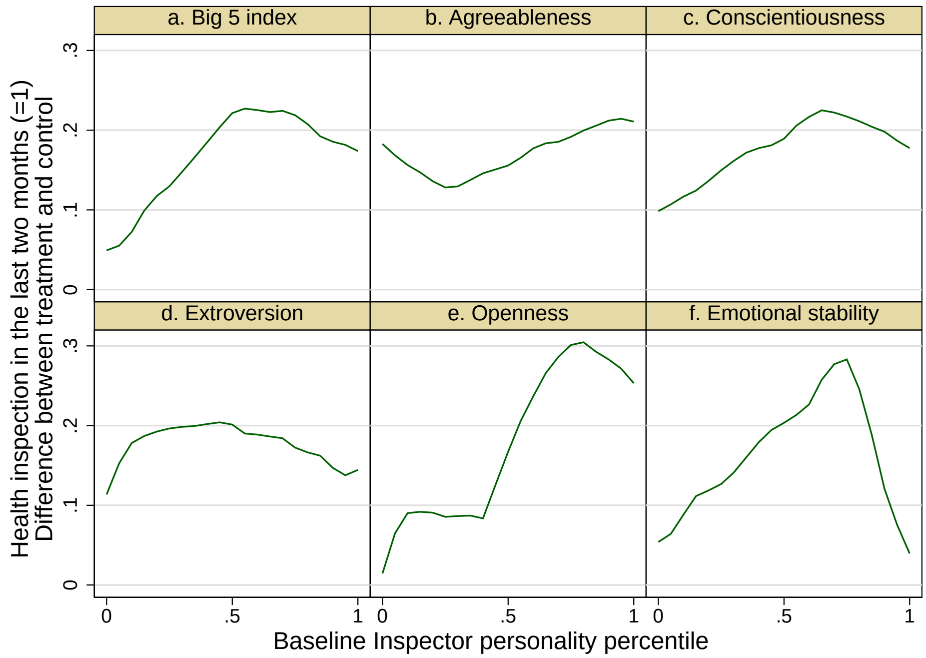


Figure A.9: Health Inspector Non-parametric Heterogeneous Effects, Trait-by-Trait, Big Five

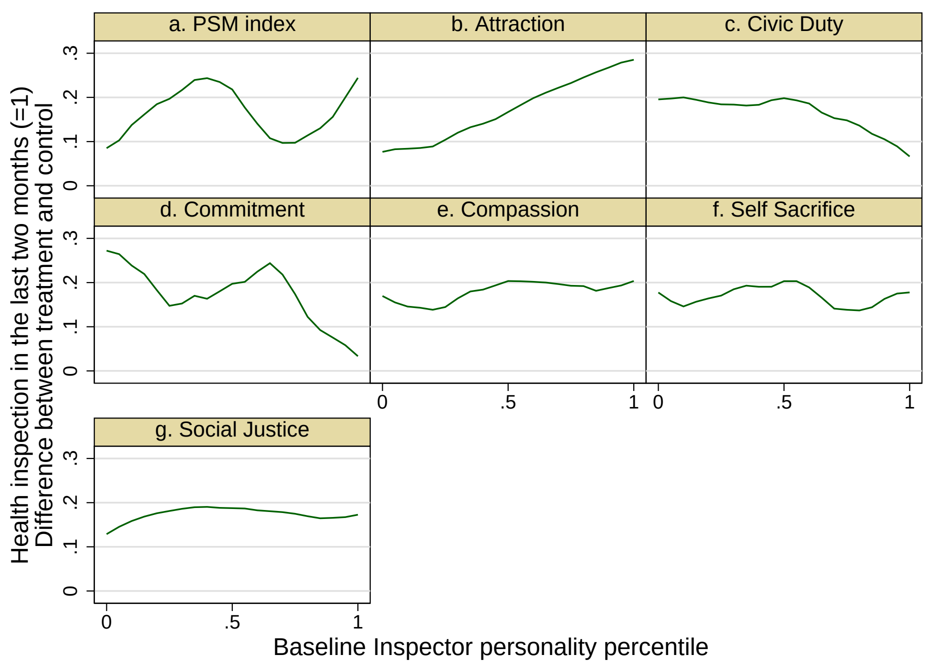


Figure A.10: Health Inspector Non-parametric Heterogeneous Effects, Trait-by-Trait, PSM

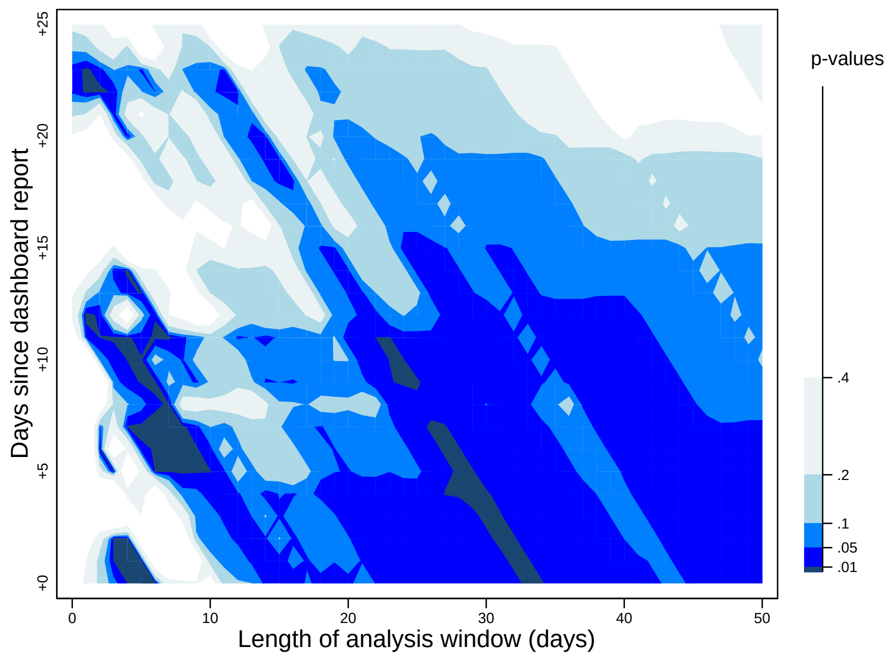


Figure A.11: Robustness to Different Windows for Flagging- Big Five Index

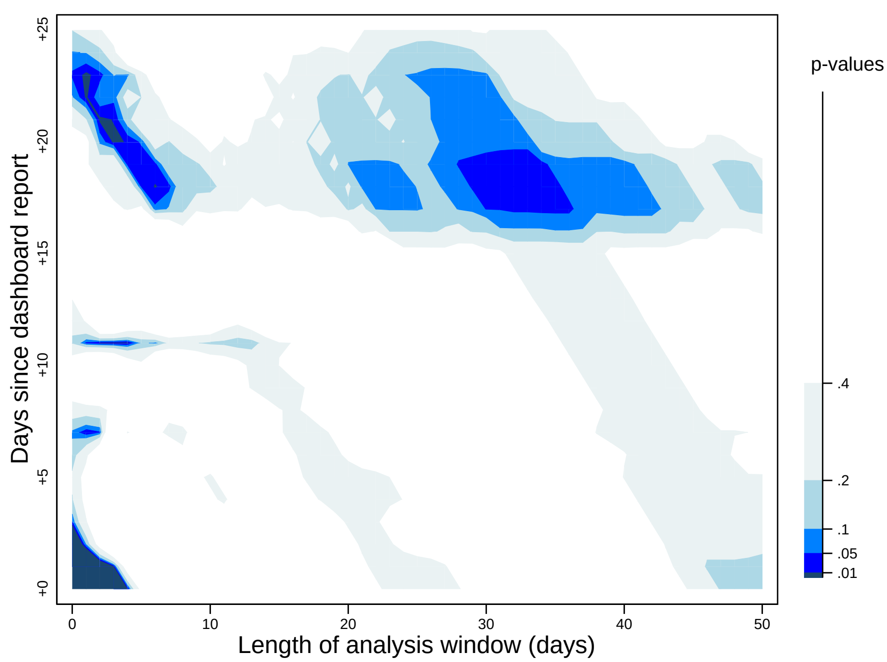


Figure A.12: Robustness to Different Windows for Flagging- PSM Index

A.4 Personalities Survey Instrument—Translation

Name

Designation

Union Council number

Name of BHU

HMIS code

Part 3

Medical Officer

(Self Reporting Section)

In this part of the on-going LUMS study, we are trying to collect data regarding the level of job satisfaction of health officers appointed in BHUs and the factors affecting their decision to retain their posts. We will be very thankful to you for taking some time out to fill out the form enclosed in this envelope, putting it back in and then handing it to the interviewer. We would like to remind you that, as with the rest of the survey, all of your responses for this section will be kept confidential by our research team and will not be shared by any official from the health department. Nevertheless, like before, your participation is voluntary.

Instructions for filling out the questionnaire:

1. Read every statement carefully and encircle the response you agree with.
    a. If you completely disagree with the statement, encircle (1).
    b. If you mostly disagree with the statement, encircle (2).
    c. If you are indifferent to the statement, encircle (3).
    d. If you mostly agree with the statement, encircle (4).
    e. If you completely agree with the statement, encircle (5).
2. This test has no concept of right or wrong, nor do you have to be an expert to solve it. Respond as sincerely as possible. Write your opinion as carefully and honestly as possible. Answer every question and ensure that for every response, you have encircled the right option. During the test, if you encircle the wrong option by mistake or if you change your mind after encircling a response, do not erase it. Instead, mark the wrong response with a cross and encircle your correct one.

Section 1

Statements:

1. Politics is a bad word
2. I respect elected officials who can convert good ideas to laws
3. The attitude of an elected official is just as important as his/her competency
4. I am indifferent to political give and take based on the concept of losing something to gain something
5. I don't care much for politicians
6. People do talk about the welfare of the general public but in reality they are only interested in their personal gains
7. It is very difficult for me to take a lot of interest in the events that take place in my community
8. I work selflessly for my community
9. Meaningful public service is really important to me
10. I would prefer that elected officials work for the welfare of the community even if it goes against my self interests
11. For a government employee, loyalty to the public should take precedence over loyalty to his/her officers
12. I consider serving the public my social responsibility
13. I believe that there are a lot of public issues that need to be addressed
14. I don't believe that the government can do anything to make the society more just
15. If any group is excluded from social welfare, we will stay in bad times
16. I am ready to spend every ounce of my energy to make this world a more just place
17. I am not afraid of raising my voice for the rights of others even if I am mocked for it
18. When government employees take their oaths, I believe that they are ready to take on responsibilities not expected from common citizens
19. I can go to any lengths to fulfill my civic responsibilities
20. Government service is the highest level of citizenship
21. I believe that no matter how busy a person is, it is his/her ethical responsibility to do his/her part in dealing with social issues
22. It is my responsibility to take care of the poor
23. The words 'work', 'honor' and 'country' evoke strong emotions in the bottom of my heart
24. It is my responsibility to solve the issues arising from mutual dependence of people
25. I am rarely moved by the plight of underprivileged people
26. A lot of social programs are very important and cannot be lived without
27. Whenever I see people in need, It becomes difficult for me to control my emotions
28. For me, working for the welfare of others is an expression of patriotism
29. I rarely think about the welfare of people I don't know personally
30. Day to day incidents make me appreciate time and again how much we depend on each other

31. I don’t feel any sympathy for people who don’t even bother to take the first step to fulfill their needs
32. There are only a few public programs that have my full support
33. For me, bringing a change in the society is more significant than personal success
34. I give obligations precedence over personal tasks
35. I consider being financially strong to be more important than doing good things
36. Most of the causes I work for are more important than my personal benefit
37. Serving the public is a source of satisfaction for me even if I don’t get anything in return
38. I believe that people should give more to the society than what they take from it
39. I am one of the few people who are willing to help people even if it leads to personal losses
40. I am prepared for any sacrifice for the welfare of the society

Section 2

Statements:

1. I plan everything in advance
2. I take decisions quickly
3. I save routinely
4. When I am away from my work I am eager to go back to my work
5. I can think of a lot of occasions when I kept on working diligently while others gave up
6. I continue working on difficult projects even when others opposed it
7. I like working on multiple tasks at the same time
8. Rather than completing parts of multiple projects, I prefer to complete one project every day
9. I believe that it is better to complete old tasks before starting a new one
10. It is difficult to know who my real friends are
11. I don’t try to do something that I’m not sure about
12. In general it can be said that the people in this area are honest and can be trusted
13. A person can become rich by taking risks
14. If, during the coming week, you inherit or receive a huge amount of money, would you still continue working with the health department?
15. How much money, if given to you, would convince you to leave your job or retire?
16. If someone finds your wallet which has Rs. 2000 in it, how likely do you expect is it that the wallet with the complete amount would be returned to you if the wallet was found by:
    a. Your neighbor
    b. The police
    c. A stranger

Section 3

Statements:

1. I am not depressed
2. I like to be amongst lots of people
3. I don’t like to waste time day-dreaming
4. I try to be polite to everyone I meet
5. I keep all my things clean and tidy
6. I often feel inferior to other people
7. I laugh easily
8. When I find out the right way to do something, I stick with it
9. I often get into quarrels with my family members and coworkers
10. I pace my work such that I am able to complete everything on time
11. Sometimes when I am under intense psychological pressure, I feel as if I am about to fall to pieces
12. I don’t consider myself to be a jolly person
13. Art and wonders of nature fascinate me
14. Some people think that I am selfish and egoistic
15. I am not a very organized person
16. I rarely feel lonely or sad
17. I really enjoy talking to people
18. I think that listening to controversial speakers can confuse students and lead them astray
19. I prefer cooperation over conflict
20. I try to complete all tasks entrusted to me according to my conscience
21. I often feel mentally stressed and anxious
22. I often long for thrilling situations
23. Poetry has very little or no influence on me
24. I am mistrustful and skeptical about the intentions of others
25. My objectives are very clear and I work to achieve them in a very organized way
26. Sometimes I feel completely worthless
27. I usually prefer to work alone
28. I often try new and exotic dishes
29. I believe that if you give them the chance, people will always exploit you
30. I waste a lot of time before starting to work
31. I rarely feel scared or depressed
32. I often feel full of energy
33. I don’t pay much attention to the moods and feelings evoked my surroundings and circumstances
34. People who know me usually like me

35. I work very hard to achieve my goals
36. I often get frustrated by the way people treat me
37. I am a jolly and optimistic person
38. I believe that we should consult religious leaders for making decisions involving moral affairs
39. Some people think I am cold-hearted and selfish
40. When I start something, I don't rest until I finish it
41. Often when things start taking a turn for the worse, I give up and abandon my work
42. I am not a jolly and optimistic person
43. Sometimes while studying poetry or looking at masterpieces of art, I feel chills of thrill and excitement
44. I am strict and stubborn in my attitude
45. Sometimes I am not as trustworthy as I ought to be
46. I am rarely sad or depressed
47. Fast pace is a highlight of my life
48. I have little interest in pondering over the working of the universe or the human condition
49. I usually try to be concerned and care about others
50. I am useful person and always do my work
51. I often feel helpless and wish someone else would resolve my problems
52. I am a very active person
53. I have a lot of intellectual curiosity in me
54. If I don't like someone I let him/her know about it
55. I feel that I can never keep myself organized
56. Sometimes I want to hide myself due to shame
57. I would prefer to live on my own terms as opposed to being a leader for others
58. I often enjoy abstract ideas and theories
59. If need be, I am ready to use people to get my own work done
60. I try to do everything perfectly

Section 4

Note: The following questions have two possible answers

1. Did you do any charity work during the past year?
2. Have you ever contested for an electoral seat?
3. Have you ever done any volunteer work?
4. Did you vote in the last election for the National Assembly?
5. Have you ever donated blood?
6. Do you visit the Masjid regularly?
7. Do you agree with this statement: "People can be relied upon"

8. Do you agree with this statement: “Rules are made to be broken”