Jobs for Sale: Corruption and Misallocation in Hiring

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Abstract

This paper investigates a common yet poorly understood form of corruption, the payment of bribes to acquire public sector jobs. I collect novel data from a hiring process for managerial positions in a developing country health bureaucracy, and find that hires paid large bribes, averaging 17 months' salary. I then characterize the structure of these markets, showing that job allocations are made as if via a first-price, winner-pay, sealed bid auction. To determine the consequences of corruption, I use a structural model of entry to determine the identity of hires under counterfactual hiring procedures, such as standardized testing, and compare them to actual hires. I identify the set of characteristics related to better delivery of health services and utilize an instrumental variable approach to demonstrate that the effects of these characteristics are both causal and of an economically large magnitude. Based on these characteristics, actual hires are of comparable or superior quality to the counterfactual hires, e.g. as compared to hires under a knowledge-based test, actual hires are 4.3-8.7 percentage points closer to the predicted optimal set of hires. This is in contrast to the previous literature, but explained by a mechanism in my model: although hiring decisions are based primarily on bribes, hires are high quality because applicant wealth and willingness to pay for the position are strongly positively correlated with quality. Applying this to a general model of hiring, I identify the environments in which corruption will lead to misallocation, discuss how anti-corruption efforts should be allocated, and argue for a greater focus on hiring for mid-level government managers.

Latest draft of the paper can be found here

1 Introduction

Development agencies have recently placed a major focus on corruption, with World Bank President Jim Yong Kim labeling it “public enemy number one” in developing countries. Most corruption research has focused on situations in which corruption acts as a tax on individuals or businesses (e.g. Olken and Barron 2009, Sequeira and Djankov 2014) or resources are siphoned by corrupt individuals (e.g. Olken).
This paper investigates a form of corruption about which little is known, the payment of bribes to obtain employment.

Corruption in the allocation of government jobs is widespread in many countries. Kristiansen and Ramli (2006) interviewed 60 Indonesian civil servants and found that all had paid a bribe in order to be hired; Russian Prime Minister Dmitry Medvedev once stated that all but 5 posts in Russia could be purchased (NewsRu 2008). Additional accounts from countries comprising over half the world’s population, such as China, India, and Nigeria, corroborate the ubiquity of markets for jobs. Such accounts are likely only the tip of the iceberg, since if there were a high probability of journalistic exposure for taking bribes, hiring agents would be unlikely to engage in corruption.

Existing treatments of corruption in hiring have assumed that low quality individuals will be hired (e.g. (Wade, 1985; Sukhtankar and Vaishnav, 2015; Muralidharan, 2015; Jauregui, 2014b)). Hiring of poor quality public sector workers could potentially have serious consequences, such as if corruption in health worker hiring leads to selection of incompetent health workers. Negative outcomes in hiring are particularly harmful since public sector workers often have a long tenure. However, in some cases, corrupt hiring may yield similar or superior outcomes to traditional selection processes. For example, if hires were paid at a socially optimal piece rate, the most productive would have the highest willingness to pay, and when jobs are allocated via bribery, those individuals would be most likely to be selected. The extent of misallocation in hiring due to corruption is thus an empirical question, but there is no empirical evidence for either case, likely due to the difficulty of collecting data. In this paper, I create a model and utilize an original dataset to provide the first estimates of misallocation from corrupt hiring procedures.

The paper begins with a model of hiring that establishes the conditions under which corruption will produce more or less misallocation. Given that anti-corruption capacity is limited, it is useful to know the settings in which corruption produces the greatest distortions so as to focus monitoring on those processes. In the model, candidates decide whether to apply for a job, and applicants make a private bribe offer to the agent responsible for hiring. This agent chooses among applicants based on bribe offers, applicant characteristics, or some weighted combination of the two. Hires pay their bribe offer, while others pay nothing. In the model, there are two mechanisms that determine the quality of hires. The first is the metric by which selection agents make their decisions; they may place some weight on applicant characteristics correlated with quality, leading to selection on quality. Second, selection based on bribes induces selection of wealthier applicants and those with higher willingness to pay/valuation. Thus if wealth and valuation are positively (negatively) correlated with quality, this engenders selection of better (worse) hires. The signs and relative magnitudes of these two mechanisms determine the result of corrupt hirings.

The second section of the paper describes original data that I collected from a hiring process for supervisors of rural community health workers (CHWs). This is, to the best of my knowledge, the first comprehensive data set on corruption in hiring. It includes information on both bribes paid by hires and bribe offers made by non-hired job applicants. Hires paid bribes averaging 17 months’ salary, an amount similar to other accounts of corrupt hiring processes. My data set is further unique in containing extensive

Note that the mechanism here differs from other cases in which corruption leads to efficient outcomes. In the other cases, an individual’s willingness to pay is defined to be equivalent to the social value of the good, and so allocation to the individual with the highest willingness to pay is socially efficient. Here, a hire provides services to others, and so allocating a job to the person with the highest willingness to pay need not be socially optimal if that person is not the best service provider.

Kristiansen and Ramli (2006) find an average payment of 2.5 years salary for 60 civil servant positions in Indonesia. Journalistic sources have reported other similar pricing: Afghani border officials- $15,000 (Walsh, 2014); Afghani provincial
information on not only those selected for a given position, but also on the full sample of applicants and those eligible to apply for these positions. I use this, alongside job performance data, to establish the effect of corruption on quality of hires.

The data comes from a rural area of a large developing country. This area contains approximately 2 million individuals, 1200 active CHWs, and 70 CHW supervisors. Due to concerns about individuals who assisted the data collection being identified and retaliated against, it was agreed that the identity of the country would be removed from the paper. Exposing corruption in developing countries can be costly: there are many cases of anti-corruption activists or bureaucrats losing their jobs or even being murdered for fighting against corruption. This precaution is similar to that taken in Tran (2015) and Cole and Tran (2011), which utilize a firm’s records of bribe payments in procurement auctions.

Third, I empirically characterize the structure of the market and how hiring decisions were made. Since bribe offers and characteristics of both hired and non-hired applicants are observed, the preferences of selection agents can be recovered from their hiring decisions, i.e. their revealed preference over applicants. Hiring decisions are made almost entirely based on bribe offers, with a small weight placed on having political connections and the educational attainment of the applicant. Given most of the decision is based on bribe amount, the model indicates that the correlations between quality/willingness to pay and quality/wealth will be the primary determinant of hires’ quality. I demonstrate that valuation and wealth are both positively correlated with higher quality, which implies that relatively high quality individuals should be selected.

Fourth, I evaluate the quality of hires with measures such as education and job-specific knowledge tests. My data set contains extensive information on not only applicants and those selected for a given position, but also the universe of those eligible to apply. This allows me to compare across two margins: 1) selection into the pool of applicants (comparing across those who applied and those who did not); and 2) selection from among the pool of applicants (comparing hired and non-hired applicants). Examining both margins is important since both the decision to apply and selection among applicants may be affected by corruption, e.g. high quality applicants may select out of applying if they know that selection is based on bribery rather than merit. I document significant positive selection along both margins on most observable dimensions of quality, with no evidence of negative selection. In other words, despite the fact that bribery determined most of the hiring decisions, those that applied were stronger than those who did not apply, and those who were selected were stronger candidates than those who were not selected.

Fifth, although this suggests that hires are of a high quality, it may be that these measures are not actually related to performance in this position. I collect multiple measures of supervisor performance, such as performance evaluations and process data, as well as the main policy outcome of interest, delivery of health services. Using a LASSO estimator, I find five supervisor characteristics that are predictive of

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3 see [1][2][3][4][5][6] for examples of such retaliation over the last 12 months
4 Only current community health workers were eligible to apply for the position, and information is collected on all the health workers in the area.
improvements in health services delivery after hiring, and show that there is positive selection on all but one of these characteristics. Based on these estimates, I construct a formula to predict performance as a supervisor for all possible candidates. There is a strong positive selection on this measure at both the application and hiring stages, demonstrating that hires are of a high quality.

Furthermore, this relationship is large in magnitude: estimates suggest that hiring a supervisor with 1 SD higher value on the predicted quality index leads to a 37% increase in TB patients served and a 7% increase in institutional deliveries (as opposed to home births), among other outcomes. This finding highlights the importance of selecting high-quality supervisors and suggests that hiring of high quality mid-level bureaucrats could have large returns in developing country bureaucracies. One concern with this strategy is that assignment of workers to supervisors may be endogenous, and so the improvements in service delivery are not attributable to the supervisor. As a check, I leverage a source of exogenous variation in the supervisor-worker match and construct an instrument for the predicted quality of supervisor assigned to a given worker. Results based on instrumented supervisor quality are nearly identical.

Sixth, I make counterfactual comparisons between the hires and those who would have been hired under alternative selection methods, such as a knowledge-based test. I create and estimate a structural model of candidates’ application decisions and the selection agent’s allocations under alternative selection methods. Surprisingly, those hired based on bribery compare favorably to those who would have been hired under counterfactual hiring systems. For example, as compared to hires under a knowledge-based test, actual hires are 4.3-8.7 percentage points closer to the predicted optimal set of hires; applying estimates of how supervisor characteristics affect services, this is equivalent to a 9-15.9% increase in tuberculosis patients served, a 3.6-6.4% increase in newborn checkups performed, and a 3.5-6% increase in institutional deliveries, among other positive outcomes.

I also find that some counterfactual hiring systems substantially outperform others. For example, selection based on a test of problem-solving ability outperforms the observed selection process and greatly outperforms selection based on the knowledge-based testing instrument, perhaps because general problem-solving ability is more important for a manager. However, in other settings, where job-specific knowledge is more important for performance, the relationship might be reversed. This indicates the importance of identifying factors related to better performance and explicitly crafting hiring systems to select on those factors.

The paper concludes with a discussion of corruption in hiring for other types of jobs. For the studied hiring process, the positive correlations between willingness to pay/quality and wealth/quality resulted in minimal allocative inefficiency. However, there are many environments where these correlations are likely to be negative, leading to low quality hires. I discuss the determinants of the correlations and create a table listing the types of positions in which misallocation is most likely, such as hiring of police officers. For policymakers interested in improving civil service quality, it is useful to know the types of job for which corruption in hiring will have the most distortionary impact and thus for which monitoring of hiring processes will have the highest return. I also discuss different ways in which hiring systems may be corrupted (e.g. test score-based regimes in which individuals can pay bribes to receive unmerited high scores), and how these systems compare to the one observed in this paper.

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literature on corruption in hiring to address a broad set of research questions. The only other papers on contemporary markets for jobs are purely descriptive [Wade 1982, Kristiansen and Ramli 2006, Zhu 2008, Engvall 2015]. Their data comes from small, convenience samples, and the papers do not look at the quality of hires. In economics, this area has been unexplored empirically outside of the historical sale of offices in medieval Europe (e.g. Allen 1998, 2005), colonial governorships (Guardado 2016), and tax farming (e.g. Johnson and Koyama 2014, White 2004). As these papers are historical in nature, they typically lack the data to look deeply at quality or performance of those purchasing their positions. These also differ from the context of this paper since they are about the sale of offices by the state. In the contemporary context, sale by unauthorized, non-state actors is much more common, with potentially more negative consequences. A separate literature examines the role of nepotism or ethnic connections in selecting and deploying civil servants (e.g. Fafchamps and Labonne 2015, Ponzo and Scoppa 2010, Scoppa 2009, Iyer and Mani 2011), but not the role of bribery or how bribery interacts with these factors. These papers are also limited in their ability to comment on service delivery outcomes.

Second, the paper provides evidence on the importance of managers in developing country bureaucracies. I show that quality of managerial hires is important for service delivery, where supervisors with particular characteristics are able to elicit increased performance by those that they supervise. Given the dysfunction of many developing country bureaucracies, the magnitude of the effects is noteworthy. This is related to evidence on monitoring of developing country health workers (e.g. Hanna and Wang 2014, Callen et al. 2015) as well as the literature on the importance of management practices (Bloom et al. 2013, 2015). These results suggest that improving quality of mid-level managers in developing country bureaucracies is an effective way of improving service delivery and should be a greater focus of reforms.

Third, this paper contributes to the study of the structure of corrupt markets. Existing papers in this literature are from very different settings, such as petty police bribery (e.g. Olken and Barron 2009), kickbacks to businesses in bidding (e.g. Cole and Tran 2011), and bribery of customs officials (e.g. Sequeira and Djanikov 2014). Similar to Olken and Barron (2009) and Burgess et al. (2012), I confirm the utility of IO models for describing corruption (in this case, auction models), and, based on these models, discuss policy responses.

Fourth, this paper is closely related to the literature on recruitment and hiring of public sector workers. These papers, such as Dal Bo et al. (2013), DeSerranno (2014), and Ashraf et al. (2014), attempt to understand how different hiring schemes, such as changes in compensation or advertising, change the pool of applicants for a given position, and through this, who is selected. Similarly, Hanna and Wang (2014) and Banerjee et al. (2015) show that those who act more dishonestly in lab experiments are more likely to apply for government jobs. While those papers focus on selection of potential candidates into applying, this paper looks at selection both into and from the applicant pool. While it considers a specific case, the selection of candidates under corruption, it is one that has import in many developing country contexts.

Fifth, the paper speaks to broad questions of governance and service delivery in developing countries. As in Banerjee et al. (2008), Ferraz et al. (2012), Olken (2007), and Duflo et al. (2012), the focus is on how corruption may reduce the level of service provision by government agents. Unlike those papers, which focus on graft and absenteeism by public sector workers, this paper looks at an earlier step in the process, how the characteristics of selected civil servants influence their delivery of services.

The remainder of the paper is organized as follows. Section 2 creates a theoretical model of bribery in
hiring. Section 3 details the context and the data collection process, focusing on methods used to elicit data on bribery. Sections 4 and 5 provide results on the nature of the selection process and quality of hires. Section 6 estimates a model of job search and uses this to compare the selected applicants to those who would be selected under counterfactual selection processes. Section 7 discusses applying the model to other contexts and Section 8 concludes.

2 Model

The existing theoretical literature on corruption and personnel decisions deals with developed country firms rather than developing country governments. Firms face a different problem than governments, since they can make the selection agent a partial claimant on firm profits, incentivizing them to make the firm’s desired hiring decisions. Government agencies cannot do this, and as a result, corruption is likely to be more prevalent in public sector personnel decisions. It is thus necessary to develop a new theory focused on this problem. This section reframes the problem of hiring as a game of incomplete information between potential applicants and the selection agent. Utilizing an auction structure leads to simple theoretical predictions and significant power in explaining outcomes. This is also consistent with the collected data and journalistic accounts from other contexts.

2.1 Model

The setting is modeled as a game between two sets of players: candidates vying for a single job opening and a selection agent who decides to whom the job will be allocated. Each candidate must decide whether to apply for the job, and those who apply make a private bribe offer to the selection agent. The selection agent allocates the job to the applicant maximizing the selection agent’s utility, and if selected agent offered a bribe, then they pay the specified amount to the selection agent. I assume that only the person hired makes a payment, meaning that this is a winner-pay sealed bid auction. Corrupt selection agents may not always use a winner-pay, sealed bid auction, but are observed to do so here; section 7 considers alternative allocation mechanisms.

Candidates Each candidate $i$ is a member of a set $I$ of $N$ potential applicants. A candidate $i$ is characterized by a vector $\zeta_i = \{C_i, v_i, W_i, \alpha_i\}$ containing four attributes: an individual-specific cost of

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6 One strand of the literature follows work by Milgrom (1988) and focuses on influence costs, in which agents can exert socially unproductive effort into developing relationships that aid their promotion. Another set of papers considers favoritism (e.g. Prendergast and Topel 1996; Chen and Tang 2015), in which hiring agents have exogenously set preferences for promoting a certain group of workers. Both of these literatures consider advancement within a firm, where incentivizing effort is the key issue. This is different from hiring, where the main problem is selecting high quality applicants. Two papers (Kim et al. 2004; Fairburn and Malcomson 2001) explicitly consider bribery within a firm, but both examine incentive effects on current workers rather than hiring. These papers omit ex-ante differences in worker quality, while quality is the main focus of this project. The most similar work to this one is Ponzo and Scoppa (2011), which combines influence costs and bribery in the context of hiring decisions. However, in their setup, the hiring decision is solely based on influence costs, but in the context of this paper, influence costs are not relevant.

7 An all-pay auction is unlikely for two reasons. First, if unsuccessful applicants made payments, they will have an incentive to expose the corruption of the selection agent in hopes of having their payment returned; the selection agent wants to minimize this risk. If unsuccessful applicants do not make a payment, it is likely to be too personally costly to report the selection agent. Second, those who pay and did not receive a job may retaliate with violence or with other extra-legal methods. Based on other accounts and in my data, I find no evidence of all-pay auctions used in markets for jobs. In my data, applicants paid their bribe value and submitted the bids in apparent secrecy, as in a first-price, sealed bid auction.
applying for the job, $C_i$, a valuation for the job, $v_i$, a wealth level $W_i$, and a vector of other personal characteristics $\alpha_i$. I assume that each $\zeta_i$ is an independent draw from the distribution $f(.)$, i.e. $\zeta_i \sim f(.)$. Players simultaneously and privately select an action $y_i \in e \times b$, where $e \in \{0,1\}$ is the choice to apply and $b$ is a bribe offer. Players that are hired for the job receive a payoff of $v_i - b_i - C_i$. Non-hires have a payoff of $-C_i$ if they applied and 0 if they chose not to apply.

I additionally assume that each candidate $i$ faces a credit constraint when offering a bribe $b_i$, where $b_i \leq W_i$. In the context of this paper, survey results suggest credit constraints. Of those with a positive valuation for the job, but who chose not to apply, 40% stated that they did not apply because they did not have enough money. Credit constraints are likely to be a general phenomenon in corrupt hiring processes given that jobs offer large, long-term rents. Applicants for a job presumably do not have resources on-hand approaching that value; if they did, they might not need the job. Furthermore, credit constraints in developing countries are well-established, and lending institutions may be unwilling to extend credit for bribes. While the assumption of only being able to pay bribes from wealth, i.e. no credit markets, is a simplification, it reflects the reality that wealthier applicants are less credit constrained.

**Selection Agent** The selection agent is characterized by a preference function $h : b \times \alpha \rightarrow \mathbb{R}$ that maps from a candidate’s characteristics and bribe offers into the agent’s utility. The selection agent picks a candidate $i$ from the set of entrants $E$ in order to maximize their personal utility. For simplicity, I assume that there are no complementarities between elements of $b \times \zeta$, and that $h(b, \zeta) = \pi b + \theta \alpha$ takes a linear form, where $\pi$ is the weight placed on bribe values and $\theta$ is a vector of weights placed on various dimensions of $\alpha$.

The value of $\pi$ and $\theta$ in the selection agent’s utility function will depend on the institutional context. If a selection agent does not care about the productivity of hires, they will have little incentive to hire a quality person and so it may be that $\theta = \vec{0}$. On the other hand, they may be motivated by fear of punishment for hiring poor quality applicants or value hire quality because it directly boosts their future payoffs or they care about social welfare. Rather than modeling these factors explicitly, I treat $h(b, \alpha)$ as their reduced form representation, where the linear weights take on values to incorporate these factors. For example, if there is an increasing probability of being punished for hiring someone with low education, instead of modeling the punishment function, the dimension of $\theta$ related to education increases to incorporate the probability of punishment. Ongoing work in a separate project considers various levers that an anti-corruption policymaker can use to influence the selection agent and the resulting implications for quality of hires.

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8 Valuation is equal to the difference in utility for the candidate between getting the job and remaining in their current job. The cost of applying for the job is equal to any costs incurred in the application process, such as travel for an interview or studying for an exam. It does not include any bribe payments. The additional characteristics $\alpha_i$ may be relevant to the selection agent’s utility, such as the candidate’s political connections, or to the candidate’s productivity in the job, such as job relevant skills.

9 I also explicitly test for constraints by showing that wealth shocks strongly affect application decisions and bribery, which should only happen if bidders are credit constrained (see section 4.1).

10 Credit constraints could be incorporated more realistically as an increasing marginal cost of finance for bids greater than wealth, as in Che and Gale (1998), but this substantially complicates the model.

11 Section 4.2 explicitly tests for and reject complementarities in the data. Appendix section C.4 discusses the theoretical reasons why lexicographic preferences are unlikely to occur, as well as evidence against them in the data.
Information Structure  In the model, candidates are unable to observe others’ $\zeta_i$ or bids $b_i$, but know the distribution $f(\cdot)$ from which $\zeta_i$ is drawn and total number of other candidates, i.e. this is an independent private values context. Given the difficulty of observing valuation or factors relevant to selection, such an assumption seems plausible. If it were possible to observe the bids of other candidates, this would simply be an English auction, and the general predictions would remain the same. The selection agent is assumed to be unable to observe candidates’ $v_i$ and $W_i$, but perfectly observes $b_i$ and $\alpha_i$.

2.2 Solution

In order to build intuition, I first solve for the simple case where $\theta = 0$, i.e. the selection agent only cares about bribe offers, and there is no cost of entry. I progressively add features that build towards the complete model. For simplicity, assume that bidders all draw $v_i$ from a uniform distribution over $[0, 1]$, where draws are independent across bidders and bidders cannot observe the draw of others. Let $b(x)$ be the function mapping from valuation to bids and a commonly known proportion of the bidders be constrained by their wealth $w_L$, where they cannot offer bids of value greater than $w_L$. The set of credit constrained bidders $i$ are denoted as $i \in C$, or having $c = 1$, while the unconstrained $i \notin C$ have $c = 0$.

I solve for a symmetric, pure strategy equilibrium. A bidder will select $b_1$ to maximize expected utility, $(v_1 - b_1)P(b_1 > \max \{b(v_2), \ldots, b(v_n)\})$. Appendix C.1 demonstrates that the following bid strategy will hold in equilibrium:

**Proposition 1 (Equilibrium Bid Strategy with Credit Constraints, No Cost of Entry, $\theta = 0$)**

The bid function, $b(v, c)$ will be equal to the below. Over a range $v \in [0, m_1)$, the bid function of low and high wealth bidders is the same. At $m_1$, the high wealth (unconstrained) applicants prefer to bid more than $w_L$ so as to have a higher bid value than any low wealth bidders (constrained). For low wealth bidders, the bid function increases over $[m_1, m_2)$, and at $v = m_2$, they prefer to bid $w_L$. The bid function is constant at $w_L$ over $v \in [m_2, 1]$.

$$b(v, c) = \begin{cases} \frac{N-1}{N}v & \text{if } v \leq \min \{m_1, m_2\} \\ \frac{(1-p)N-1}{(1-p)N}v + \frac{K}{v(1-p)N-1} & \text{if } v > \min \{m_1, m_2\}, c = 0 \\ \frac{p^N-1}{p^N}v + \frac{1-p}{p^N}m_1v^{1-pN} & \text{if } m_2 > v \geq \min \{m_1, m_2\}, c = 1 \\ w_L & \text{if } v \geq m_2, c = 1 \end{cases}$$

Depending on the parameters, there may be a discontinuity at $m_2$ as constrained bidders pool at a bid of $w_L$. $m_2$ may also be the point at which the bid function for the unconstrained equals $w_L$. The value of $m_2$ is derived in the appendix. At significant algebraic cost, it is straightforward to extend this to $N$ levels of credit constraints, i.e. where each bidder has a different level of wealth.\textsuperscript{14}

\textsuperscript{12} Data on bribe offers by hires and non-hires are more consistent with a sealed bid auction. If an English auction were used, we would expect the first and second place bids to be separated by a small margin, which is not typically the case.

\textsuperscript{13} As discussed in the appendix, it is trivial to generalize this to general probability density functions over wealth and valuation where both are unobservable, but comes at an algebraic cost with no qualitative benefit. With these simplifications, there are intuitive closed form solutions.

\textsuperscript{14} The nature of each candidate’s bid function will depend on the parameters of the model, but the iterative intuition for its construction is simple. Imagine that candidates had one of three levels of wealth. There will exist a value $m_1$ such that over $[0, m_1)$, the function mapping between valuations and bids will be the same across the groups. To solve for $m_1$, the same
The model predicts that wealthy (unconstrained) and high valuation candidates are more likely to be selected because they offer larger bids. However, this version of the model does not allow for entry, which is an important component of the application process. To incorporate this margin, I solve for a symmetric, pure strategy equilibrium where, for simplicity, all applicants have the same cost $C_i = C$ of applying. Section C.2 shows that two types of bid functions are possible depending on parameter values (e.g. $p, w_L$):

**Proposition 2 (Equilibrium Bid Strategy with Credit Constraints, Cost of Entry, $\theta = 0$)** Two types of bid functions are possible. The first case is qualitatively the same as the above, but there is some $\nu$ such that $\forall \nu \leq \nu$, $b(\nu, c) = 0$ (left-side panel in 2). Under the second, there also exists a $\nu$ s.t. $\forall \nu < \nu$, $b(\nu, 1) = 0$, but for unconstrained candidates, $b(\nu, 0) > w_L$ for $\nu \geq \nu$. The remainder of the bidding function is qualitatively the same as before (right-side panel in 2).

The solution strategy is used: finding the point where those in the second highest wealth group prefer to leap-frog those in the lowest group. This will also hold true for those in the highest wealth group at the same valuations. Next, after solving for the bid function for the second highest group, it remains to solve for the point at which the highest wealth group prefers to leap-frog the second-highest given the candidate bid function. If this point is less than $m_1$, this slightly changes the shape of the bid function, but the intuition is the same. For $N$ levels of wealth, there are increasingly complex conditions on the piecewise bid functions, but the process of construction is the same.
In this case, the predictions on bids are the same, but level of wealth may affect the valuation at which candidates choose to apply for the job. In the second case, higher wealth candidates enter at lower valuations and bid more than the lower wealth candidates can afford. The type of bid function that results will depend on the parameters (see appendix section C.2 for the conditions). For example, the second case is more likely when there are more low wealth candidates, since it is then more advantageous for low valuation, high wealth candidates to enter and outbid them.

Finally, it may be the case that a selection agent cares about a combination of bribes and applicant characteristics, selecting the applicant whose combined package of bribe offers and characteristics maximizes the function \( \pi b_i + \theta \alpha_i \). These applicant characteristics might include positive inputs to productivity, such as education or job-specific skills. For simplicity, assume that \( \alpha \) is uni-dimensional, \( \alpha \in \{\alpha_L, \alpha_H\} \) and \( \alpha_L < \alpha_H \). This case does not admit a closed form solution (see section C.3 for details), but has intuitive results. In particular, candidates with \( \alpha = \alpha_H \) will enter at lower valuations than those with \( \alpha = \alpha_L \), as well as being more likely to be selected.

There are three main predictions of the model that are testable in the data. First, those with higher valuation, wealth and values of characteristics in the selection agent’s utility function will be more likely to apply. Second, probability of applying is decreasing in the valuation/wealth/selected-upon characteristics of potential opponents. Third, bids will vary positively with applicant valuation and wealth, but negatively with the value of characteristics that the selection agent selects upon. This is because applicants with higher values of those characteristics can shade their bids by more.

Under this model, the quality of selected applicants will depend on three factors. The first is the correlation between the selected upon dimensions of \( \alpha_i \) and job performance. If the selection agent makes hiring decisions based even partially on characteristics relevant to job performance or correlated with those relevant to job performance, this affects the quality of hires.

Second, the correlation between valuation and quality will determine the quality of hires. If higher valuation candidates tend to be of a higher quality, this leads to positive selection on quality since higher quality candidates will offer larger bribes (e.g. if there are higher returns to quality in this position relative to outside options). On the other hand, if the correlation is negative, this leads to lower quality hires (e.g. if the candidates who will extract the most bribes in the position are willing to pay the most).

Third, if credit constraints bind for at least some applicants, the correlation between wealth and quality will be important for the quality of selected hires. If the correlation is positive (e.g. if wealthier individuals have a higher stock of human capital), this leads to selection of higher quality candidates, and if it is negative, this causes selection of lower quality candidates (e.g. if wealthier individuals are more politically connected and so less subject to censure for poor performance). If few candidates are credit constrained, then valuation will be the primary determinant of bid values, and so the valuation/quality correlation will be more important. Section 7 discusses why correlations will take on certain signs and values, and how this varies across different types of jobs.

The importance of each of these factors depends on the relative size of \( \pi \) and \( \theta \). If \( \theta \) takes on a small or zero value across all of its dimensions, then selection will primarily be based on bribe offers. As a result, the quality of hires will depend on the correlations of wealth and valuation with quality. On the other hand, if applicant characteristics are the primary determinants of the hiring decision, then valuation and wealth will determine fewer of the hires, and so their correlations will be less important. In section 4.1 I explicitly
estimate the selection agent’s utility function in my data and use these estimates to make predictions on
the quality of hires. These quality predictions are confirmed in section 5.1.

These findings are highly related to theoretical work on government allocation of permits, such as Banerjee (1997) and Esteban and Ray (2006). In those settings, agents have a valuation for a slot (which could be a license, or, as in this case, a job) and attempt to acquire it through bribery or lobbying. However, in their models, the social value of allocating a slot to a particular agent is necessarily equal to the agent’s valuation for the position, while mine allows the two to differ. In Esteban and Ray (2006), wealth confounds the ability of the government to allocate slots to the highest valuation individual, who is assumed to also be the socially optimal beneficiary of the slot. In my setting, the wealth confound could improve outcomes if wealth is more positively related to social value of allocations or conveys an additional signal value\(^\text{15}\). As discussed further in section 7, allowing the correlation between valuation, wealth, and social welfare to vary can lead to substantially different predictions from previous work.

3 Data and Context

3.1 Setting

Community health worker (CHW) programs have taken on an increasing importance in developing countries with over 5 million CHWs globally\(^\text{16}\). In general, these programs attempt to extend health care services among underserved populations, fill healthcare gaps in areas with low coverage of skilled providers, and provide targeted services for which a highly skilled provider is not required. CHW programs often focus on promotion of health literacy (e.g. usage of oral rehydration salts, importance of breastfeeding) and distribution of nutrition supplements (e.g. vitamin-A, zinc or iron folate tablets) and medicines. CHWs may also take on more complicated roles, such as delivering babies, giving medical advice, or serving as tuberculosis DOTS treatment providers. In contrast to doctors and nurses, CHWs are usually hired without having an extensive background in health. Instead, they are provided training by their hiring organization, with a focus on the tasks they will perform. CHWs usually live in the communities that they serve since these local linkages are thought to be crucial in effectively extending their services.

The data in this study are from a rural area of a large developing country. The study area contains approximately 2 million individuals and is served by 1200 active CHWs. I study the hiring of 70 supervisors for these CHWs, each of whom oversees 15-25 CHWs. Due to concerns about individuals who assisted the data collection being identified and retaliated against, it was agreed that the identity of the country would be removed from the paper. Exposing corruption in developing countries can be costly: there are many cases of anti-corruption activists or bureaucrats losing their jobs or even being murdered for fighting against corruption\(^\text{3}\).

In the study area, all of the CHWs are women hired from the communities that they later serve and are given training by the government. The typical CHW is between 30 and 40 years of age, married (94%), and has between 8 and 12 years of education (median is 10 years). Depending on the local geography, an individual CHW typically provides services to between 850 and 1500 individuals. On average, CHWs\(^\text{15}\) For example, suppose that there is large variation in individuals’ propensity for corruption, and so the most corrupt were willing to pay the most for the job, producing a negative correlation between quality and valuation. If wealth and quality were positively related, this would partially disrupt the selection on valuation, leading to better outcomes.\(^\text{16}\)See this map for a visualization of CHW programs in Sub-Saharan Africa
Table 1: Applicants Per Competition

<table>
<thead>
<tr>
<th>Number of Applicants</th>
<th>1 (Uncontested)</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7 or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of Contests</td>
<td>3%</td>
<td>11%</td>
<td>21%</td>
<td>13%</td>
<td>21%</td>
<td>12%</td>
<td>20%</td>
</tr>
</tbody>
</table>

earn slightly more than the median household income in the area and have substantial attachment to their work: sixty percent expect to remain in their current CHW position for the rest of their lives, while an additional 24% expect to remain as health workers, but be promoted. Such attachment is a function of their relatively high pay and job security.

The primary responsibility for these CHWs is provision of health services to pregnant women and children. The average CHW has an clientbase of 11.5 pregnant or recently delivered women, and visits each around once a month. During the visits, they distribute iron supplements (to an average of 6.8 women within the two months prior to the survey), provide basic antenatal counseling, and perform post-natal checkups on newborns. They often serve as frontline health workers, with over half having been visited within the week prior to the survey for medical advice. This is typically for issues related to women’s health, minor ailments such as fever and diarrhea, or detection of more serious conditions that require hospitalization. Over the month prior to the survey, the median CHW distributed 6 oral rehydration salt packages and 5 paracetamol tablets (used for reducing fever). Slightly less than half have served as tuberculosis treatment (DOTS) providers, and at the time of the survey, 25% had actively worked as a DOTS provider in the previous six months. While the CHWs provide additional services, this gives a snapshot of some of their most important functions.

Proper supervision is critical as a check on worker effort and quality of services. Prior to the hiring studied in this paper, CHWs lacked supervisors specifically tasked with monitoring their work. In an attempt to improve services delivery, program heads decided to hire supervisors to: 1) Go at least once a month to the village of each CHW in order to review their records; 2) Go through the village to confirm that a CHW is properly carrying out their work; 3) Observe CHWs during their duties to provide feedback; 4) Collect data on scope of CHW activities and giving feedback, based on centrally-defined criteria, on whether a given CHW’s performance is satisfactory; and 5) Holding meetings at which they provide training and individual-level feedback for each CHW.

Only current CHWs were eligible to apply to become a supervisor, and all were informed about the nature of the position and pay. Since I collect information on all the CHWs, I thus observe the universe of potential applicants. All current CHWs were grouped into geographically based clusters of 15-25, from and for which one supervisor would be hired. 34% of CHWs applied for a position as a CHW supervisor, and most competitions were relatively competitive, as seen in table 1. Supervisors are compensated on a salary basis, with the average supervisor earning 40% more than they had as a CHW. Given their lack of direct financial incentives to supervise and the general difficulty of motivating managers, it is important to select managers who, due to prosociality or other motivations, will perform tasks for which they are not directly incentivized.

Higher-level government officials attempted to standardize selection via a clearly defined points system, with a committee of local health officials responsible for implementation. Under this system, applicants would be assigned points based on their past work as a CHW, education, and an interview with the hiring committee. The applicant within a cluster who had the most points was supposed to be assigned the
position, but as shown below, allocations were instead made on the basis of bribery.

Based on data collected from CHWs, supervisors typically visit CHWs in their villages between once and twice a month, with each visit lasting between 1-2 hours. During these visits, they almost always review the records and recent work of the CHW (96% of visits) and give feedback and advice (81% of visits). In around half of visits, they directly observe the CHW’s work in the village, such as their counseling of pregnant women. CHWs generally appreciate their supervisors, with 71% telling surveyors that their supervisors are helpful or very helpful, and only 6.5% stating that their supervisors are not helpful. Section 5.1 shows that some supervisors notably improve the performance of their workers, while there is little change in performance among workers under the worst supervisors.

### 3.2 Data Collection

The survey data used in this paper were collected in two rounds (see Appendix B.1 for details). For both rounds of surveying, CHWs and supervisors were contacted via phone, and appointments to take the survey were scheduled at a convenient central location. Respondents were compensated at 1.5 times the prevailing daily wage for participation. They could earn even more during the second survey based on their performance in the behavioral games, but were not informed about this prior to arrival.

The first round of surveying occurred after the hiring was complete, but prior to the start of the supervisor program. In this round, a random sample of CHWs and 98% of supervisors were interviewed. This survey focused on the work of CHWs over the preceding six months, as well as administering a test of health knowledge and numerous psychometric instruments. We also asked questions about the selection process for supervisors.

The second round of surveying was conducted six months after supervisors began their work and interviewed all CHWs and supervisors in the study area. It focused on the performance of supervisors and CHWs over that time period, as well as administering two tests of general ability (Raven’s Progressive Matrices; Digit Span memory test), a test of health knowledge, a behavioral game measuring pro-social preferences, and a behavioral game measuring honesty. We were able to contact 96.4% of the sample frame, and of those contacted, 92% were administered the second survey. Outright refusal rates were very low (0.5%), with most attrition due either to transitory illness of household members or other obligations.

Using government administrative data, I find no statistically significant difference between surveyed and non-surveyed CHWs on 19/24 measures of quality/performance. On the other measures, non-surveyed CHWs are slightly worse than surveyed CHWs, but the discrepancy was minimal.

I combine the survey data with 20 months of administrative data on delivery of health services by the CHWs. This dataset begins after the supervisor program had started, since I was not able to access earlier data. The data is collated monthly and contains outcomes such as service as a tuberculosis treatment provider, promoting institutional delivery among pregnant mothers, conducting check-ups on recently delivered infants, and providing medical advice and nutritional counseling. Section 5.1 uses these data to investigate how CHW performance responds to the presence of supervisors.

Finally, I collect three direct measures of supervisor performance in the job. The first is process data collected from CHWs during the survey on the last two visits of their supervisor (frequency of visits; length of visit; activities performed during visit; and helpfulness of the visit). Second, CHWs were asked to rate their supervisor on a 4 point scale as well as their opinion of whether another CHW from their area would
perform better than the hired supervisor. Third, I collected performance evaluations from individuals overseeing the CHW program in which they ranked the supervisors on a series of 9 metrics (overall quality, quality of meetings with CHWs, health knowledge, overall intelligence, selflessness, interest in improving health outcomes, competitiveness, desire to help CHWs improve). Those individuals were not involved in the selection of supervisors, but regularly monitor the fieldwork of supervisors, so are well acquainted with their work. Collectively, these data give a relatively complete picture of supervisor activities.

3.3 Corruption Data

Collecting accurate data on illegal or stigmatized activities such as paying bribes is difficult. Respondents typically have little incentive to report truthfully, and so self-reported data on bribery may be subject to significant under-reporting. The degree of under-reporting may be lower in environments where bribe-paying is less stigmatized, and practically all papers in the corruption literature rely on self-reporting (see Sandra Sequeira (2012) and section 3 of Pande and Olken (2013) for an excellent review of research methodology in the corruption literature). Under-reporting may be lower in the cases of businesses paying bribes to police and other interactions for which the bribe-paying party is unlikely to face sanction. In the case of paying bribes to gain employment, it is much riskier for respondents to report their behavior, since the bribe-payer is more active in the corrupt act and may fear loss of employment as a result of their admission.

Other studies have used methods such as list randomization to improve accuracy of reporting of stigmatized activities (e.g. Karlan and Zinman (2012); Clarke et al. (2015)). That would not have sufficed in this context, since it was necessary to identify bribe offers and payment amounts. After substantial piloting, the final question wording yielded a relatively high rate of response (see section §B for details). Consistent with an auction environment, 82% of applicants said that they had been solicited for a bribe offer. Conversations with respondents suggest that members of the selection committee typically solicited offers during routine meetings or over the phone, although in some cases, the applicants first approached the selection committee. Only those selected for the job paid any money, with payments made prior to hires beginning in the position.

47% of surveyed hires were willing to share how much they had paid, while 33% declined to answer and 18% claimed that they did not pay anything. Given that those who did not answer are likely to have paid bribes, this suggests that at least 80% of successful applicants paid money to receive their position. Since it was expected that not all supervisors would divulge bribe payments, other CHWs were surveyed as a secondary source of bribe payment data. Even though CHWs typically work in non-overlapping areas, they interact regularly at trainings and health facilities. Bribe payments were a popular topic of conversation, and many CHWs heard directly from the hires about the bribes that the hires paid. In other cases, unsuccessful applicants learned the winning offer from members of the selection committee.

The other CHWs were first asked if they knew whether their supervisor had paid a bribe, and if so, we inquired how much the person had paid and whom they had heard this from. 77% of respondents

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17 Due to concerns about backlash, the survey did not ask explicitly about the identity of persons collecting bribes or how the bribes were solicited.

18 In order to avoid making respondents uneasy, surveyors were instructed to not probe supervisors on this question: if the respondent did not give a response on the first query, they moved to the next question. This is likely responsible for the high rate of declining to answer.
replied that their supervisor had paid money, with 19% stating that they didn’t know, and 3.8% stating that their supervisor had not paid a bribe. Of the first group, 70% also stated that they knew how much their supervisor had paid. If one or more respondents heard about the bribe directly from their supervisor, these more direct accounts are privileged, and their average is used as the estimated bribe for that supervisor. In the remaining cases, I take the average of all respondents who heard about it from another reliable source, such as a member of the hiring committee or another CHW. Secondary sources enable estimation of bribe payments in 92% of cases with missing data, where most of those estimates are based on information heard directly from the supervisor.

As a validation, I take cases in which the supervisor reported their payment and regress this on the bribe amount estimated from the secondary sources. As seen in figure 3, the fit is remarkably tight, with an $R^2$ value of 0.69. There does not appear to be a systematic pattern in the errors, which are more consistent with recall error than any other source of bias. The appendices contain additional validations of the bribery data, with a particular focus on possible biases in the secondary sources.

Non-selected candidates were also asked about their bribery behavior. In 49% of cases, they told the surveyor that they had made an offer for the job and how much they offered. It was not possible to collect secondary data to cross-check these offers, but there is little reason for the non-selected individuals to report an inaccurate value. This data is later used to estimate selection agent preferences.

Figure 4 shows the distribution of winning bribe amounts, where the average bribe was 17 months salary in the new position. Applicants appear to have faced credit constraints: of those who were interested in the job but elected not to apply, the most common reason was that they didn’t have enough money (40% of interested non-applicants). Another notable feature of the data is the large variation in bribe prices. Section 4.1 establishes that variation in the competition pool across areas caused these differences.

While these are large amounts, given the large and long-term stream of rents associated with a job, it

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19 The data strongly suggest that the last group is incorrect. For half of these 3.8%, the supervisor herself admitted to paying a bribe. Second, no supervisor had more than one of her CHWs reporting that she did not pay a bribe.

20 Results are similar if I always take the average of all reports, but it performs slightly worse in the below validation, consistent with information directly from the supervisor being of higher quality.
is not surprising that applicants would be willing to pay this much. They also have a high degree of job security. Over the roughly two years of the program to date, none have left or been fired. Furthermore, 65% expect to work in this job for the rest of their lives, and 86% of the rest only expect to leave in the case of a promotion. Given the roughly 40% increase in pay upon assuming the supervisor position, they would pay off the bribe in 4-5 years.

4 Characterizing the Market for Jobs

As a result of money changing hands during the hiring process, many would expect the hires to be of poor or middling quality. This section investigates the two factors that the model predicts will determine the quality of hires: 1) the extent to which the selection agent makes decisions based on applicant characteristics other than bribes; and 2) the nature of correlations between wealth/quality and valuation/quality. These findings generate predictions on quality that are tested in the next section of the paper.

4.1 Estimating Selection Agent Preferences

To estimate the degree to which hiring decisions are based on applicant characteristics, I recover the decision-rule/utility function of the selection agent. The selection agent can be thought of as solving a discrete choice problem over the set of candidate characteristics and bribe offers. They aim to maximize their personal utility, where utility over candidate $i$ in a contest $j$ will be equal to $\pi b_{i,j} + \theta \alpha_{i,j} + \epsilon_{i,j}$, a weighted linear combination of bribe offers, candidate characteristics, and any idiosyncratic preference for a particular applicant, $\epsilon_{i,j}$. If it were the case that only bribes mattered, then $\theta$ would be equal to the zero vector, whereas if a characteristic enters the selection agent’s utility, then the component of $\theta$ that corresponds to that characteristic will have a non-zero value.

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21For simplicity, I assume that candidate characteristics and bribes are substitutes, and thus that selection agent utility is over a weighted linear combination of characteristics and bribe offers. In the robustness checks, I check and confirm the lack of complementarities.
Table 2: Selection Decision

The revealed preference of the agent is used to infer the values of $\pi$ and $\theta$: by definition, $\pi b_{w,j} + \theta \alpha_{w,j} + \epsilon_{w,j} > \pi b_{i',j} + \theta \alpha_{i',j} + \epsilon_{i',j}$, where $w_j$ is the applicant selected in competition $j$. Putting this into a maximum likelihood framework, I estimate the $\pi, \theta$ that maximize the probability that the agent has the highest utility from the observed hire. I assume that $\epsilon_{i,j}$ has a type-1 Gumbel distribution and exploit the well-known properties of this distribution. In particular, when considering the choice that the selection agent has between two applicants, $i$ and $i'$, the difference between error terms, $\epsilon_{i,j} - \epsilon_{i',j}$, follows a logistic distribution. As a result, $\pi$ and $\theta$ can be estimated via the likelihood equation:

$$
\prod_j \prod_{i \in I_j} d_{i,j} \frac{e^{\pi b_{i,j} + \theta \alpha_{i,j}}}{\sum_{i' \in I_j} e^{\pi b_{i',j} + \theta \alpha_{i',j}}}
$$

where $d_{i,j}$ equals 1 if individual $i$ is selected, and 0 if individual $i$ is not selected.

Table 2 shows the coefficient estimates from maximum likelihood for statistically significant predictors of selection. Bribe amount and political connections are robustly predictive of selection decisions in all specifications. In the preferred specification, Model 1, the coefficient on political connections implies that use of a political connection increases the selection agent utility over that applicant by the same amount as offering an additional 4.68 salary-months of bribe, approximately a third of the average bribe value.

The selection agent also values each additional year of education at 1.64 salary-months of bribe, but this is typically non-pivotal in selection decisions since educational attainment rarely varies by more than 2 years among competitive applicants.

Although these factors are statistically significant, they may not be economically significant. Using the estimated coefficients to generate $\hat{u}_i$, the estimated utility of the auctioneer from selecting candidate $i$, I check how well $\hat{u}_i$ predicts actual selection decisions. This generates two goodness of fit measures: first, for each contest, the percent of applicant-winner pairs in which $\hat{u}_{w_j} > \hat{u}_i$, i.e. predicted utility from selecting

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Table 2: Selection Decision

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bribe Amount</td>
<td>1.00***</td>
<td>0.89***</td>
<td>(0.10)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Political Connections</td>
<td>4.68***</td>
<td>5.22***</td>
<td>(1.16)</td>
<td>(1.10)</td>
</tr>
<tr>
<td>Education</td>
<td>1.64***</td>
<td>1.32***</td>
<td>(0.28)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Pairwise % Correct</td>
<td>0.88</td>
<td>0.82</td>
<td>0.56</td>
<td>0.43</td>
</tr>
<tr>
<td>Pairwise GOF p-value</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Winner % Correct</td>
<td>0.86</td>
<td>0.76</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>Winner GOF p-value</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

***p < 0.01, **p < 0.05, *p < 0.1

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22Estimations where $\epsilon_{i,j}$ follows a normal distribution yield nearly identical results.

23As a robustness check, I also calculate placebo p-values by randomly permuting the identity of the winner and rerunning the estimation. I do this 2000 times to produce a sampling distribution of coefficient values under a null of no relationship. This yields qualitatively identical results to standard errors based on the likelihood function.

24Use of connections was self-reported by individuals who applied for the job. I also collect information about relatives who work as politicians, but this does not independently predict selection.
the winner is higher than another applicant; and second, the percent of winners who are correctly predicted based on \( \hat{u}_i \). For each specification, these values are listed at the bottom of the table.

In this main specification, \( \hat{u}_i \) correctly predicts the revealed preferred person in 88% of comparisons between selected/non-selected candidates. More importantly, \( \hat{u}_i \) predicts the correct winner in a remarkable 86% of contests. To place a p-value on the goodness of fit measures, I randomly permute the identity of the winner of each contest, and re-estimate the model based on these randomly selected winners. I do this 2000 times to produce a sampling distribution of both goodness of fit statistics under the null of no relationship. All of the goodness of fit values are well above what would be expected by chance at the 1% level.

The goodness of fit measures can be used to gauge the relative importance of each of the variables in the selection decision. Models 2-4 test the predictive power of each variable individually. Bribes are the main driver of the selection decision, given that they correctly predict 82% of the pairwise comparisons and 76% of the competition winners, while the other variables only slightly increase predictive power. In appendix D.3, I add other variables that could plausibly drive selection. None of the other variables are statistically significant or noticeably change the estimates. I interpret this as evidence that bribery, political connections, and education level are the main drivers of selection, with bribery as the dominant factor.

Appendix D.1 carries out robustness checks. It first shows that findings are robust to different functional form assumptions on the utility of the selection agent and addresses concerns about possible omitted variables. It then re-runs the estimation under different methods of dealing with missing data, and shows that results remain the same.

### 4.2 Applicant Behavior and the Auction Model

This section examines the determinants of the application decision and bribe offers to test if they are consistent with the model. The model predicts that the application decision is determined by own valuation for the job, own wealth, and any own or competitor characteristics that affect one’s probability of winning. Although I do not observe valuation directly, I construct a measure based on survey questions. A wealth index is constructed using principal components analysis on survey questions on earnings and assets ownership of their household (see appendix B for details).

Column (1) of table 3 confirms most of the model’s predictions on the determinants of applying. Those with higher valuations are more likely to apply, as are those with more education. The latter relationship could result from their higher probability of selection, but is also likely due to the coarse nature of the valuation proxy, where the positive correlation between education and valuation is not fully controlled for. Those with more highly educated candidates in their applicant pool are less likely to apply, which I interpret as a response to their diminished probability of selection. Surprisingly, there is no statistically significant relationship between own wealth or competitors’ wealth and the decision to apply. This could

\[25\] During the survey, respondents were asked whether they would decide to apply if the hiring were re-done without bribery under various probabilities of being selected. A series of questions specified a probability of winning beginning at 1 and declining to .25 in an attempt to identify the cutoff probability at which they are no longer willing to enter (see B for details). Those who are willing to enter at lower probabilities have higher valuations, so I flip the variable for interpretational ease; it varies between 0 and 1, with 1 as the highest valuation. The variable is highly censored since it cannot distinguish between the valuations of those who are willing to enter at .25, coded as a valuation of 1.
Table 3: Application Decision and Bribe Offers

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Wealth</td>
<td>0.00114</td>
<td>4.334***</td>
<td>0.0792</td>
<td>6.106**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0435)</td>
<td>(1.685)</td>
<td>(0.0822)</td>
<td>(2.671)</td>
<td></td>
</tr>
<tr>
<td>Average Wealth</td>
<td>0.0530</td>
<td>14.64**</td>
<td>0.293</td>
<td>16.43**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.143)</td>
<td>(5.262)</td>
<td>(0.286)</td>
<td>(7.807)</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.0814***</td>
<td>0.340</td>
<td>0.0688***</td>
<td>0.218</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00675)</td>
<td>(0.215)</td>
<td>(0.0129)</td>
<td>(0.380)</td>
<td></td>
</tr>
<tr>
<td>Average Education</td>
<td>-0.0519***</td>
<td>1.276**</td>
<td>-0.0890***</td>
<td>2.046**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0160)</td>
<td>(0.628)</td>
<td>(0.0316)</td>
<td>(1.007)</td>
<td></td>
</tr>
<tr>
<td>Valuation Proxy</td>
<td>0.356***</td>
<td>8.822***</td>
<td>0.304***</td>
<td>9.719*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0308)</td>
<td>(5.160)</td>
<td>(0.0594)</td>
<td>(5.209)</td>
<td></td>
</tr>
<tr>
<td>Post-Selection Shock</td>
<td>0.135**</td>
<td>0.104**</td>
<td>2.536*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0561)</td>
<td>(0.0478)</td>
<td>(1.460)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations 979 189 290 288 56
Proportion Applied 0.344 15.20 0.324 0.324 14.87

be caused by a negative correlation between wealth and valuation that is not fully controlled for by the valuation proxy or the endogeneity of wealth; a sharper test is used below.

In column (2), nearly all of the model’s predictions on determinants of bribe hold. Those with greater wealth offer substantially larger bribes, where an individual at the 25th percentile of wealth offers 3.66 fewer months-salary of bribe than an individual at the 75th percentile. Facing a pool of wealthier or more educated competitors is positively related to size of bribe offer, as expected in a competitive process. Own education is unrelated to bribe offers, while the model would predict that those with higher educational attainment should shade their bids. This may be because the valuation proxy does not sufficiently control for the strong positive correlation between education and valuation or due to the relative insignificance of own education in the selection decision, particularly since many applicants have similar educational attainment.

Columns (3)-(5) use negative wealth shocks to test for credit constraints and examine the relationship between wealth and application behavior. As part of the second survey round, respondents were asked about any major negative shocks to their household finances during the previous three years, such as theft, damage to their business/farm or medical treatments for a family member. Although experiencing a shock may be related to applicant characteristics, the timing of the shock relative to the timing of the hiring process should not be. Taking those CHWs who experienced exactly one shock over the previous three years (28% of the sample), there is no difference on observables between those who experience a shock prior to the hiring process and those who experience the shock after (appendix table table A1). Furthermore, the shocks experienced before and after hiring are of the same size (Kolmogorov-Smirnov distributional test: $p = .88$).

A transitory negative wealth shock should only influence bribery and application decisions if applicants are credit constrained. Furthermore, this is an ideal test of the relationship between wealth and application decisions/bribe offers, since this variation in wealth on hand is unrelated to other applicant characteristics. In columns (3) and (4), experiencing a negative shock prior to the hiring process decreases probability of applying by 10.3-13.5 percentage points relative to those who experienced it after the conclusion of the hiring process (around a third of the mean application probability). In column (5), they also offer bribes that average 2.54 months-salary less than those experiencing the shock post-hiring. These tests are consistent with selection agent hiring decisions based predominantly on bribe offers, confirm the presence
of credit constraints, and indicate that wealth is an important determinant of application behavior.²⁶

### 4.3 Relationship Between Quality, Wealth and Valuation

Given that bribes are the primary determinant of hiring, the model predicts that the quality of hires will depend on the correlations of wealth/quality and valuation/quality. Table 4 displays the correlations of wealth/quality and valuation/quality with a number of quality measures related to performance as a supervisor (see the next section for details on these measures). Both valuation and wealth are strongly positively correlated with these quality measures, implying that those who are hired will be of a higher quality than the median applicant and that applicants will be of a higher quality than non-applicants. However, this does not necessarily mean that these hires compare favorably to hires under alternative systems: section 6 tests this empirically.

### 5 Quality of Hires

Having established how this market functions, this section investigates the quality of hires. The first method of comparison is to compare the selected supervisor to others in her area, such as against her median competitor. This method implicitly compares the observed selection process to one in which the selection agent randomly selects among a particular pool of candidates. Random selection may not itself be credible, but serves as a useful benchmark. A second method compares the selected applicant to the person who would have been selected under a counterfactual hiring process, such as if hiring were based on test scores. This section focuses on the first method, while section 6 carries out the second.

A key feature of the paper is that since only current CHWs are eligible to apply for the position, I can compare hires not only to those who applied and were not selected, but also to those who chose not to apply in the observed hiring process. Typically, papers on hiring are not able to observe non-applicants, but ignoring them could lead to incorrect inference in this context. High quality individuals may not apply in a corrupt process due to an inability to pay bribes or distaste for bribery, but they may apply under counterfactual, non-corrupted hiring processes.

²⁶Regressions in table 3 use estimated bribe value for supervisors in cases where there is no primary report. Removing those observations has no effect on the results.
5.1 Basic Quality Comparisons

I first take a broad set of quality measures collected during the survey and compare across those (see appendix section D.2 for tables). This yields a consistent pattern: first, the median applicant is of a much higher quality than the median non-applicant; and second, those hired are of a higher quality than their median competitor. While the second relationship is not always statistically significant, the first is strongly statistically significant in nearly every case. A joint test across all of the quality measures indicates that applicants are vastly superior to non-applicants ($z = 10.54; p < .001$) and hires are higher quality than applicants who were not hired ($z = 3.39; p = .001$) (Kling et al., 2007).

5.2 Construction of a predicted Supervisor Performance Index

While this positive selection is suggestive, this set of variables may not actually be related to better performance as a supervisor. I thus check what supervisor characteristics are related to performance as a supervisor, aggregate these into an index, and compare across hires and non-hires on this index. The index is also used in section 6 in making comparisons to counterfactual hires.

I collect a number of measures that could be used to define supervisor performance, such as performance evaluations. However, the most important outcome for policy is improved delivery of health services, and so I focus on that, measuring supervisor performance using changes in service delivery after their hiring. The administrative data contains monthly information on delivery of ten health services by the CHWs under a supervisor, such as number of newborn checkups conducted, institutional deliveries assisted, and serving as a tuberculosis DOTS treatment provider. It would be cumbersome to check characteristics related to each service individually, so they are instead aggregated into a single index. To do this, I use a government formula that aggregates these outcomes into a score between 0 and 100. The score for a CHW $i$ under a supervisor $j$ in month $t$ is denoted as $y_{ijt}$ and regressed on the characteristics $v$ of each supervisor $j$ to determine which are related to changes in CHW performance:

$$y_{ijt} = \alpha + t \sum v \beta v X vj + \gamma_i + \phi_t + \epsilon_{it}$$

$\beta v$ equals the average monthly change in $y_{ijt}$ as a function of supervisor characteristic $v$: a positive value indicates that CHWs under a supervisor with a higher value of $v$ improve over time relative to CHWs under a supervisor with a lower value of $v$. CHW fixed effects $\gamma_i$ account for time-invariant heterogeneity across CHWs and month fixed effects $\phi_t$ account for seasonal patterns and overall time trends. Standard errors are clustered at the supervisor level. Section 5.3 checks for pre-existing trends in $y_{ijt}$ or endogenous matches of workers and supervisors that would invalidate this strategy.

Since there are a large number of variables $v$ and relatively few supervisors, OLS is likely to overfit the data or could lead to specification searching by the researcher. I instead utilize LASSO for variable selection (e.g. Tibshirani, 1996; Belloni and Chernozhukov, 2009; Belloni et al., 2011). LASSO minimizes

---

27 Using performance evaluations, worker evaluations of the supervisor and process measures of supervisor effort to define performance gives similar results.

28 Since my data only begins after the supervisors had been in place for two months, this approach ignores changes that might have occurred immediately as a result of their presence. For outcomes in which I do have data from prior to the introduction of supervisors, appendix section D.4 tests for such a response. There is little evidence for any immediate change outside of one outcome (hours worked per week, which shows a moderate increase).

29 In order to use LASSO and incorporate the clustered structure of the data, I take differences and collapse the data to the supervisor level. I then run a LASSO regression for average change under the supervisor on supervisor characteristics. After variable selection and inference is complete, I return to the regression specified above.

21
\[
\hat{\beta}_{\text{lasso}} = \arg \min_{\beta \in \mathbb{R}^p} ||y - X\beta||_2^2 + \lambda \sum_{j=1}^p |\beta_j|
\]

the sum of squared prediction errors and a penalty term that penalizes the sum of the absolute value of the estimated coefficients. Depending on the severity of the penalty, governed by the term \(\lambda\) in the below equation, coefficients are shrunk towards zero, with many having a value of exactly zero. This can be seen in the left-side of the figure, where each line represents the coefficient estimate for a particular variable in \(X\) at a given \(\lambda\). There is shrinkage towards zero as \(\lambda\) increases.

The parameter \(\lambda\) is chosen using 10-fold cross-validation, as is standard in the statistics literature (see Hastie et al., 2005). Following this, I use the procedure of Brink-Jensen and Ekstrom (2014) to establish statistical significance of variables selected by the LASSO. These are: 1) score on Raven’s Progressive Matrices, a test of problem-solving; 2) Education; 3) scores on tests of writing and reading abilities administered by the surveyors; and 4) extroversion, as measured by the Big Five Index. Appendix table A3 shows a post-LASSO regression with these variables.

I could now examine the pattern of selection on each of the five variables across hires, non-selected applicants, and non-applicants, but this would not account for the relative influence of each in determining health services outcomes. For example, Raven’s score is more influential in determining service delivery than extroversion. Instead, I use the estimated coefficients \(\beta_v\) to capture the relative import of each variable and aggregate the five indicators into an index, denoted as the predicted supervisor performance index.

\[\text{Figure 5: LASSO Coefficients and Cross-Validation MSE}\]

30 Under 10-fold cross-validation, the dataset is split into 10 randomly selected sets. For a grid of values of \(\lambda\), LASSO is estimated ten times, where one of the ten splits is left out at each iteration. For each of the splits, predicted values of \(y_{ijt}\) are estimated for the left-out data using the coefficient efficiencies from that split, and mean squared error is generated from those predictions. \(\lambda\) is selected so as to minimize the sum of the left-out mean-squared error. This can be seen in the right-hand diagram in figure figure which plots the left-out mean squared error against the value of \(\lambda\). Errors are larger for small values of \(\lambda\), since a low penalty leads to overfitting to irrelevant regressors, and for large values of \(\lambda\), since the extreme penalty leads to the omission of relevant regressors.

31 Although since there is positive selection on all but one at the application and hiring stages, the overall selection is unambiguously positive.
Figure 6: Selection on Predicted Supervisor Performance Index

Since the variables used in construction of the index are observed for all the candidates, the index can be used to compare across hires, counterfactual hires, unsuccessful applicants, and non-applicants.

Figure 6 plots the cumulative density functions of SPI for each group. An incredibly strong pattern of positive selection is evident at both the application and hiring stages, where differences between all the distributions are statistically significant at the 1% level. The solid gold line gives the density function in the predicted first best case, i.e. where the candidate with highest SPI is selected in each competition. It is notable that actual hires closely approach the predicted first best case: the predicted first best candidate is selected in 35% of competitions, and one of the top three predicted candidates is selected in 66% of competitions. Despite the presence of bribery, hires are of a high quality.

5.3 Robustness Checks for Inference with Supervisor Performance Index

While encouraging, there are three major concerns with inference based on the predicted supervisor performance index. First, an aggregated measure of health services delivery was used to generate SPI, but that aggregation may be a poor representation of individual services. Furthermore, the relationship may be statistically significant, but not economically meaningful. As seen in table 5, this is not the case. There is a strong relationship between the SPI of the supervisor and improvements in delivery of tuberculosis treatment, newborn care, nutritional counseling and care for pregnant women (as well as other services not included in this table). These estimates imply that a health worker’s probability of serving as a tuberculosis treatment provider would increase by 4.6 percentage points if transferred from their supervisor.

\[ s_j = \sum \beta X_{vj} \] for each supervisor and supervisor performance index is defined by normalizing \( s_j \), i.e. \( SPI_j = \frac{s_j}{\text{std}(s_j)} \).
\[ y_{ijt} = \alpha + t\beta_{spi} SPI_{j} + \gamma_{i} + \phi_{t} + \epsilon_{it} \]

<table>
<thead>
<tr>
<th></th>
<th>Govt Grade</th>
<th>Institutional Delivery</th>
<th>Newborn Check-ups</th>
<th>Nutritional Counseling</th>
<th>TB provider</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted Supervisor Score</td>
<td>0.56***</td>
<td>0.0080***</td>
<td>0.0049***</td>
<td>0.0059***</td>
<td>0.0023**</td>
</tr>
<tr>
<td>(0.063)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>15570</td>
<td>15570</td>
<td>15570</td>
<td>15451</td>
<td>15570</td>
</tr>
<tr>
<td>Mean</td>
<td>61.2</td>
<td>2.09</td>
<td>0.67</td>
<td>0.089</td>
<td>0.13</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Standard errors clustered at supervisor level

Table 5: Supervisor Performance Index and Health Services Delivery

to a different supervisor whose SPI is one standard deviation higher. Given that the mean probability of serving as a treatment provider in a given month is 13%, this is a large increase; the other estimates are also large.

A second concern is that the relationship between supervisor characteristics and services delivery could be the result of endogenous matching of supervisors to clusters of CHWs, and so the improvements are not attributable to the supervisor. For example, supervisors who are more educated or have higher Raven’s scores may oversee clusters that were already on an upwards performance trajectory or whose performance was easier to influence.

I devise two checks of this concern, but find no evidence for it. First, I re-estimate the effect of SPI on CHW performance with separate coefficients for each quarter and check if they are consistent with differential trends. Figure 7 shows no evidence of differential trends: a positive trend only appears after the supervisors had been working for 7-9 months. This is consistent with anecdotal accounts of the supervisors needing time to adjust to their new positions, as most had never previously worked in such a role.

Second, I construct an instrument for the SPI of the supervisor. Note that the endogeneity concern is not one of omitted variable bias, but of the match of supervisors to workers. Thus what is required is a source of exogenous variation in the SPI of a supervisor assigned to a given cluster. The instrument is derived from the timing of financial shocks to CHWs, as described in section 4.2. CHWs who experienced a shock prior to the competition are less likely to apply than those who experienced the shock after, but otherwise do not differ on observables; experiencing a shock is not exogenous, but the shocks’ timing

\[ y_{ijt} = \alpha + \sum_{q=2}^{7} \beta_{q} \text{quarter}_q X SPI_{j} + \gamma_{i} + \phi_{t} + \epsilon_{it} \]

Second, I construct an instrument for the SPI of the supervisor. Note that the endogeneity concern is not one of omitted variable bias but of the match of supervisors to workers. Thus what is required is a source of exogenous variation in the SPI of a supervisor assigned to a given cluster. The instrument is derived from the timing of financial shocks to CHWs, as described in section 4.2. CHWs who experienced a shock prior to the competition are less likely to apply than those who experienced the shock after, but otherwise do not differ on observables; experiencing a shock is not exogenous, but the shocks’ timing

Note that the differences would have to be in trends rather than levels: if stronger supervisors are selected from a pool of CHWs that is stronger in levels, this will be fully controlled for by the CHW fixed effects.

The ideal test would use data from the quarters prior to the start date of supervisors in a differences-in-differences framework and then check for parallel trends in the pre-period, but these data were not accessible. However, a difference-in-differences regression that uses either the first six or nine months as a pre-period yields qualitatively the same results, and shows parallel trends over that period. For those variables on which I collect pre-hiring data, I also do not find evidence of pre-trends (see appendix section D.4).

I.e. that rather than the driver of improved services delivery being Raven’s score/education/etc, it is an unobserved quality of the supervisor that is correlated with these characteristics. This is irrelevant, since the paper seeks only to predict supervisor performance, not explain why one supervisor performs better than another.
Figure 7: Event Study Graph of Predicted SPI on Service Delivery

<table>
<thead>
<tr>
<th></th>
<th>Govt Grade</th>
<th>Govt Grade (IV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supervisor</td>
<td>0.56***</td>
<td>0.48**</td>
</tr>
<tr>
<td>Performance Index</td>
<td>(0.063)</td>
<td>(0.241)</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>First Stage F-Stat</td>
<td></td>
<td>7.57</td>
</tr>
<tr>
<td>P-value (A-R)</td>
<td>.</td>
<td>.047</td>
</tr>
</tbody>
</table>

Standard errors clustered at supervisor level

Figure 8: Instrumented Regression and Anderson-Rubin Confidence Interval

relative to the hiring process is. Clusters whose better candidates happen to experience shocks before, rather than after the competition, will tend to have a lower quality pool of applicants and thus may end up with worse supervisors.

For each competition, the instrument is equal to the difference in average SPI between candidates who experience negative wealth shocks prior to the competition and those that experience the shock afterwards. The timing of shocks is unrelated to any applicant characteristics (appendix table table A1), and the instrument is unrelated to pre-existing area characteristics (appendix table table A2). This will thus deal with any concerns about matches of supervisors to CHWs.

Estimates using the instrumented SPI are statistically significant at the 5% level and nearly identical to point estimates in the non-instrumented regression in column (1); the similarity suggests that there was not endogenous matching related to the performance outcomes. Unfortunately, the first stage F-statistic indicates that the instrument is somewhat weak, so I create a confidence interval and p-values based on inverting the Anderson-Rubin test statistic (Mikusheva and Poi 2006; Finlay et al. 2016). This confidence interval is robust to weak instruments and optimal in the case of a single instrument (Moreira 2009). Figure 8 shows the confidence intervals under standard (Wald) and Anderson-Rubin test statistics: a 95% Anderson-Rubin confidence interval excludes zero, indicating statistical significance at the 5% level.

A third major concern is that comparisons based on SPI only account for differences in supervisor
quality that are predictable using observed supervisor characteristics. If a large component of supervisor quality were unexplained by these characteristics, then comparing only on the predicted component could give misleading results. Conceptually, this is similar to being unable to measure all outcomes of interest, such as a program evaluation that doesn’t measure long-term outcomes, but utilizes short-term outcomes to estimate them. I collect data on a wide variety of characteristics that may predict supervisor quality, including psychometrics, behavioral games, and peer ratings (see section 3.2 for a description), but the extent to which they capture the variation in supervisor quality is an empirical question.

To address this concern, I collect three independent measures of supervisor performance: 1) supervisor performance evaluations by staff overseeing the program; 2) ratings of supervisors by the CHWs; and 3) process measures such as frequency and quality of supervisor interactions with CHWs (see 3.2 for a description). These were designed to capture different types of variation in supervisor performance, including that which may be unrelated to observed supervisor characteristics. I create an index for each of these measures and then add them to regressions alongside SPI.

Column (1) of table 6 regresses these indices of supervisor performance on the index of service delivery outcomes. Controlling for the others, only the coefficient on performance evaluations is statistically significant (though all are individually significant when the others are omitted). However, the coefficients on the additional indices drop to insignificance upon the inclusion of SPI. This suggests that even if there are aspects of supervisor performance that SPI does not capture, those aspects are not as predictive of improvements in health services delivery, the main policy metric of interest. Using predicted SPI captures much of the variation in health services delivery driven by supervisors, and so using it to measure supervisor quality should be meaningful.

Earlier drafts of the paper took the complement of the current approach: comparisons based on a index (SPI2) created by regressing evaluation data (performance evaluations, evaluation by CHWs, and process measures of activity as a supervisor) on supervisor characteristics. Changes in CHW performance are shown to be strongly related to the predicted SPI2 of their supervisor, but not related to the residuals from the creation of the index, i.e. the component of supervisor performance not predicted by their characteristics. Results on the quality of selected supervisors relative to non-hires or counterfactual hires are similar or slightly stronger using SPI2, but the SPI method is preferred due to its greater conceptual simplicity.

### Table 6: Supervisor Performance Index and CHW Performance Outcomes

<table>
<thead>
<tr>
<th></th>
<th>Services Score</th>
<th>Services Score</th>
<th>Services Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance</td>
<td>0.098**</td>
<td>0.11***</td>
<td>0.048</td>
</tr>
<tr>
<td>Evaluations</td>
<td>(0.041)</td>
<td>(0.041)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Process-Based Rating</td>
<td>-0.065</td>
<td>(0.105)</td>
<td></td>
</tr>
<tr>
<td>Worker Rating</td>
<td>0.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted SPI</td>
<td></td>
<td></td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.058)</td>
</tr>
<tr>
<td>Observations</td>
<td>15807</td>
<td>15807</td>
<td>15570</td>
</tr>
<tr>
<td>Mean</td>
<td>61.2</td>
<td>61.2</td>
<td>61.2</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Standard errors clustered at supervisor level*
6 Counterfactual Simulations

This section considers plausible counterfactuals, such as if hiring decisions were based on exam scores, and compares candidates selected under these regimes to hires from the observed, corrupt hiring process. While it seems obvious that hiring based on ability measures should outperform selection via bribery, this need not be the case. For example, measures of ability that are observable to the selection committee may be poor predictors of job performance, while willingness to pay may be more strongly correlated with productivity. This is especially likely if pay reflects productivity, such as under a piece rate system. The most productive applicants would be willing to bid the most, and an auction may be an optimal allocation method. In general, the efficacy of a hiring method will depend on the relationship between its selection criteria and the production function for the job.

An ideal comparison would be an experiment in which a random subset of hires are determined based on bribery and the remainder are selected using more typical methods. Since bribe-paying is typically illegal, and poor hiring decisions can impose substantial social costs, ethical considerations preclude conducting such an experiment outside of a lab context. For the questions considered in this paper, lab experiments are unlikely to replicate important aspects. A different experimental approach would be to randomly assign a crackdown on corruption to hiring processes for certain positions or in certain areas. However, for a true counterfactual, it would be necessary to publicize such a crackdown prior to candidates deciding whether to apply, which may be impossible to do credibly. Furthermore, if done credibly, there would likely be spillovers onto the control group (who will presumably have an increased fear of punishment for taking bribes) that would invalidate the experiment.

Fortunately, it is possible to construct credible counterfactuals using methods similar to the industrial organization literature on entry into auctions (e.g. Guerre et al., 2000; Athey et al., 2011; Li and Zheng, 2009). My method is flexible and permits estimation of a wide set of counterfactuals. I first estimate outcomes under counterfactual systems similar to those used in other contexts, such as tests of knowledge and ability, and past performance. I then estimate other types of counterfactuals to highlight the mechanisms of the model, such as disentangling the role of credit constraints in producing the observed outcomes.

6.1 Model

A counterfactual hiring process is one in which the selection agent places weights $\pi$ and $\theta$ on bribe values and applicant characteristics that differ from the weights in the observed hiring process. For example, a selection agent that only cared about health knowledge would place full weight on that dimension of $\alpha$, with a weight of zero on $b$ and the other dimensions of $\alpha$. To determine the set of counterfactual hires, it is necessary to create a model that produces: 1) the entry decision of each potential applicant in the counterfactual setting; and 2) the hiring decision among the counterfactual applicant pool under the counterfactual weights.

The application decision is particularly crucial, since a candidate may apply under hiring rules that favor them, but would not under rules less favorable to them. A key feature of my data is that it covers the universe of potential applicants, whereas the literature typically must make strong assumptions about

\[36\text{In addition to these “honest” counterfactual systems, journalistic accounts describe alternative ways of corruptly allocating jobs. Section 7.3 addresses these, as well as estimating hiring decisions under one of these systems: standardized testing regimes in which individuals can offer bribes to receive higher than merited marks.}\]
non-entrants/applicants when estimating entry games. Once the application pool is determined, the counterfactual weights dictate the selection decision, so I need only observe the variables that would be relevant to such a decision.

The theoretical model from section 2 is used for the estimation. The selection agent picks an applicant $i$ among the set of entrants $E$ in order to maximize $\max_{i \in E} \{ \theta \alpha \}$, where the value of $\theta$ will depend on the counterfactual at hand. $I$ candidates are eligible to apply, where each has a privately observed set of attributes $\zeta_i = \{ C_i, v_i, W_i, \alpha_i \}$ that are independently drawn from a common distribution $f(C, v, W, \alpha)$. Candidates will no longer offer bribes, since doing so is costly and does not increase their probability of selection. As a result, wealth is no longer relevant. They will decide whether or not to enter the competition based on whether the expected value exceeds the cost of entry, i.e. $p_i v_i - C_i > 0$, where $p_i$ is their probability of selection.

Taking this entry condition, candidates will have some cutoff probability $e_i = \frac{C_i}{v_i}$ for which they will prefer to enter if $p_i > e_i$ and not enter if $p_i < e_i$. Furthermore, for a given competition, applicants are differentiated by the selection agent along a unidimensional $\kappa = \theta \alpha$. For example, if selection were based on a knowledge-based test, $\kappa$ would be their score on that test. Taking these transformations, the joint distribution $f(C, v, W, \alpha)$ implies a second distribution $g(\kappa, e)$ over $e$ and $\kappa$. The estimation focuses on this simpler distribution and proceeds in five stages. In general, the goal is to estimate the function $p(\kappa)$ mapping from $\kappa$ to a probability of being hired under the counterfactual system of interest, as well as bounds around $e_i$. I then combine these elements to determine whether an individual will choose to apply.

6.2 Estimation

I first establish bounds on $e_i$ using behavior in the observed contest (bribe offers and entry behavior) to recover valuations in a manner similar to Guerre et al. (2000), but adopted for a scoring auction. For those that did not previously apply, I utilize survey questions on entry behavior under different probabilities of selection, which line up well with observed behavior. The details of this process are somewhat involved, and can be found in appendix E.

In the second stage, I use the bounds on $e$ and observations of $\kappa$ to estimate parameters of the joint distribution $g(\kappa, e)$. Some applicants have $e_i \notin [0, 1]$. The distribution of $(\kappa, e)$ over these applicants is irrelevant, since a candidate who has $e \notin [0, 1]$ will never choose to apply. Instead of estimating the distribution over these candidates, I estimate $p_{ne}$, the probability that a particular candidate has $e \notin [0, 1]$, as $\hat{p}_{ne} = \frac{\sum_i 1(e_i \notin [0, 1])}{N}$.

For the remaining candidates, I assume that $g(\kappa, e)$ follows a bivariate-beta distribution (Olkin and Liu, 2003; Olkin and Trikalinos, 2015) where:

\[
g(e, \kappa) = \frac{\kappa^{a-1}e^{b-1}(1 - \kappa)^{b+c-1}(1 - e)^{a+c-1}}{B(a, b, c)(1 - \kappa e)^{a+b+c}}\]

This distribution is relatively flexible: unlike the normal distribution, it need not be symmetric, and it allows a wide range of correlations between $\kappa$ and $e$. The density function is defined over $[0, 1]^2$ (see appendix E for additional details), so $\kappa$ is normalized to fit within those bounds. Using maximum likeli-
Figure 9: Probability of Hiring, $p(\kappa)$

hood, I separately estimate parameters ($p_{ne}, a, b, c$) for eight geographical groupings to account for possible heterogeneity across applicant pools.

Third, I solve for the function $p(\kappa)$, which maps from $\kappa$ to a candidate’s probability of being hired. A candidate’s probability of selection will be equal to the probability that no other candidate has a higher draw $\kappa$ and chooses to enter the competition given their value of $e$. For example, under counterfactual with a knowledge-based test, this is the probability that none of their competitors would choose to apply and get a higher score on the test. Stated more precisely, this is equal to:

$$p(\kappa_i) = \left(p_{ne} + (1 - p_{ne}) \left(1 - \int_{\kappa_i}^{\kappa} \int_{0}^{\kappa(\kappa, e)} \partial e \partial \kappa \right)\right)^{N-1}$$

The equation within the parentheses gives the probability of being selected if facing one opponent. The first term is the probability of their competitor drawing a value of $e$ such that the competitor would never enter. $(1 - p_{ne})$ is the probability that the competitor draws a value of $e$ such that they might choose to enter. $\int_{\kappa_i}^{\kappa} \int_{0}^{\kappa(\kappa, e)} \partial e \partial \kappa$ is the probability that this competitor has a draw $\kappa > \kappa_i$ and chooses to enter, i.e. the competitor’s entry cutoff probability $e$ is less than their probability of being selected, $p(\kappa)$. Since this competitor would have $\kappa > \kappa_i$, the competitor would be selected.

This can be seen visually in left-hand panel of figure [9] which contains the possible combinations of $\kappa$ and $e$. The green region is the set of candidates who: 1) have higher values of $\kappa$ than a example candidate of interest ($\kappa = .7$); and 2) who would choose to enter. The yellow region contains non-entrants ($p(\kappa) < e$), while the red region contains those who enter but have lower levels of $\kappa$ than the example candidate of interest. The right-hand panel maps this onto the relevant estimated beta-bivariate joint distribution $g(e, \kappa)$.

In order to solve for $p(\kappa)$, so it is necessary to differentiate the expression defining it and solve for a differential equation $p'(\kappa)$. Taking the derivative with respect to $\kappa$ yields:
The entry stage.

respondent beliefs on predicted to perform slightly better relative to counterfactual hires than in this estimation.
in performance within a given competition. Results are qualitatively similar, although actual hires are
These assumptions allows me to relax functional form assumptions and introduce individual-level variation
in performance within a given competition. Results are qualitatively similar, although actual hires are
predicted to perform slightly better relative to counterfactual hires than in this estimation.

2) estimated values of the knowledge-based counterfactual align well with the application decisions that my method predicts;

Appendices E.3 and F contains six robustness checks of the counterfactual method.

In appendix F, I rerun the counterfactual under stronger assumptions about the information structure.
These assumptions allows me to relax functional form assumptions and introduce individual-level variation
in performance within a given competition. Results are qualitatively similar, although actual hires are
predicted to perform slightly better relative to counterfactual hires than in this estimation.

\[ p'(\kappa) = (n - 1) \left[ p_{ne} + (1 - p_{ne}) \left( 1 - \int_{\kappa}^{\tilde{\kappa}} G_2 (\kappa', p (\kappa')) \partial \kappa' \right) \right]^{n-2} (1 - p_{ne}) \frac{\partial}{\partial \kappa} \left[ 1 - \int_{\kappa}^{\tilde{\kappa}} G_2 (\kappa', p (\kappa')) \partial \kappa' \right] \]

where \( G_2 (\kappa, p(\kappa)) = \int_0^{p(\kappa)} g(\kappa, e) de \). Since \( g(\kappa, e) \) was estimated empirically in the previous step, \( G_2(\cdot) \)
can be numerically estimated. \( p(\kappa) \) is solved numerically given the initial condition \( p(\tilde{\kappa}) = 1 \). This must
be the case since \( g(\kappa, e) \) is non-atomic, and so an individual with the highest draw \( \tilde{\kappa} \) will have probability
1 of being selected.

In the fourth step, I calculate \( p(\kappa) \) for each candidate and compare it to the candidate’s bounds on \( e \)
to determine whether they would prefer to enter the competition. This sorts candidates into three sets: 1) definite
entrants, \( S_1 \); 2) non-entrants, \( S_2 \); and 3) possible entrants, \( S_3 \). For example, an individual with
\( p(\kappa_i) = .34 \) and an upper bound on \( e_i \) of .25 would be a definite entrant since \( p(\kappa_i) = .34 > .25 > e \).
Similarly, if \( p(\kappa_i) = .24 \) and the lower bound on \( e_i \) is 0.5, then the applicant would be a non-entrant since
\( e_i > .5 > .24 = p(\kappa) \). Finally, if an applicant has \( p(\kappa_i) = .29 \) and the bounds on \( e_i \) are .33 > \( e_i > .25 \), they
would be a possible entrant, since it is uncertain whether \( p(\kappa_i) \) is greater than or less than \( e_i \). Since the
set of entrants is not point-identified, it is only possible to place bounds on expected SPI under a given
counterfactual. Fortunately, the bounds are reasonably tight.

The fifth step is the construction of lower and upper bounds on expected SPI under the counterfactual
system. For each competition, the set of possible hires is equal to \( P = \{ i \in S_1 \cup S_3, \kappa_i \geq \tilde{\kappa} \} \), where
\( \tilde{\kappa} = \max_{i \in S_1} \kappa \). That is because members of \( S_1 \) will certainly enter, and so the hire must have a value of \( \kappa \)
that is at least as high as maximum in \( S_1 \). The upper bound and lower bounds on SPI for the competition
will be \( \max_{i \in P} (SPI_i) \) and \( \min_{i \in P} (SPI_i) \) respectively, the highest and lowest values of SPI among possible
hires. One can then compare these bounds on SPI to the realized SPI of actual hires. The bounds turn
out to be reasonably tight because the strongest candidates have low upper bounds on \( e_i \) in most cases, so
they are members of \( S_1 \) and \( P \) is a singleton.

Robustness Checks Appendix E.3 and F contains six robustness checks of the counterfactual method.
Appendix E.3 demonstrates that: 1) direct elicitations of survey respondents’ application decisions under
the knowledge-based counterfactual align well with the application decisions that my method predicts;
2) estimated values of \( e_i \) are consistent with behavior in the observed hiring process; 3) directly elicted
respondent perceptions of \( p_i \) are close to the actual value of \( p_i \); 4) results do not change significantly if
respondent beliefs on \( p_i \) are somewhat biased; and 5) findings are robust to eliminating the estimation of
the entry stage.

In appendix F I rerun the counterfactual under stronger assumptions about the information structure.
These assumptions allows me to relax functional form assumptions and introduce individual-level variation
in performance within a given competition. Results are qualitatively similar, although actual hires are
predicted to perform slightly better relative to counterfactual hires than in this estimation.
6.3 Results

The relative quality of hires under counterfactual systems is evaluated based on the differences in SPI. Figure 10 provides the upper and lower bounds for each of the estimated counterfactuals, e.g. hires under a health knowledge test have an average SPI that is 0.25-0.44 standard deviations lower than that of actual hires. The green line denotes the predicted first-best outcome, i.e. the highest SPI candidate is hired from each competition.

**Government System**

The first counterfactual determines who would have been hired under the intended government procedure. This is the method that would have been used absent corruption, so is the true counterfactual. The government created a formula to assign points to applicants based on past performance as a CHW, and the applicant with the most points was supposed to be hired. Although I was able to access the government documents detailing their formula, it was not possible to access the points as allegedly tallied by the hiring committee. However, since almost all of the points are based on performance as a CHW, I am able to approximate 65% of the possible points using administrative data and survey responses.

The average SPI of those hired under this method is weakly lower than that of actual hires (lower bound is 0.33 SD lower, \( p = 0.034 \) in a paired t-test; upper bound is 0.01 SD lower, \( p = .95 \)). While the wide bounds preclude definitively conclusions, it is striking that selection on past performance as a CHW

\[ \text{Figure 10: Comparison of SPI Under Counterfactual Competitions} \]

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\[38\] The remaining 35% of points are from an interview with the selection committee, where no guidance was given for how the points should be allocated, and a performance measure on which most applicants likely received the same score.
does not outperform the corrupt hiring procedure. This is because performance as a CHW is only weakly predictive of performance as a supervisor, probably because the two jobs require quite different sets of skills. This result is a useful caution against promotion systems based on performance at lower levels, as is common in many organizations.

**Standardized Testing: Knowledge and Ability**

The second and third counterfactuals generate the set of hires under typical standardized testing procedures. Governments frequently use standardized testing for hiring civil servants, since these tests are viewed as fair and select for either knowledge or general intelligence. Whether this actually selects the best candidates will depend on the relationship between the production function and the dimension of ability measured by the test. For some positions, such as management positions, it may be the case that selecting on other measures, such as personality, would produce better results. On the other hand, hiring systems that rely more on the discretion of selection agents, such as interviews, are easier for corrupt agents to manipulate.

The first standardized test measures the health knowledge of applicants. This test was administered during the survey, and all questions are taken directly from the CHW training manuals. Since health knowledge is directly relevant to their work (e.g. knowing when to dispense oral rehydration salts), this is a prime candidate as an alternative selection method. The second standardized test is the Raven’s Progressive Matrices, which was also administered during the second survey (see appendix[B] for details). The Raven’s matrices are a test of general problem solving abilities and have been used in numerous government hiring processes (see [Dal Bo et al. (2013)](#) for a description of its use in Mexico). If problem solving ability is related to productivity, this test may select a superior set of supervisors.

The SPI of actual hires is 0.25 SD higher than the upper bound of hires under the health knowledge counterfactual ($p = 0.01$) and 0.44 SD higher than the lower bound ($p < 0.001$). On the other hand, the SPI of actual hires is weakly lower than those selected using the Raven’s matrices ($0.07 - 0.47$ $SD$; $p = 0.89$, $p < .001$), though the bounds are too wide for statistical significance. Applying coefficients from table[5], a back of the envelope calculation indicates that relative to selection via the health knowledge test, the set of actual hires led to 9-15.9% more tuberculosis patients being cared for, 3.5-6% more institutional deliveries, and 3.6-6.4% more newborn checkups, among other outcomes. Although actual hires are still not at the predicted first best, the corrupted hiring system typically picks one of the best candidates. This is a striking contrast to previous literature, but completely in line with the model, where the strong positive correlations between valuation/quality and wealth/quality leads to selection of high quality individuals.

It is noteworthy that the Raven’s matrices outperformed the other two systems. The back of the envelope calculations indicate that under hires via Raven’s relative to those under the health knowledge test, there would be a 5.5% increase in institutional deliveries, a 26% increase in TB treatment provision, and a 10.5% increase in newborn check-ups. Even though scores on the health knowledge test and Raven’s matrices are moderately correlated ($r = .33$), they yield strikingly different results. The magnitude of the discrepancy highlights an important point about hiring processes: prior to making hiring decisions, selection agents should use data to determine what factors are mostly strongly related to performance in the position and hire based on those. Without looking at the data beforehand, it would have been difficult to state which system would perform better, and in other contexts, such as for doctors, knowledge may be more important than problem solving. In general, those responsible for hiring decisions should determine
how characteristics predict performance in a job and select based on this predictive model (e.g. Chalfin et al., 2016).

Applying the Estimation to Understand Drivers of Selection

The final application of the counterfactual estimation is using it to understand the observed (corrupt) hiring process. The observed selection is on bribes, and thus willingness to pay/wealth, but it is not clear how these two factors interact or if one drives more of the quality of hires. Ideally, I would estimate counterfactual selection based solely on each, but my measure of willingness to pay is quite coarse for some candidates. However, it is possible to get a sense of the relative import of each by observing how hires selected solely via wealth compare to the actual hires. This is the fifth estimation in figure 10.

Outcomes are much worse than the actual case. This implies that the main driver of the high quality of observed hires is willingness to pay rather than wealth. Furthermore, it demonstrates that distortions due to credit constraints cannot be large, since if they were, actual hires would be of a more similar quality to those under this counterfactual. However, credit constraints need not always play a negative role. As discussed in the next section, if willingness to pay and quality are negatively correlated, credit constraints reduce the distortions created by corruption.

Another question is why the selection agents make their decisions based on bribes/education/political connections; it could be that the selection committee preferred to select higher quality candidates and realized that selection via a corrupt system would accomplish this outcome better than the government method. The fourth counterfactual belies this hypothesis by testing whether the selection committee could have selected a higher quality set of hires given the information set available to them. It estimates a counterfactual hiring process in which the weighting of performance measures from the government method are reallocated in order to to maximize the SPI of hires. In this case, counterfactual hires are $0.09 - 0.41 \text{ SD}$ better than actual hires, so the agents could indeed have used their data to select a better group. This is not a perfect test since they did not have access to information on supervisor performance, and so might not have realized what CHW performance measures were the best to select upon. Yet it is suggestive that they made selection decisions in their own interest, rather than that of the public.

7 Discussion

7.1 Mechanisms

In this context, allocation of jobs on the basis of bribery compares favorably to other hiring methods. The positive selection observed is due to the positive correlations between valuation/quality and wealth/quality in this environment[39], but these correlations may be negative in other contexts, leading to low quality hires. For policymakers interested in improving civil service quality, it is useful to know the types of job for which corruption in hiring will have a distortionary impact, since these are the positions in which monitoring of hiring processes will have the highest return. To determine the size of distortions across different types of jobs, it is necessary to determine the mechanisms underlying the signs of correlations between valuation, wealth and quality.

[39] By quality, I mean the productivity of a particular candidate in the job for which they are being hired. This productivity will be determined by a number of factors, including human capital, propensity to engage in corruption, and non-cognitive skills, where the exact production function will depend on the particular position.
One of the primary determinants of a candidate’s valuation is the return to quality in this position relative to the candidate’s outside option, which might be a different public sector job or a private sector position. These returns could come in the form of direct compensation, career incentives, or corruption. For the first two, if higher quality individuals can earn more or advance more quickly in the outside option (this) sector, this induces a negative (positive) correlation between quality and willingness to pay. Similarly, in positions where there are higher returns to corrupt behavior, the most skilled at corrupt extraction will have the highest willingness to pay for the job and thus be the most likely to be selected. While this produces a negative selection on quality, this is less of a concern in jobs where there is lower margin for engaging in corruption or less variation in candidates abilities in corrupt activities.

Two additional economic drivers are the expected longevity of tenure in the position and costs of performing the job, where those with longer expected tenure or lower costs will place a higher value on the position. If the probability of being fired is decreasing in ability, then lower ability individuals will have lower valuations. The relevance of cost will depend on the costliness of effort in this position relative to the outside option: even if costs are generically higher for low quality individuals, this will not affect relative valuation if the gap in costs is the same in the outside option.

Individuals may also have non-pecuniary motivations in applying for a position. For example, individuals with higher prosociality may gain greater utility from a public service position. If these non-pecuniary motivations are positively correlated with job performance, this will induce a positive correlation between quality and valuation of the job. However, if some individuals are ethically opposed to the payment of bribes (which would be a willingness to pay of zero in the model), and these individuals also tend to be high quality, this could go in the other direction.

In cases where applicants are credit-constrained, wealth will also play an important role. Given the large rents that applicants are bidding for, credit constraints are likely to always play an important role. If applicants could easily muster funds equal to the discounted value of the stream of rents, then they may not need the job. On the other hand, if no applicants are credit constrained, then the valuation/quality correlation alone will govern quality of hires.

An important determinant of the wealth/quality correlation is the intergenerational persistence of wealth and role of wealth as an input to quality in childhood. If wealth is persistent across generations, and wealthier households make greater investments in the human capital of their children, then wealthier individuals will tend to have more human capital. On the other hand, inherited wealth could also reduce incentives to invest in human capital, though the two are positively correlated in virtually all settings. More plausibly, there are non-human capital dimensions of quality that may have negative relationship with wealth, such as prosocial beliefs or willingness to discriminate in services provision (e.g. high wealth households come from a more powerful ethnic group, and are more likely to discriminate against poor out-groups). But on balance, this factor seems likely to push the correlation in a positive direction.

Another determinant is the return to quality in previous jobs. Higher quality candidates may tend to have earned more in their previous work, causing them to have higher wealth. It is also possible that prior earnings are negatively correlated with quality, such as if more corrupt candidates extracted more resources in previous positions. This correlation will depend on the previous work histories of applicants for a given position.

Finally, the relationship between wealth and valuation may be important. Even if there is no reason
for valuation and measures of quality to be related, there may be a correlation between wealth and quality, as well as between wealth and valuation, and this will induce a correlation between valuation and quality. Most obviously, if there are diminishing marginal returns to income, higher income people may place a lower value on a particular job. On the contrary, if there are characteristics that lead both to higher wealth and a desire for economic advancement, such as intrinsic motivation, this correlation may be positive.

### 7.2 Extrapolating to Other Occupations

Taking these factors into account, table 7.2 speculates on the results of a corrupt hiring process for common types of government jobs. Each column is one of the inputs into the sign of the valuation/quality or wealth/quality correlation. A cell with a (+) indicates that this factor pushes the correlation in a positive direction, (0) means that it has no effect, and (-) implies a negative effect. The final column aggregates the others for the likely sign of the overall selection on quality. Note that even if the overall selection is positive, this need not mean that a corrupt hiring process will outperform a traditional one. That depends on the relative strength of the correlations, as well as the strength of the correlation between quality and the counterfactual selection mechanism.

I consider a few representative rows of the table to highlight the logic. In rural areas of developing countries, being a teacher or a health worker is one of the most remunerative jobs, and precluding migration, the returns to quality in outside options are unlikely to be large relative to the return to holding one of these positions. Furthermore, there are more limited opportunities for corruption in these positions, and those that exist are unlikely to vary strongly with quality in the position. As a result, financial returns relative to outside options should not have much of an effect, though it may be weakly negative. The rest of the categories are likely to push the correlations between valuation/quality and wealth/quality in a positive direction for the reasons stated before. However, if the applicants do not have any prior earnings, since these are entry-level positions, this relationship could be weakened. In general, the selection on quality for these positions is likely to be positive since nearly all of the components are positive.
<table>
<thead>
<tr>
<th>Job Role</th>
<th>Valuation/Quality Correlations</th>
<th>Wealth/Quality Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Financial Returns</td>
<td>Tenure</td>
</tr>
<tr>
<td>Rural Teachers and Community Health Workers</td>
<td>(0)</td>
<td>(+)</td>
</tr>
<tr>
<td>Urban Teachers</td>
<td>(-)</td>
<td>(+)</td>
</tr>
<tr>
<td>Doctors and Nurses</td>
<td>(0)/(-)</td>
<td>(+)</td>
</tr>
<tr>
<td>Entry Level Police/Revenue Collectors</td>
<td>(-)</td>
<td>(?)</td>
</tr>
<tr>
<td>Promotion for Police/Revenue Collectors</td>
<td>(-)</td>
<td>(?)</td>
</tr>
</tbody>
</table>

Figure 11: Speculated Selection on Quality for Jobs under Corruption in Hiring
For entry-level police or revenue collection (e.g. tax or tariff collectors) positions, the selection on quality is likely to be negative. Since these positions have substantial ability to extract bribes and individuals may vary in their extractive capacities, the most extractive candidates will have the highest willingness to pay. The effect of length of job tenure on the correlation is ambiguous. On the one hand, the most corrupt may be caught and punished, but on the other hand, those that refuse to engage in corruption could also be censured by higher-ups expecting kick-ups. The remaining factors are unlikely to overcome the negative effect of these factors, resulting in an overall negative selection on quality.

For promotion for police/revenue collection positions, the selection could be even more negative. The most corrupt will have the highest earnings in lower level positions and thus would have a greater ability to pay for a promotion. Furthermore, in systems characterized by high levels of corruption, non-corrupt individuals will have lower economic returns to their position from kick-ups, and may find it more costly to oversee those who are corrupt. Due to the strongly negative selection that results from corruption in promotions for these positions, this should be a major focus for policymakers cracking down on corruption.

7.3 Alternative Corrupt Hiring Procedures

This paper has focused on a setting in which all jobs are allocated via a bidding process. However, journalistic accounts describe three other ways in which hiring systems are corrupted. In the first, allocations are according to an honest system, but hires are extorted by selection agents. In the second, selection is along clientelistic lines. In the third, an “honest” system, such as an exam, is used to allocate educational or employment opportunities, but individuals are able to pay bribes to receive unmerited high marks.40

In this section, I discuss these procedures and demonstrate that the main insights of the paper hold, albeit with some modifications.

First, bribery in hiring can take the form of extortion, where hiring decisions are made according to an honest system, but the selection agent threatens to withhold the position unless the hires pay a bribe. Depending on how the negotiations are structured (discussed further in appendix section C.4), the set of hires will be roughly the same as under the honest system, but with a transfer of rents from hires to the selection agent. As a result, misallocation will be roughly the same as under the honest system, and so the effect of corruption is minimal.

Second, hiring processes may be corrupted by clientelism, where politicians or bureaucrats favor those with connections in the allocation of jobs. This is a special case of my earlier model, where in the selection agent’s utility function the weight placed on bribes (π) is equal to zero, but the weight placed on the dimensions of α related to political connections is positive. As a result, the quality of hires will depend on the correlation of those dimensions of α with performance in the job. These correlations could be positive, such as if connected hires are more carefully screened or monitored by those doing the hiring, or negative, such as if clientelistic hires are less subject to punishment for poor performance.

Finally, exams with corruption are a specific case of a system in which some slots are allocated cor-

40The Vyapam scam in India is a particularly good example of this, where an investigation identified corruption in 3.2 million exams for educational and employment opportunities. Although over 2000 individuals were arrested in connection with this case, it unfortunately also illustrates the dangers of investigating corruption: there have been over 20 reports of suspicious deaths as part of cover-up attempts (link).

41A similar form of cheating is paying a more highly skilled individual to take the exam in the place of the applicant. Assuming that a market exists for these services, this will still lead to matches between the highest willingness to pay individuals and the best test-takers, so the intuition below will hold.

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ruptly, with the remainder allocated under a honest allocation rule. This is illustrated with the simple supply and demand model in figure 12. The supply curve is equal to the selection agent’s marginal cost of allocating a slot corruptly, which may be non-zero due to fear of exposure and punishment. The demand curve derives from applicants’ willingness to pay for the post. The selection agent will balance the risk of punishment with the benefit of selling an additional slot. \( n_c \) of the \( N \) total slots are sold, with the remainder presumably allocated via the honest allocation rule. In panel (a), the marginal cost of allocating a slot is constant, while it is increasing in number of slots allocated in panel (b), e.g. if it becomes progressively harder to hide malfeasance. In panel (c), the marginal cost of detection is sufficiently low that all slots are allocated corruptly.

Now consider the application behavior of candidates. For simplicity, first suppose candidates perfectly observe their rank under the honest allocation method. This could be because the selection agent informs the candidates of their ranking after the test, at which point bribe offers are made. If there are a total of \( N \) slots, of which \( n_c \) are to be allocated corruptly, then the top \( (N - n_c) \) candidates will refuse to pay bribes and be selected for the honest slots. For the remaining slots, the \( n_c \) with the highest willingness to pay (net of credit constraints) will be selected. The model of this paper will thus apply to the hires for those \( n_c \) slots, and so the quality of those hires will be determined by the correlations of wealth/willingness to pay with quality.

In reality, candidates are likely to be uncertain about their ranking, but have a sense of their place in the overall distribution. In this case, candidates towards the top of the distribution may refuse to offer bribes since it is possible that they would receive a slot without paying a bribe. This reduces their probability of getting the position, which could lead to a worse pool of individuals being selected. Under these systems, wealth and willingness to pay will still drive much of the selection decision, but with the twist that uncertainty over ranking could lead to worse outcomes.

I devise a new estimation strategy to study this type of corruption in my data. In this model, one slot is available per competition, and applicants can offer a bribe to the tester to have their score altered/be selected. If more than one bribe is offered, the individual with the highest offer will be selected and pay their bid; if no one offers a bribe, then the slot is allocated to the person with the highest test score. Each

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42 If prices are fixed for all candidates, then there is a second reason to allocate only a limited number of slots via bribery: they can extract monopoly rents by allocating a limited number of posts at a higher price.
applicant has a test score \( t_i \) and valuation \( v_i \) drawn from a joint distribution \( r(t, v) \). Applicants know the total number of other applicants, \( I \), and their own score, but not the scores and valuations of others. They must decide whether to make a bribe offer prior to the realization of the others’ test scores.

The selection agent administering the test has a cost \( b \) of allocating a slot, which can be thought of as their risk of being caught/punished due to monitoring. The size of \( b \) will vary depending on the monitoring environment. The selection agent will refuse to accept a bribe lower than \( b \) and \( b \) is common knowledge. The details and the strategy for solving the model can be found in appendix E.4.

I estimate the model over a range of \( b \), where the testing procedure is the Raven’s matrices. Figure 13 plots the resulting SPI under each \( b \), as well as a dashed line denoting SPI under the set of actual hires. Depending on the value of \( b \), a system of testing with bribery may lead to better or worse outcomes than the actual hiring process. However, the shape of the response to \( b \) is somewhat surprising: quality of hires is U-shaped in \( b \), i.e. a moderate amount of monitoring is worse than either poor or significant monitoring. A moderate amount of monitoring slightly deters corruption, e.g. bribes are paid in 85% of contests when \( b = 12 \), as opposed to 97% of contests when \( b = 2 \). However, under moderate monitoring, many individuals with high test scores prefer not to offer bribes, since their probability of acquiring the position without bribery has increased sufficiently. As a result, they are less likely to be hired, and since many of the best candidates have high scores on the Raven’s matrices, this lowers the quality of hires. Quality increases in cases with higher levels of monitoring and punishment. For example, when \( b = 40 \), bribes are only paid in 6% of contests, and so high scoring individuals have a reasonable chance of being selected. These results demonstrate that incomplete anti-corruption efforts may lead to worse outcomes than no anti-corruption efforts at all, a cautionary note for implementers.
A companion project discusses these alternative mechanisms further. That project also takes up how higher-level planners could design incentives for selection agents to hire high quality candidates when the wealth/quality and valuation/quality correlations are negative. For example, imposition of a full set of selection criteria may be infeasible, but it may be possible to enforce minimum quality thresholds for particular characteristics. This may be sufficient to select a relatively high quality group of individuals, but depends on the context and set of enforceable characteristics.

7.4 Limitations

There are a number of limitations to this paper. First, as discussed in this section, hiring for community health worker positions is similar to hiring for many types of jobs, but different from others. I do not have data from other hiring processes, so use the theory developed in the paper in order to speculate on them.

Second, when considering the effects of corrupt hiring processes, I have ignored dynamic incentives; if one expects to be able to purchase a job in the future, this reduces the return on human capital investments. To the best of my knowledge, there is no empirical evidence on the magnitude of such an effect, but it is likely to be small. Public sector jobs are often scarce, and it would be risky to underinvest in capital formation when such a job is by no means certain. Furthermore, if there are complementarities between human capital investments and bribes in pursuit of a job (e.g. minimum educational qualifications) or human capital investments can substitute for bribes (as in this context), the effect will be muted. Regardless, the prescription of the paper is not that corruption in hiring should be ignored, but that in situations where corruption is endemic and costly to eliminate, it is important to know the sectors in which the marginal benefit of elimination is the highest.

Third, I have focused on the allocational efficiency of hiring, but there are other costs from corruption. Corrupted hiring processes may decrease social trust or confidence in institutions, or individuals may act more corruptly in other enterprises due to decreased belief in probability of punishment. While these effects are plausible, the allocational effect of hiring is likely to be more important for welfare. Selection based on wealth is also regressive, even if it selects higher quality individuals. Given the importance of better service delivery, regressive policies may still be socially optimal. In general, while corruption can have costs like these ones, allocational efficiency is the most important outcome for overall social welfare.

Fourth, the payment of a bribe may cause hires to behave differently, such as acting in more venal fashion to recoup their bribe repayment. To the best of my knowledge there is no existing empirical evidence on the relationship between this type of bribe payment and performance. Since all hires in this context paid a bribe, it is not possible to compare to a case with no bribes. However, I can compare the performance of hires who paid larger or smaller bribes. Presumably the relationship between bribe and performance, if any, would be somewhat continuous (e.g. paying a bribe of $\epsilon$ seems unlikely to affect behavior relative to paying no bribe), and so this type of comparison is informative. Ones own bribe offer is endogenous, so I instrument for realized bribe payment using the average bribe offers of competitors in their cluster. This first stage is strong ($F = 29.06$), but there is little evidence of a relationship between bribe size and any of four measures of performance (performance evaluations, process data on performance, CHW ratings of their supervisor, and changes in services delivery; see appendix table A4).
8 Conclusion

This paper examines the nature of corrupt hiring processes and the degree to which corruption during a hiring process leads to allocative inefficiency. I collected data from a hiring process for community health managers in a developing country context and document the presence of substantial corruption. All of the hired managers were required to pay bribes, and bribe values averaged nearly a year and a half of pay.

Despite a selection process characterized by corruption, those choosing to apply were of a significantly higher quality than non-applicants, and hires were of a higher quality than most of their competitors. Using measures of productivity in the new job, I found the variables that predict better performance and build a predicted supervisor performance index for all candidates. There is a strong positive selection on this index, showing that more productive individuals were hired. As a validation of this methodology, I construct an instrument for the SPI of hires and demonstrate that the instrumented results are virtually the same. I also structurally estimate a model to determine the identity of those who would have been selected under alternative hiring policies. Under these hiring policies, including the policy that the government wished to be used, counterfactual hires are similar to or sometimes worse than actual hires.

I then create a general model of hiring under corruption and show that hiring is well described by an auction with entry costs and credit constraints. Based on estimates of the selection agent’s utility function, hiring decisions are based primarily on bribe amounts. The higher quality of hires occurs because bribery leads to selection on wealth and willingness to pay, both of which are positively correlated with quality.

These results have several implications for policy. First, the paper demonstrates that under the right set of circumstances, the presence of corruption need not cause a hiring process to deviate far from selection of the best applicants. Given that the distortionary effects are minimal in some sectors and policymakers have limited capacity to enact changes, this suggests that they should focus attention on the specific set of sectors in which the benefits of reducing corruption will be the greatest, as highlighted in section 7.

Second, the paper suggests ways in which policymakers can reduce the injurious effects of corruption in hiring. Although it may be difficult to eliminate payment of bribes, misallocation need not be significant when willingness to pay is aligned with quality. Alternatively, if a hiring agent has some utility over the quality of their hires, the damaging consequences of bribery can be limited. In the private sector, hiring agents can be made residual claimants on profits, but this is difficult for government agencies. Instead, government agencies could set minimum quality levels on metrics that are easily verifiable, such as education, and punish hiring agents when hires do not conform to these standards. Ongoing work tests the efficacy of these types of solutions.

Aside from the results on corruption, this paper is one of the first to demonstrate how the quality of mid-level developing country bureaucrats affects services delivery. The large positive impact of higher quality managers is somewhat surprising given their limiting sanctioning ability and overall dysfunction of developing country bureaucracies. This suggests that simple, partial reforms, such as improving promotion processes, could have substantial benefits and should be considered as part of bureaucratic reforms.

This paper has established a number of general economic mechanisms involved in hiring. Some of these are not possibly to identify in the current data, as they require data from hiring processes for different classes of work. While it may prove impossible to collect data on corruption for many of these processes, it may be possible to collaborate with government partners and test different methods of applicant selection. Similarly, the paper suggests different methods for reducing the detrimental effects of corruption. These
could be applied to different hiring processes in order to determine their efficacy. Examining different methods for selection of civil servants, particularly in mid-level management positions, is an important area for future research.
References


Mikusheva, Anna and Brian P. Poi, “Tests and confidence sets with correct size when instruments are potentially weak,” Stata Journal, 2006, 6 (3), 335–347.


Moreira, Marcelo J., “Tests with correct size when instruments can be arbitrarily weak,” Journal of Econometrics, 2009, 152 (2), 131–140.


NewsRu, “Medvedev priznal, chto gosudarstvennye posty v Rossii prodayutsya, a Zhirinovsky nazval tsemy [Medvedev admitted that government posts are sold in Russia, and Zhironovsky named the price],” Novosti Rossii [Russian News], July 2008.


Table A1: Individual Balance on Covariates for Shocks Before and After the Hiring Process
<table>
<thead>
<tr>
<th></th>
<th>SPI shock</th>
<th>SPI shock</th>
<th>SPI shock</th>
<th>SPI shock</th>
<th>SPI shock</th>
<th>SPI shock</th>
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</thead>
<tbody>
<tr>
<td>Avg. Supervisor Performance Index (Predicted)</td>
<td>0.24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. Education</td>
<td></td>
<td>0.32</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. Percentile Rank in Wealth</td>
<td></td>
<td></td>
<td>-4.51</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. Intelligence (Raven’s)</td>
<td></td>
<td></td>
<td></td>
<td>0.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. Health Status</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.73</td>
<td></td>
</tr>
<tr>
<td>Avg. Hours Worked (as CHW)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.053</td>
</tr>
<tr>
<td>Observations</td>
<td>66</td>
<td>66</td>
<td>66</td>
<td>66</td>
<td>66</td>
<td>66</td>
</tr>
</tbody>
</table>

Table A2: Relationship between Shock to SPI and Composition of Cluster

<table>
<thead>
<tr>
<th></th>
<th>Services Delivery Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>0.094**</td>
</tr>
<tr>
<td>IntelligencE</td>
<td>0.077***</td>
</tr>
<tr>
<td>(Raven’s)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Writing Skill</td>
<td>-0.21***</td>
</tr>
<tr>
<td>Reading Skill</td>
<td>-0.40**</td>
</tr>
<tr>
<td>Extroversion</td>
<td>-0.29***</td>
</tr>
<tr>
<td>Observations</td>
<td>15570</td>
</tr>
<tr>
<td>Mean</td>
<td>61.2</td>
</tr>
<tr>
<td>Individual FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Standard errors clustered at supervisor level

Table A3: Post-LASSO Regression on CHW performance

<table>
<thead>
<tr>
<th></th>
<th>Performance Evaluation (IV)</th>
<th>CHW Rating (IV)</th>
<th>Process Data (IV)</th>
<th>Services Delivery (IV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bribe Paid</td>
<td>0.048 (0.095)</td>
<td>-0.051 (0.044)</td>
<td>0.026 (0.057)</td>
<td>0.071* (0.042)</td>
</tr>
<tr>
<td>Observations</td>
<td>55</td>
<td>55</td>
<td>55</td>
<td>11395</td>
</tr>
<tr>
<td>Individual FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>First Stage F-Stat</td>
<td>29.1</td>
<td>29.1</td>
<td>29.1</td>
<td>29.1</td>
</tr>
</tbody>
</table>

*Standard errors clustered at supervisor level

Table A4: Bribe Payments on Hire Performance
B Data Collection Details

This appendix contains further information on surveying methodology, non-response, and the details of the behavioral games and tests utilized.

B.1 Survey Details

All surveying operations were managed and overseen by the author. Surveyors were selected based on observed performance on prior surveying assignments and were very familiar with both rural health care systems and the sample area. All surveyors were female, since all of the CHWs were female, and this was thought to increase level of comfort during the survey. Most had a postgraduate degree, and all had completed at least a college degree.

As privacy was determined to be a high priority, particularly during discussions of corruption, intelligence tests and behavioral games, respondents were surveyed at a central location rather than at their homes. These spaces were selected due to their availability, proximity to transit hubs, the familiarity of all CHWs with their location, and ample space for surveying in private. Survey teams remained in a particular location over multiple days and made appointments with CHWs via phone for surveys throughout the day. All respondents were paid 150% of average CHW daily earnings in compensation for taking the survey. During the second round of surveying, they had the potential to earn up to an additional 75% of average CHW daily earnings based on their performance in behavioral games, but they were not informed about this prior to arrival. Since the survey took between 1-2 hours, and payment exceeded the typical daily wage rate, almost all were eager to participate in the survey.

All current CHWs have a phone number, and an accurate list of CHW phone numbers was kept at a central level. We were able to contact 96.4% of our sample frame, and of those contacted, 92% were administered the survey. In cases where it was not possible to contact a particular CHW by phone, we attempted to contact them via other health workers who lived near them. Outright refusal rates were very low (0.5%), with most attrition due either to illness in their family (1.5%) or other obligations, such as participation in a family event or being out of town during survey dates (2%). Using administrative data, I find that there is no statistically significant difference between surveyed and non-surveyed CHWs on 19/24 measures at the 5% level. On the other 5/24, non-surveyed CHWs performed slightly worse than surveyed CHWs, but the discrepancy was minimal.

B.2 Collecting Bribery Information

The most difficult part of corruption research is collecting accurate and representative information. Most previous survey measures of corruption rely on a lack of stigma or prosecution for bribe-paying in their context. This is reasonable for businesses paying bribes to police and other interactions in which the bribe-paying party is unlikely to face any major sanction. The risks are much higher with survey questions about paying bribes to gain employment since the bribe-payer is more active in the corrupt act and may fear losing their job as a result of their admission. Including questions about this on a survey could also increase reticence to provide honest responses in other important areas of a survey.

43Among those that we were not able to contact, some have likely discontinued their work as a CHW. However, in cases where we were unable to confirm this, I leave them in the sample frame.
The following question wording appeared to generate the most openness in response, and was thus selected for the survey: “Many CHW supervisors told us that it was necessary to give some money to become a supervisor. Did you have to give anything?”. The most important modification was adding the sentence “Many CHW supervisors told us that it was necessary to give some money to become a supervisor”. Informing the respondents that others had already admitted to bribe payments seems to have increased willingness to reveal ones own bribe payments by normalizing or reducing stigma around the behavior. It might also have reduced their level of suspicion, given that others had reported this behavior without sanctioning. The surveyors also had substantial previous experience surveying this type of population and building rapport with respondents.

Another interpretation is also possible: that this sentence acted as a prime, and caused some who did not pay bribes to report that they did. This is unlikely for two reasons. First, paying of bribe is still illegal and it is possible that they could lose their job if the bribe payments were uncovered. Indeed, in the project area, multiple unsuccessful applicants for the job had registered court cases against members of the selection committee. A mild prime, such as the one used, seems unlikely to cause a respondent to falsely assume this risk. Second, the following question queried them about the bribe amount. Respondents did not have difficulty answering this question, as one would expect if they had falsely reported having paid a bribe.

In cases without a primary report of bribe payments, I estimate bribe payments using secondary sources. It is possible that these secondary sources will introduce bias, such as if those upset with their supervisors wish to cast aspersions upon hires by falsely reporting that bribes were paid or misreporting their value. I first check whether disaffected CHWs are more likely to report that their supervisor paid a bribe. I measure disaffection using two survey questions. The first is a 4-point scale on which CHWs rate the helpfulness of their supervisors. The second asks them whether they feel that another person in their area would be a better supervisor. I also include the average services delivery score of the CHW, in case those CHWs with low performance are more likely to disparage their supervisor. As seen in column (1) of table A5, neither is related to reporting that their supervisor paid a bribe. For some reason, more educated individuals are more likely to report bribe payments; perhaps they are more closely integrated in social networks, and thus more likely to receive this information. Given that those with the highest incentive to report bribes are no more likely to report them, it seems that these incentives did not bias reporting.

<table>
<thead>
<tr>
<th></th>
<th>(1) Reported Bribe Dummy</th>
<th>(2) Bribe Report Error</th>
<th>(3) Bribe Report Abs Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>0.063***</td>
<td>-0.13</td>
<td>-0.35*</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.239)</td>
<td>(0.200)</td>
</tr>
<tr>
<td>CHW rating of supervisor</td>
<td>-0.081</td>
<td>-1.32</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(1.202)</td>
<td>(1.004)</td>
</tr>
<tr>
<td>Prefers different supervisor</td>
<td>0.034</td>
<td>1.38</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(1.332)</td>
<td>(1.112)</td>
</tr>
<tr>
<td>Average Grade</td>
<td>0.0023</td>
<td>0.038</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.063)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Observations</td>
<td>298</td>
<td>83</td>
<td>83</td>
</tr>
<tr>
<td>Supervisor FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*p < 0.10, ** p < 0.05, *** p < 0.01. Trimmed top and bottom 1% of bribe report error

Table A5: Validations of Secondary Bribe Reports
Even if other CHWs accurately reported that hires paid bribes, they may give an inaccurate account of how much was paid. In the paper, figure 3 shows that in cases where there are primary and secondary accounts, the bribe estimate from the secondary accounts closely aligns with the primary report. As an additional check for systematic bias, I measure reporting error, the absolute difference in secondary and primary reports in cases where both are available. If the bribe values are being reported in a biased fashion, those with the greatest dislike of their supervisor should systematically overreport the bribe paid by their supervisor. Columns (2) and (3) of A5 show that there is no difference in the bribe report error or absolute value of bribe report error depending on the feelings of the CHW about their supervisor. Interestingly, those with more education offer slightly more accurate reports (lower absolute value of error), reinforcing the idea that they may be more closely integrated into social networks.

B.3 Tests and Behavioral Games

Ability (Problem solving): The Raven’s Progressive Matrices measure general cognitive ability and have been used in hundreds of academic papers, as well as by some government agencies in hiring (e.g. Dal Bo et al. (2013); similar problems have recently been included in Mexican and Indian civil service exams). The test consists of a series of visual patterns of abstract shapes. From each pattern, a piece is missing, and respondents must identify the missing piece of each pattern from a list of options. It is an especially useful in my setting, as solving the problems does not require literacy or learned knowledge other than basic numeracy. Due to time constraints, we were not able to administer the full instrument, and instead utilized Pearson’s Set I, which contains 12 matrices. This was also done in Dal Bo et al. (2013) for similar reasons. This shorter version of the test is not able to discriminate within the top 5% of the distribution, but that proved irrelevant in our context, since few respondents were within that range.

In order to induce effort, respondents were given an incentive payment per correctly answered problem: if a respondent gave all correct answers, they would earn slightly more than a third of the prevailing daily wage. The set of 12 matrices used were taken from the Advanced Progressive Matrices, Set I, as published by Pearson Clinical. Instructions were taken directly from Raven and Court (1998), with slight modifications to fit the local context. During pre-testing, we found that no respondents were able to successfully complete the most difficult matrices, so we replaced two matrices with slightly easier ones in order to increase the spread of response values.

Ability (Memory): The digit span memory test measures a different aspect of ability, short term memory. Since both CHWs and supervisors have a great deal of information that they must synthesize and act upon, memory may be relevant in their performance. In this test, surveyors recite a string of digits (e.g. 1-8-3-4-5) to the respondents and ask the respondents to repeat the string in same order. Respondents are only given one chance to do this, with no repetition of the original string. Following this, they are given a second string containing the same number of digits, and again have single opportunity to give a correct answer. If either response is correct, then the number of digits increases by one, and the process repeats. This continues until the respondent cannot successfully repeat either of their opportunities for a given number of digits. This begins with a string of three digits, and the longest number of digits that they can repeat correctly is their score on the test.

Pro-social Preferences: In order to measure pro-social preferences, we conducted a modified dictator game, which other studies have found is predictive of real-world pro-social actions (e.g. Ashraf et al. 2014).
Respondents were informed that after the survey was completed, we would select sixteen respondents and give them an amount approximately equal to a third of their average monthly earnings. If they desired, they could donate some fraction of this to a local orphanage, but they had to decide this at the time of the survey, prior to finding out if they had won. To increase the realism, respondents were given this amount in fake local notes and two envelopes marked “donation” and “self”. Respondents privately split the notes between the two envelopes in order to demarcate the split and then placed a seal on their envelopes to emphasize the secrecy. They were told that if selected, they would be called to our office and the envelopes would be opened in front of them, after which we would give them the amount in the “self” envelope and donate the amount in the “donation” envelope.

A large range of donation amounts was observed, as seen in the below figure. As is typically for this type of game, most of the mass is at a low level of donation, with a spike at an even split, and some mass at the upper end of donation values.

**Dishonesty:** Finally, since our project focuses on corruption, we measured honesty using a modified version of a behavioral game from [Hanna and Wang (2014)](http://example.com). After completing the survey and other games, CHWs were given a dice and told to roll it 40 times, noting their rolls on a sheet. They were told that for each roll of 5 or 6, they would receive one currency unit, but for any other roll, they would not receive anything. They could earn slightly less than half the prevailing daily wage if they reported all 5’s or 6’s. In the original game in [Hanna and Wang (2014)](http://example.com), the reward schedule is increasing in the value of the roll, with some reward for each roll. Due to the low education level of some of the respondents, we elected to utilize a simpler, binary reward schedule. Respondents have an incentive to act dishonestly by reporting a larger number of 5’s and 6’s, and can do so without fear of repercussion, since it is never possible for others to know conclusively whether they cheated.

Figure 15 shows the front side of a typical response sheet. Respondents were instructed to roll one time for each row of the sheet and record the roll of the dice in that row. We elected to record responses in this
manner, rather than through check marks, since some respondents had trouble keeping track of 40 rolls. This game was played after the survey had been completed so as to avoid priming them on dishonesty during the survey.

As in Hanna and Wang (2014), we find substantial dishonesty (see Figure 16). The below figure gives number of reported rolls that were 5’s or 6’s, where respondents rolled the dice a total of 40 times. If all respondents honestly reported their rolls, the mean number of winning rolls would be 13.333, and the number of winning rolls would fall along the distribution outlined in red, with 95% lying below the green vertical line. Instead, 58% of rolls lie above the vertical line and only 14% of total winning rolls are for 13 or fewer.
C Theory appendix

In this appendix, I solve for equilibrium bidding strategies in the theoretical model. In order to build intuition, I first solve for an auction with credit constraints, and then add entry costs and selection agent preferences over bidder characteristics. At the end, I discuss a model where the selection agent has lexicographic preferences.

C.1 Auctions with Credit Constraints

In this model, bidders draw their valuation for the position from the unit uniform distribution \( x \sim \text{uniform}[0,1] \), draws are independent across bidders, and bidders cannot observe one another’s draws. In each of the models that follow, a fraction \( p \) of bidders are credit constrained, where they cannot offer bids larger than the credit constraint \( w \), which is fixed across bidders. Each credit constrained bidder \( i \) are denoted as \( i \in C \) or having a value of \( c = 1 \).

Define \( b(x) \) as the function mapping from valuation to bids. I conjecture, and later show, that this function is weakly increasing and differentiable at all but a finite number of points. \( G(v,c) \) is the function giving the probability of bidder \( x \) having made the highest offer. I conjecture and then show that the bid function is weakly increasing in \( v \) over the entire support, so holding \( c \) fixed, \( b(v_1,c) \geq b(v_2,c), \forall v_1 > v_2 \).

The expected profit from bidding will be:

\[
\pi(b) = (v - b) \Pr(b > \max(b(v_2), \ldots, b(v_N)))
\]

In order to solve for the bid function, I conjecture a general form of the function and solve for each component. This form is visualized in Figure 1. In the next portion of this section, I show that this is an equilibrium with no profitable deviations for any player. Note that the proposed bid function is bounded above by some \( \bar{b} \) and below by some \( \underline{b} = 0 \). The bidder will never wish to bid more than \( \bar{b} \), since this leads to a higher payment without any commensurate increase in the probability of winning; similarly,
they will never wish to bid less than \( \bar{b} \), since then there is no chance of winning. Even though the bid function is discontinuous, for all possible bribe values \( \hat{b} \in [\underline{b}, \bar{b}] \), there exists an \( x \in [0, 1] \), \( c \in (0, 1) \) such that \( \hat{b} = b(x, c) \). Thus, solving for the bid function, I consider the problem of the bidder as selecting a valuation \( x \in [0, 1] \) to emulate the bidding strategy of a bidder with another valuation (see Menezes and Monteiro, 2005, chapter 6 for more on this approach).

In the conjectured form, since the bid function is strictly increasing over \( v \in [0, m_1] \) and weakly increasing over the entire support, a bidder with \( v \in [0, m_1] \) will only have the largest bid if all bidders have a lower valuation than them. That occurs with probability \( v^{N-1} \). This is the classic first-price, independent private values auction setup, yielding a solution of \( b(v) = \frac{N-1}{N} v \). This result can be found in any introductory auction theory textbook, so I omit it for the sake of brevity.

When \( c = 0 \) and \( v \in [\min \{m_1, m_2\}, 1] \), bids are conjectured to be greater than \( w \). As a result, these bidders have probability 1 of being larger than the bids from credit constrained bidders. Since the bid function is strictly increasing over this subset, their bid will be the largest if their valuation is the highest among non-credit constrained bidders, which occurs with probability \( G(v) = v^{(1-p)N-1} \). Their problem is:

\[
\max_x (\pi(x)) = \max_x [(v - b(x)) G(x)]
\]

I differentiate this expression and set it equal to zero, as well as substituting \( v \) for \( x \), since at the symmetric equilibrium, the optimal \( x \) is \( v \):

\[
0 = (v - b(v)) G'(v) - b'(v) G(v)
\]

By the product rule for differentiation, \( [b(v)G(v)]' = b'(v)G(v) + b(v)G'(v) \), or \( b'(v)G(v) = [b(v)G(v)]' - b(v)G'(v) \). Substituting this into the above expression for the final term:

\[
0 = (v - b(v)) G'(v) - [b(v)G(v)]' + b(v)G'(v)
\]

\[
[b(v)G(v)]' = vG'(v)
\]

By the Fundamental Theorem of Calculus, this yields:

\[
b(v) = \frac{1}{G(v)} \int_0^v xG'(x)dx
\]

Based on the conjecture, for this value of \( x \), \( G(x) = x^{(1-p)N-1} \). Integrating and simplifying the expression, this yields:

\[
b(v) = \frac{1}{v^{(1-p)N-1}} \left( \frac{(1-p)N - 1}{(1-p)N} v^{(1-p)N} + K \right)
\]

\[
= \frac{(1-p)N - 1}{(1-p)N} v + \frac{K}{v^{(1-p)N-1}}
\]

For this to be consistent, the value of \( K \) must be such that \( \frac{(1-p)N-1}{(1-p)N} m_1 + \frac{K}{m_1^{(1-p)N-1}} = w + \epsilon \), where \( \epsilon \)
is the smallest possible bid interval. Thus $K = m_1^{(1-p)N-1} \left(w + \epsilon - \frac{(1-p)N-1}{(1-p)m_1} m_1\right)$, and so the bid function is 

$$b(v) = \frac{(1-p)N-1}{(1-p)m_1} v + \frac{K}{v^{(1-p)N}} \text{ over the interval } [m_1, 1] \text{ for non-constrained bidders.}$$

When a bidder is credit constrained and has a valuation of $v \in (\min \{m_1, m_2\}, m_2)$, the bid function is again strictly increasing in $v$. As a result, their bid will be the largest if their valuation is the largest among the credit-constrained, and none of the non-credit constrained have a valuation of greater than $\min \{m_1, m_2\}$. This probability is equal to $\nu^{pN-1}m_1^{(1-p)N}$. The solution strategy for this case is the same as in the previous one, except that $G(x) = x^{pN-1} (\min \{m_1, m_2\})^{(1-p)N-1}$. Thus, where $L$ is the constant of integration,

$$b(v) = \frac{1}{\nu^{pN-1}m_1^{(1-p)N}} \left(m_1^{(1-p)N} \frac{pN-1}{pN} v + \frac{L}{\nu^{pN-1}m_1^{(1-p)N}} \right)$$

$$= \frac{pN-1}{pN} v + \frac{L}{\nu^{pN-1}m_1^{(1-p)N}}$$

In order to be consistent, constrained bidders of valuation $m_1$ must bid $\frac{N-1}{N} m_1$, so

$$\frac{pN-1}{pN} m_1 + \frac{L}{m_1^{(1-p)N}} = \frac{N-1}{N} m_1$$

$$\frac{L}{m_1^{(1-p)N}} = m_1 \left( \frac{pN-p1}{pN} - \frac{pN-1}{pN} \right) \to L = \frac{1-p}{pN} m_1^{N}$$

Thus, $b(v) = \frac{pN-1}{pN} v + \frac{1-p}{pN} m_1^{N} v^{1-pN}$.

The value of $m_2$ will depend on the parameter values, where for some parameter values, this is the point at which $\nu^{pN-1} m_1^{N} v + \frac{1-p}{pN} m_1^{N} v^{1-pN}$ intersects $w$, while for others, bidders will prefer to jump to a bid of $w$ in order to mix with the higher-valuation but credit constrained bidders. This may be advantageous because it produces a discrete increase in their probability of winning the auction. If the bidder jumps to a bid of $w$, they will win the auction if: i) all non-credit constrained bidders have valuations less than $\min \{m_1, m_2\}$; and ii) all credit constrained bidders have valuations lower than $m_2$ or this bidder wins the random tie break with all the credit constrained bidders who have valuations greater than $m_2$. In the case of a tie between $i$ bidders, each wins with probability $\frac{1}{i}$. The probability of a tie between $i$ bidders occurring is a binomial random variable with probability $(1-m_2)$ of each occurrence of a tie and $m_2$ of each failure to tie. Putting this together, the probability of winning with a bid of $w$ will be equal to $M$, where:

$$M = (\min \{m_1, m_2\})^{(1-p)N} \left(m_2^{pN-1} + \sum_{i=1}^{pN-1} \frac{1}{i} \left( \frac{pN-1}{i} \right) (1-m_2)^i (m_2)^{pN-1-i} \right)$$

Using this expression, we can solve for the value of $m_2$, and determine whether bidders “jump” or not. If they do not, then $m_2$ will be equal to $\tilde{m}_2$, which solves $\nu^{pN-1} \tilde{m}_2 + \frac{1-p}{pN} m_1^{N} \tilde{m}_2^{1-pN} = w$. If they do, then there exists some $\tilde{m}_2 < \tilde{m}_2$ such that $(\tilde{m}_2 - w) \cdot \tilde{M}(\tilde{m}_2) = 0$, so $\tilde{m}_2 = \min \{m_2, \tilde{m}_2\}$. We can solve for both $\tilde{m}_2, \tilde{m}_2$ using these equations, and set $m_2 = \min \{m_2, \tilde{m}_2\}$.

Finally, if $v \geq m_2$ and $c = 1$, the bid is conjectured equal to $w$. This will be shown to be a best response in the next subsection. Putting all four cases together, the probability density function will be
and show that these yield the same value.

To show that there are no profitable deviations, I first show that the expected profit function is continuous in \( x \), holding \( c \) fixed, at all but two points. I then calculate the derivative with respect to \( x \) over each piece of the expected profit function, and show that for \( x < v \), the derivative is always positive and for \( x > v \), the derivative is always negative. Next, I show that over the two discontinuous points, the difference in limits along both sides of the discontinuity has the same sign as the derivative of the expected profit function there. Combining this with the continuity and sign of the derivative of the expected profit function elsewhere, this implies that holding \( c \) fixed, the optimal choice is at \( x = v \), i.e. there is no profitable deviation. Finally, I show that those with \( c = 0 \) prefer not to deviate to bids corresponding to \( c = 1 \). Those with \( c = 1 \) are unable to deviate to bids corresponding to \( c = 0 \), so this implies that there are no profitable deviations anywhere.

At all but two points, \( m_1 \) and \( m_2 \), the expected profit function is the product of two continuous functions, and thus is itself continuous. At \( m_1 \), I take the limit of the expected profit function for \( c = 1 \), and show that these yield the same value.

\[
\lim_{c \in \{0,1\}, x \to m_1} \left( v - \frac{N - 1}{N} x \right) x^{N-1} = \left( v - \frac{N - 1}{N} m_1 \right) m_1^{N-1}
\]

This function is consistent with all the assumptions that were needed to derive it, such as being continuous and differentiable at all but a finite number of points. It is also weakly increasing in \( v \) over the entire support and strictly increasing in \( v \) over the first three pieces.

**Checking for profitable deviations** Having solved for the bid function, I now show that there are no profitable deviations. For all \( b \in [b, \bar{b}] \) that are not strictly dominated, there exists some \( x \in [0,1] \), \( c \in \{0,1\} \) such that \( b = b(x,c) \). Thus, we can conceptualize a profitable deviation as deviation to the bid for \( (x,c) \), and consider the corresponding probability value \( G(x,c) \). The expected profit function for a deviation \( x \) will be equal to \( \pi(x,c) = (v - b(x,c)) G(x,c) \).

To show that there are no profitable deviations, I first show that the expected profit function is continuous in \( x \), holding \( c \) fixed, at all but two points. Then I calculate the derivative with respect to \( x \) over each piece of the expected profit function, and show that for \( x < v \), the derivative is always positive and for \( x > v \), the derivative is always negative. Next, I show that over the two discontinuous points, the difference in limits along both sides of the discontinuity has the same sign as the derivative of the expected profit function there. Combining this with the continuity and sign of the derivative of the expected profit function elsewhere, this implies that holding \( c \) fixed, the optimal choice is at \( x = v \), i.e. there is no profitable deviation. Finally, I show that those with \( c = 0 \) prefer not to deviate to bids corresponding to \( c = 1 \). Those with \( c = 1 \) are unable to deviate to bids corresponding to \( c = 0 \), so this implies that there are no profitable deviations anywhere.

\[
G(v,c) = \begin{cases} 
  v^{N-1} & \text{if } v < \min \{m_1, m_2\} \\
  v(1-p)^{N-1} & \text{if } v \geq \min \{m_1, m_2\} \text{ and } c = 0 \\
  v^{pN-1}m_1^{1-pN} & \text{if } m_1 < m_2, m_1 \leq v < m_2 \text{ and } c = 1 \\
  M & \text{if } v > m_2 \text{ and } c = 1
\end{cases}
\]

and the bid function is:

\[
b(v,c) = \begin{cases} 
  \frac{N-1}{N} v & \text{if } v \leq m_1 \\
  \frac{(1-p)^{N-1} v + \frac{K}{v^{1-pN+1}}}{(1-p)^N} & \text{if } v > \min \{m_1, m_2\} \text{ and } c = 0 \\
  \frac{N-1}{pN} v + \frac{1-p}{pN} m_1^{Np} v^{1-pN} & \text{if } m_2 > v \geq \min \{m_1, m_2\}, \text{ and } c = 1 \\
  w & \text{if } v \geq m_2 \text{ and } c = 1
\end{cases}
\]

There may be a gap in bids from \( b \in (\frac{N-1}{N} m_1 + (m_2 - m_1) \frac{m_2 - m_1}{pN}, w) \), i.e. where unconstrained bidders “jump” to the credit constraint. Bid values in this range are strictly dominated by a bid of \( \frac{N-1}{N} m_1 + (m_2 - m_1) \frac{m_2 - m_1}{pN} \), since this has the same probability of winning as any bid in that range, but has a lower benefit upon winning. For the same reason, bidding more than \( \bar{b} \) or less than \( \underline{b} \) is also strictly dominated.
\[
\lim_{c=1,x \to m_1^+} \left[ \left( v - \frac{pN-1}{pN} x + \frac{1-p}{pN} m_1 N \right) x^{(1-p)N-1} \right] = \left( v - \frac{N-1}{N} m_1 \right) m_1^{N-1}
\]

Thus for \( c=1 \), the expected profit function is continuous over \( m_1 \). For \( c = 0 \), the value of the expected profit function will be:

\[
\lim_{c=0,x \to m_1^+} \left[ \left( v - \frac{(1-p)N-1}{(1-p)N} x + \frac{K}{x^{(1-p)N-1}} \right) x^{(1-p)N-1} \right] = (v - w + \epsilon) m_1^{(1-p)N-1}
\]

In considering profitable deviations, I care about the difference between the two. Taking the difference,

\[
(v - w + \epsilon) m_1^{(1-p)N-1} - \left( v - \frac{N-1}{N} m_1 \right) m_1^{N-1}
\]

By the definition of \( m_1 \), \( (m_1 - \frac{N-1}{N} m_1) m_1^{N-1} = (m_1 - w - \epsilon) m_1^{Np-1} \), so substituting this and rearranging the terms:

\[
= v \left( m_1^{(1-p)N-1} - m_1^{N-1} \right) + m_1^{Np} - m_1^{N-1}
\]

Since \( 0 < m_1 < 1 \), the derivative of this expression is positive, so as \( v \) increases, the gap increases. Furthermore, when \( v = m_1 \), the difference is equal to zero. Thus for \( v > m_1 \), the gap is positive and increasing, while for \( v < m_1 \), the gap is negative and decreasing in absolute value. This means that for valuations less than \( m_1 \), the expected profit function is decreasing over the discontinuity, while for \( v > m_1 \), the expected profit function is increasing over the discontinuity.

I now show that the same pattern holds over the second discontinuity at \( m_2 \) for \( c = 0 \). The difference in expected profit across the discontinuity will be equal to:

\[
(v - w) M - \left( v - \frac{pN-1}{pN} m_2 - \frac{1-p}{pN} m_1 N m_2^{1-pN} \right) \left( m_2^{pN-1} m_1^{(1-p)N} \right)
\]

By the definition of \( m_2 \), this equals zero when \( v = m_2 \). The derivative of the function with respect to \( v \) is equal to \( M - m_2^{pN-1} m_1^{(1-p)N} \), which is greater than or equal to zero by the definition of \( M \). Thus for \( v > m_2 \), the gap is positive and increasing, while for \( v < m_2 \), the gap is negative and decreasing in absolute value. This means that for valuations less than \( m_2 \), the expected profit function is decreasing over the discontinuity, while for \( v > m_2 \), the expected profit function is increasing over the discontinuity. At the end of the proof, these facts about the discontinuity will be used in combination with the sign of the derivative for all other values of \( x \) to show that there are no profitable deviations.

I now calculate the derivative of each piece of the expected profit function with respect to \( x \). Suppose that a bidder with valuation \( v \) deviated to a bid value corresponding to \( x \in [0, m_1] \). The expected utility function \( \pi = (v - b(x)) G(x, c) \) will be equal to \( \left( v - \frac{N-1}{N} x \right) x^{N-1} \). The derivative of this function with respect to \( x \) is
The derivative of the expected profit function is:

\[-\frac{N-1}{N}x^{N-1} + \left(v - \frac{N-1}{N}x\right)(N-1)x^{N-2} = (N-1)x^{N-2}[v - x]\]

When \(v > x\), the derivative is positive, and when \(v < x\), the derivative is negative.

Second, consider deviations to \(x\) over \([\min \{m_1, m_2\}, 1]\), where the bid value is equal to \(v - \frac{(1-p)N-1}{(1-p)N}x - Kx^{1-(1-p)}\).

The derivative of this function is equal to:

\[\frac{p N - 1}{p N} - 1\]

Finally, consider bidders with \(v \geq m_2, c = 0\). Bid and probability are constant over this range, so the derivative of the expected profit function is equal to zero. There is no profitable deviation within this range, since there is no deviation here.

Putting all of these pieces together, when \(c\) is held fixed, the expected profit function is increasing in \(x\) when \(v > x\) and decreasing in \(x\) when \(v < x\). Thus the maximum will be at \(v = x\), and there are no profitable deviations. This only holds with \(c\) held constant, so it remains to consider whether those with \(v > m_1, c = 0\) may wish to deviate to a bid corresponding to \(x \in (m_1, 1), c = 1\).
To do this, I consider the gap between the expected profit functions. Based on the derivative of the expected profit function calculated before, the best possible deviation for a bidder of valuation $v$ with $c = 1$ will be to the bid of $v = v, c = 0$. The difference between the two functions over $v \in (m_1, m_2)$ is:

$$
\pi(v, 0) - \pi(v, 1) =
$$

$$
(v - \frac{(1 - p)N - 1}{(1 - p)N} v - \frac{K}{v(1 - p)N - 1}) v^{(1 - p)N - 1} - \left( v - \frac{pN - 1}{pN} v - \frac{1 - p}{pN} m_1 v^{1 - pN} \right) v^{pN - 1} m_1^{(1 - p)N}
$$

$$
= v^{(1 - p)N} \left( 1 - \frac{(1 - p)N - 1}{(1 - p)N} \right) - K - v^{pN} m_1^{(1 - p)N} \left( 1 - \frac{pN - 1}{pN} \right) + \frac{1 - p}{pN} m_1^{2N - Np}
$$

Taking the derivative of this with respect to $v$,

$$
\pi_v(v, 0) - \pi_v(v, 1) = (1 - p)N v^{(1 - p)N - 1} \left( \frac{1}{(1 - p)N} \right) - pN v^{pN - 1} m_1^{(1 - p)N} \frac{1}{pN}
$$

$$
= v^{(1 - p)N - 1} - v^{pN - 1} m_1^{(1 - p)N} = v^{-1} \left[ v^{(1 - p)N} - v^{pN} m_1^{(1 - p)N} \right]
$$

$$
= v^{-1} \left[ m_1^{(1 - p)N} \left( \frac{v}{m_1} \right)^{(1 - p)N} - v^{pN} m_1^{(1 - p)N} \right] = v^{-1} m_1^{(1 - p)N} \left[ \left( \frac{v}{m_1} \right)^{(1 - p)N} - v^{pN} \right]
$$

When $v > m_1$, $\frac{v}{m_1} > 1$ and thus $\left( \frac{v}{m_1} \right)^{(1 - p)N} > 1$. Since $v \in [0, 1]$, $v^{pN} < 1$. As a result, the interior term must have positive sign whenever $v > m_1$, and so the entire derivative has positive sign. Since the difference between the expected profit functions is 0 when $m_1 = 0$, this implies that the difference in expected profit between $c = 0$ and $c = 1$ is increasing as $v$ increases. Thus $\pi(v, 1) > \pi(v, 0)$ over $v \in (m_1, m_2)$, and so there is not a profitable deviation from $b(v, 1)$ to any $b(x, 0)$ where $x \in (m_1, m_2)$. This trivially extends to $x \in (m_2, 1)$, since bidding $w + \epsilon$ strictly dominates bidding $w$ for any $v > m_1, c = 1$ as $\epsilon$ gets arbitrarily small, and it was previously shown that for $v > m_1$, they prefer not to deviate to a bid of $w + \epsilon$. Thus there are no profitable deviations, and the proposed bidding strategy holds in equilibrium.

### C.2 Auctions with a Fixed Cost of Entry and Credit Constraints

Now suppose that candidates must also pay a fixed cost $C$ in order to enter the contest. In the context of this paper, that could be the cost of filling out an application or other tasks necessary in applying. If there were no cost of entry, as assumed before, then all candidates with positive valuation of job would enter the contest. The data indicate that this is not the case: at least 64% of those eligible had a positive valuation for the job, but only 34% applied.

The solution to this game is qualitatively similar to the above. Regardless of the value of $C$, the lowest-valuation, credit-constrained bidder who enters the auction will place a bid of zero. Suppose that this were not true. In this case, that bidder could increase their expected utility by lowering their bid, since that reduces their payment in the case of winning, and does not affect their probability of winning. I denote this valuation as $v_c$, and solve for it below.
Now consider a bidder of valuation \( v_c \) who is not credit constrained. They have the same expected utility placing a bid of 0 as the constrained bidder of valuation \( v_c \), so will enter and either place a bid of either 0 or some value greater than or equal to \( w \). Intuitively, in those cases where it is quite beneficial to leapfrog the credit constrained bidders (e.g. there is a large set of credit constrained bidders with a low value of \( w \)), they will immediately place large bids, while in cases where that is less beneficial, they will behave identically to credit constrained bidders with the same valuation.

Suppose that the non-credit constrained entrant of valuation \( v_c \) bids more than 0. In this case, there may be other unconstrained bidders of valuation \( v \leq v_c \) who enter. I denote the lowest valuation unconstrained entrant as having valuation \( v \leq v_c \). The following set of equations gives conditions for \( v_c \) and \( v \). First, if the lowest valuation unconstrained and constrained bidders have the same valuation (\( v_c = v \)), both place bids of zero. These bidders will be those on the margin between entering and not entering, and so

\[
C = (v - 0) v^{N-1} \rightarrow \sqrt[2]{\frac{N}{2}} = v
\]

This will be rational for the unconstrained bidder as long as it is better than just overbidding the credit-constrained bidders, where \( \epsilon \) is the minimum bid interval. That gives the following conditions determining if there would be a profitable deviation.

\[
\left( \frac{N}{\sqrt[2]{\frac{N}{2}}} - (w + \epsilon) \right) \left( \frac{N}{\sqrt[2]{\frac{N}{2}}} \right)^{(1-p)N-1} - C < \left( \frac{N}{\sqrt[2]{\frac{N}{2}}} - 0 \right) C^{\frac{N-1}{N}} - C
\]

\[
C^{(1-p)\frac{1}{N}} + \frac{1}{1-p} C < w + \epsilon
\]

**Unconstrained and Constrained Enter at the Same Valuation**  If this condition is satisfied, then all bidders with \( v > \sqrt[2]{\frac{N}{2}} = v = v_c \) will enter, and all those with lower valuations will not. This leads to a truncated value distribution, but otherwise, the strategies are qualitatively the same as above, with formulas rescaled to incorporate the truncation. I thus omit the proof for optimal deviations, and simply solve for the bid function. Over the first non-zero part of the bid function, they will select

\[
b(v) = \frac{1}{G(v)} \int_0^v xG'(x)dx = \frac{1}{G(v)} \int_0^v xG'(x)dx
\]

Based on the conjecture, for this value of \( x \), \( G(x) = x^{N-1} \). Integrating and simplifying the expression, this yields:

\[
b(v) = \frac{1}{v^{N-1}} \left( \frac{(N - 1)}{N} x^{N} \sqrt{\frac{N}{2}} \right) + K = \frac{(N - 1)}{N} v + \frac{1}{v^{N-1}} \left( \frac{(N - 1)}{N} v^{N} - +K \right)
\]

\[
= \frac{(N - 1)}{N} v + \frac{1}{v^{N-1}} \left( \frac{(N - 1)}{N} C - K \right)
\]

The value of \( K \) must be such that \( b(v_c) = 0 \), and so

\[
\frac{(N - 1)}{N} v + \frac{1}{v^{N-1}} \left( \frac{(N - 1)}{N} C - K \right) = 0
\]
\[
K = \frac{N - 1}{N} C + \frac{N - 1}{N} \sum_{i=1}^{N} = 2 \frac{N - 1}{N} C
\]

Thus the bid function over this interval is \( b(v) = \left( \frac{N-1}{N} v - \frac{N-1}{N} C \frac{1}{v^{N-1}} \right) \). Next, \( m_1 \) is the value such that:

\[
\left(m_1 - \frac{(N-1)}{N} m_1 + \frac{N-1}{N} C \frac{1}{m_1^{N-1}}\right) m_1^{N-1} = (m_1 - w) m_1^{N(1-p)-1}
\]

which simplifies slightly to \( \left(\frac{1}{N} m_1 + \frac{N-1}{N} C \frac{1}{m_1^{N-1}}\right) m_1^{pN} = m_1 - w - \epsilon \). The remainder of the function will have precisely the same formula as in the previous section as a function of \( m_1 \). To see this, note that \( b(v) = \frac{1}{G(v)} \int_0^v xG'(x)dx \) and that \( G(x) \) is the same for all the \( x \). The only difference is the constant of integration, which will be defined in terms of \( m_1 \). Thus the functions for probability of being the highest bidder and the bid function will be:

\[
G(v, c) = \begin{cases} 
0 & \text{if } v < \underline{v} \\
v^{N-1} & \text{if } \underline{v} \leq v < \min \{m_1, m_2\} \\
v^{(1-p)N-1} & \text{if } v \geq \min \{m_1, m_2\} \text{ and } c = 0 \\
v^{N-1}m_1^{(1-p)N} & \text{if } m_1 < m_2, m_1 \leq v < m_2 \text{ and } c = 1 \\
m & \text{if } v > m_2 \text{ and } c = 1 
\end{cases}
\]

and the bid function is:

\[
b(v, c) = \begin{cases} 
\frac{N-1}{N} v & \text{if } v \leq m_1 \\
\frac{1-p}{(1-p)N} v + \frac{K}{v^{(1-p)N-1}} & \text{if } v > \min \{m_1, m_2\} \text{ and } c = 0 \\
\frac{pN-1}{pN} v + \frac{1-p}{pN} m_1^{Np} v^{1-pN} & \text{if } m_2 > v \geq \min \{m_1, m_2\}, \text{ and } c = 1 \\
w & \text{if } v \geq m_2 \text{ and } c = 1 
\end{cases}
\]

where \( K \) is defined as in the previous section, i.e. \( K = m_1^{(1-p)N-1} \left( w + \epsilon - \frac{(1-p)N-1}{(1-p)N} m_1 \right) \).

**Unconstrained and Constrained Enter at Different Valuations** If the above condition is not satisfied, then an unconstrained bidder with valuation \( \underline{v}_C \) would prefers to bid \( w + \epsilon \) rather than 0. Since this preference is strict, \( \exists \delta > 0 \text{ s.t. } \forall v \in (\underline{v}_C - \delta, \underline{v}_C) \), unconstrained bidders would prefer to enter and place a bid of \( w + \epsilon \) than not enter or place a bid of 0. There will exist some minimum \( \overline{v} \) such that the unconstrained bidder of valuation \( \overline{v} \) prefers to bid \( w + \epsilon \), i.e.

\[
(\overline{v} - (w + \epsilon)) (\overline{v})^{(1-p)N-1} = C
\]

In terms of defining the bid function, this operates in the same manner as \( m_1 \) above, where the unconstrained bidders above this valuation will compete amongst themselves. As a result, \( G(x) \) will be the same there, and thus the same formula for \( b(v, c) \) for \( v > m_1, c = 0 \) will hold, where \( m_1 = \overline{v} \).

The constrained bidder with the lowest valuation who enters \( (\underline{v}_C) \) will offer a bid of zero according to the same intuition as before. \( \underline{v}_C \) will be defined as the point of indifference between entry and non-entry, where since only unconstrained at bids of zero,
\[ \pi = (\underline{v} - 0) (\underline{v})^{(1-p)N} (\underline{v})^{p_N - 1} = C \rightarrow \underline{v} = \sqrt[p_N]{C (\underline{v})^{-(1-p)N}} \]

Those constrained bidders with valuations greater than \( \underline{v} \) will solve

\[
b(v) = \frac{1}{G(v)} \int_{0}^{v} xG'(x)dx = \frac{1}{G(v)} \int_{\underline{v}}^{v} xG'(x)dx
\]

Based on the conjecture, for this value of \( x \), \( G(x) = m_1^{(1-p)N} x^{Np - 1} \). Integrating and simplifying the expression, this yields:

\[
b(v) = \frac{1}{m_1^{(1-p)N} v^{Np - 1}} \left( m_1^{(1-p)N} \frac{(Np - 1)}{Np} x^{Np} |_{\underline{v}}^{v} + K \right) = \frac{(Np - 1)}{Np} v + \frac{K}{v^{Np - 1}}
\]

The value of the constant of integration \( K \) must be such that \( b(\underline{v}) = 0 \), and so

\[
\frac{(Np - 1)}{Np} \underline{v} + \frac{K}{\underline{v}^{Np - 1}} = 0 \rightarrow K = -\frac{Np - 1}{Np} \underline{v}^{Np}
\]

Thus the bid function over this interval is \( b(v) = \frac{(Np - 1)}{Np} (v - \underline{v})^{Np - 1} \). Finally, there may be a value \( m_2 \) such that the unconstrained bidders jump to the credit constraint. The value of \( m_2 \) will depend on the parameter values, where for some parameter values, this is the point at which \( b(v) = \frac{(Np - 1)}{Np} (v - \underline{v})^{Np - 1} \) intersects \( w \), while for others, bidders will prefer to jump to a bid of \( w \) in order to mix with the higher-valuation but credit constrained bidders. This may be advantageous because it produces a discrete increase in their probability of winning the auction. If the bidder jumps to a bid of \( w \), they will win the auction if: i) all non-credit constrained bidders have valuations less than \( m_1 \); and ii) all credit constrained bidders have valuations lower than \( m_2 \) or this bidder wins the random tie break with all the credit constrained bidders who have valuations greater than \( m_2 \). In the case of a tie between \( i \) bidders, each wins with probability \( \frac{1}{i} \). The probability of a tie between \( i \) bidders occurring is a binomial random variable with probability \((1 - m_2)\) of each occurrence of a tie and \( m_2 \) of each failure to tie. Putting this together, the probability of winning with a bid of \( w \) will be equal to \( M \), where:

\[
M = (m_1)^{(1-p)N} \left( m_2^{Np - 1} + \sum_{i=1}^{p_N - 1} \frac{1}{i} \left( \frac{p_N - 1}{i} \right) (1 - m_2)^i (m_2)^{p_N - 1 - i} \right)
\]

Using this expression, we can solve for the value of \( m_2 \), and determine whether bidders “jump” or not. If they do not, then \( m_2 \) will be equal to \( \tilde{m}_2 \), which solves \( \frac{(Np - 1)}{Np} (\tilde{m}_2 - \underline{v})^{Np - 1} = w \). If they do, then there exists some \( \tilde{m}_2 < \tilde{m}_2 \) such that \( (\tilde{m}_2 - w) M(\tilde{m}_2) = (\tilde{m}_2 - \frac{(Np - 1)}{Np} (\tilde{m}_2 - \underline{v})^{Np - 1}) \tilde{m}_2^{p_N - 1} (1 - m_1)^{Np} \).

We can solve for both \( \tilde{m}_2, \tilde{m}_2 \) using these equations, and set \( m_2 = \min \{ \tilde{m}_2, \tilde{m}_2 \} \). This gives the following bid and probability functions
\[
b(v, c) = \begin{cases} 
0 & \text{if } v < \gamma \\
0 & \text{if } v < \gamma, c = 1 \\
\frac{(1-p)N-1}{(1-p)N}v + \frac{K}{v^{(1-p)N-1}} & \text{if } \gamma \leq v, c = 0 \\
\frac{(Np-1)}{Np}(v - \sum_c v^{1-Np}) & \text{if } v_1 < v_2, v_1 \leq v < v_2 \text{ and } c = 1 \\
M & \text{if } v > v_2 \text{ and } c = 1 
\end{cases}
\]

and the bid function is:

\[
G(v, c) = \begin{cases} 
0 & \text{if } v < \gamma \\
0 & \text{if } v < \gamma, c = 1 \\
v^{(1-p)N-1} & \text{if } v < \gamma, c = 1 \\
v^{pN-1} - \sum_c (1-p)N & \text{if } \gamma \leq v, c = 0 \\
M & \text{if } v \geq v_2 \text{ and } c = 1 
\end{cases}
\]

where \( K \) is defined as in the previous sections, i.e. \( K = \sum_c (1-p)N-1 \left( w + \epsilon - \frac{(1-p)N-1}{1-pN} \gamma \right) \).

### C.3 Auctions with Preferences over Bidder Characteristics, Fixed Cost of Entry, and Credit Constraints

Finally, I address the case where \( \theta \neq 0 \), i.e the selection agent has preferences over the characteristics of the candidates. For simplicity, I will focus on a single dimensional \( \theta \) and \( \alpha \), as the basic predictions should be unchanged as more dimensions are introduced. Suppose that there are two classes of workers, educated and non-educated, where educated have bid function \( \beta_1 \) and non-educated have bid function \( \beta_0 \). Let the inverse bid functions be denoted \( \phi_1 = \beta_1^{-1} \) and \( \phi_0 = \beta_0^{-1} \), and suppose that the auctioneer places a value of \( \alpha \) on being educated. The expected profit functions will be:

\[
\pi_0 = \phi_0(b)^{n_0-1} \phi_1(b - \alpha)^{n_1} [\phi_0(b) - b]
\]

\[
\pi_1 = \phi_0(b + \alpha)^{n_0} \phi_1(b)^{n_1-1} [\phi_1(b) - b]
\]

Taking the derivative with respect to \( b \), this will yield the following FOCs:

\[
\left[ n_0 - 1 \right] \phi_0'(b)\phi_1(b - \alpha) + n_1 \phi_0(b)\phi_1'(b - \alpha) \right] (\phi_0(b) - b) + \phi_0(b)\phi_1(b - \alpha) \left( \phi_0'(b) - 1 \right) = 0
\]

\[
\left[ n_0 \phi_0'(b + \alpha)\phi_1(b) + (n_1 - 1) \phi_0(b + \alpha)\phi_1'(b) \right] (\phi_1(b) - b) + \phi_0(b + \alpha)\phi_1(b) \left( \phi_1'(b) - 1 \right) = 0
\]

This system of differential equations does not admit an analytical solution. It can instead be solved numerically, use the following algorithm.
Step 1: Solve for the entry condition of the uneducated group as a function of the entry value for the educated group.  Uneducated who enter and bid zero will only defeat uneducated and educated non-entrants, since an educated individual who bids zero will still defeat them. Thus to solve for $\Sigma_u$, the valuation at which uneducated will enter, one must know the cutoff at which educated individuals enter, $\Sigma_e$. For simplicity, I assume that candidates education and credit constraints are common knowledge: it is straightforward to add these as an additional level of uncertainty, but does not affect the qualitative predictions of the model. For now, I consider an equilibrium in which credit constraints do not affect entry, since this complicates the number of conditions, but does not add to intuition. Let $n_{eu}$ be the number of educated, unconstrained (with respect to credit constraints) individuals, $n_{ec}$ be the number of educated, constrained candidates, $n_{uu}$ as the number of uneducated, unconstrained candidates. This condition is:

$$\Sigma^u_{eu} + n_{ec} \Sigma^u_{uu} + n_{uc} - 1 (\Sigma_u - 0) = C \rightarrow \Sigma_u = \left( \frac{C}{\Sigma^u_{eu} + n_{ec}} \right) \frac{n_{uu} + n_{uc} - 1}{\Sigma^u_{uu} + n_{uc}}$$

Note that in general, it must be the case that $\Sigma_u \geq \Sigma_e$. An educated applicant of valuation $v$ that made an offer of 0 would have an expected payoff of $\phi_0(\alpha) n_{uu} + n_{uc} \Sigma^u_{eu} + n_{ec} - 1 v = \left( \frac{\phi_0(\alpha)}{\Sigma_u} \right) n_{uu} + n_{uc} \Sigma^u_{uu} + n_{uc} \Sigma^u_{eu} + n_{ec} - 1 v$.

When $v = \Sigma_u$, this is equal to $\left( \frac{\phi_0(\alpha)}{\Sigma_u} \right) n_{uu} + n_{uc} C$, and since there exists some $\delta$ s.t. $\phi_0(x), x \in (-\delta, \delta)$ is increasing and continuous, this implies that $\phi_0(\alpha) > \Sigma_u$ and thus that their expected payoff is greater than $C$. Again, since $\phi_1(.)$ is continuous, this implies that there exists some $\Sigma_e < \Sigma_u$ such that $\pi_1(\Sigma_e) \geq C$, and so there will be entry from the privileged set at lower valuations. As a result, if the two groups draw valuations from the same distribution, the educated group will be more likely to enter, with probability $(1 - F(\Sigma_e))$, than the uneducated group, who enters with probability $(1 - F(\Sigma_u))$.

Step 2: Solve for the first piece of the uneducated bid function  This will be as a function of $\Sigma_e$. As before, their bid function will solve:

$$b(v) = \frac{1}{G(v)} \int_0^v xG'(x)dx = \frac{1}{G(v)} \int_0^v xG'(x)dx$$

Based on the conjecture, for this value of $x$, $G(x) = \Sigma^u_{eu} + n_{ec} x n_{uu} + n_{uc} - 1$. Integrating and simplifying the expression, this yields:

$$b(v) = \frac{1}{\Sigma^u_{eu} + n_{ec} x n_{uu} + n_{uc} - 1} \left( \frac{n_{uu} + n_{uc} - 1}{n_{uu} + n_{uc}} \right) x n_{uu} + n_{uc} |_0^v + K \right) = \frac{n_{uu} + n_{uc} - 1}{n_{uu} + n_{uc}} v + \frac{K}{\Sigma^u_{eu} + n_{ec} x n_{uu} + n_{uc} - 1}$$

The value of the constant of integration $K$ must be such that $b(\Sigma_u) = 0$, and so

$$\frac{n_{uu} + n_{uc} - 1}{n_{uu} + n_{uc}} \Sigma_u + \frac{K}{\Sigma^u_{eu} + n_{ec} x n_{uu} + n_{uc} - 1} = 0 \rightarrow K = - \frac{n_{uu} + n_{uc} - 1}{n_{uu} + n_{uc}} \Sigma^u_{eu} + n_{ec} x n_{uu} + n_{uc}$$

and so the bid function is:

$$b(v) = \frac{n_{uu} + n_{uc} - 1}{n_{uu} + n_{uc}} (v - \Sigma_u)$$
Step 3: Solve for the point at which the educated would seek to enter, given the bid function of the uneducated. This will be the point at which entering and bidding zero gives sufficient utility to pay the entry cost. Note that this valuation will defeat all uneducated persons who offer a bid of less than \( \alpha \), i.e. all with valuation less than
\[
\frac{n_{uu} + n_{uc} - 1}{n_{uu} + n_{uc}} (v - \nu_u) = \alpha \rightarrow v^* = \frac{n_{uu} + n_{uc}}{n_{uu} + n_{uc} - 1} \alpha + \nu_u
\]

This gives the simple expression of: \( v^{eu} + ec - 1 \). Substituting for \( \nu_u \), we arrive at an equation that defines \( v^e \). This can then be used to solve for \( v^u \) using the above expressions.

Step 4: Use initial conditions to solve the differential equations numerically, and then iterate

Having solved for both of these, I now have initial conditions for both groups. I can then solve iteratively in the same manner as previously, where I solve the set of differential equations that defines the bid functions, using \( \nu_u \) and \( \nu_e \) as initial conditions. I then look for the first point at which a group would like to jump, and repeat until the entire function is mapped out.

There exists another set of possible equilibria where lower valuation, unconstrained bidders leapfrog the set of constrained bidders by bidding over their credit constraint. Since the intuition for this case is developed in the previous section and the addition of asymmetric preferences has little bearing on the qualitative predictions of the model, I omit discussion.

Model Predictions

In the text of the paper, I state three predictions of the model. The first is that those who have higher valuation, wealth and value for the selected upon characteristics are more likely to enter. The second prediction is that as the valuation, wealth, and characteristics of opponents increase, this leads to an increase in bids and a decrease in the probability of applying. The third prediction is that as valuation and wealth increase, bids increase, but as \( \alpha \) increases, those with high values on the selected upon characteristics offer smaller bids.

All the predictions on valuation and wealth can be found in the model in section C.2. The predictions on the effect of selected upon characteristics on entry are shown in step 1 of the current section, and the second and third predictions can be found in McAfee and McMillan (1989) and Jehiel and Lamy (2015), among others.\(^\text{45}^\)

C.4 Lexicographic Preferences

Suppose that the selection agent has lexicographic preferences over the quality of the applicants. This might come about if there is strict enforcement of quality standards, such as if the government can observe the quality of candidates and harshly punish the selection agent for selecting anyone other than the top applicant. In this case, the selection agent will select a winner from the set \( \tilde{V} = \{ \theta \alpha_{j,o} \geq \theta \alpha_{j',o} : \forall j' \in I \} \).

\(^{45}\)Since the setup of the model is slightly different from many others of entry, I show the entry result explicitly; the other results are documented in the literature on discrimination in procurement auctions.

\(^{46}\)A variant of this case is if the selection agent has lexicographic preferences over bribes. The analysis of this case is practically identical, except that contests with equivalent bribe bids are decided according to candidate quality, rather than chance. Since such an event has measure zero probability when the space \((W, v, \alpha)\) is defined over a continuum and gives practically identical predictions, I ignore it for purposes of brevity.
If this set is a singleton, then the lone member will be the winner. If the set contains multiple elements, then the winner will be \( j \in \tilde{V} \) such that \( b_j > b_{j'} \), \( \forall j' \neq j, j' \in \tilde{V} \). A quality-motivated selection agent would select high-quality applicants, so a purely quality-motivated agent might explain why high quality candidates could be selected.

The nature of the probability density function of applicant characteristics, \( f(\cdot) \), determines the likelihood of a \( \tilde{V} \) being a singleton. When \( f(\cdot) \) is a continuous function with positive mass over a continuous range of values, the probability of \( \tilde{V} \) containing more than one element will be zero, i.e. it is not possible that two applicants will have equal quality in the eyes of the selection agent. In this case, applicants will never offer bribes. When there are no ties, probability of winning is non-increasing in bribe offer, but only depends on fixed quality characteristics. Since it is costly to offer bribes, they will not offer a bribe.

This analysis has implicitly assumed that agents have rationalizable off-equilibrium path beliefs. Under a weaker equilibrium concept that allows non-rationalizable off-equilibrium path beliefs, lexicographic preferences and bribery can co-exist. Such a game would proceed with the selection agent selecting the applicant who maximizes their weighted quality function. They then extort that applicant by selecting a bribe amount, offering the selected applicant the job in exchange for that amount, and threatening to give the job to another applicant if their bribe offer is not met. If the applicant rejects the offer, then the selection agent will select the quality-preferred applicant (with a bribe of zero) with a probability of \( \zeta \geq 0 \), and reject that candidate to approach another candidate with a probability of \( (1 - \zeta) \). They might also enter into a bargaining game as suggested in Fudenberg et al. (1987), but this does not change the testable predictions, so I continue with the simpler model.

Due to the lexicographic preferences of the selection agent, the extortion threat is not credible and the subgame perfect equilibrium is obvious. Solving backwards, the agent would have lower utility if they ever reject the quality preferred candidate in the final stage. Thus the quality preferred candidate can reject any bribe demand, and the selection agent would never demand a bribe. However, under a weaker equilibrium concept, it is possible to have the following equilibrium strategies:

Agent strategy: \((b, \zeta) = (WTP_j, 0)\); Applicant strategy: \((A)\)

Here the applicant believes the threat of the agent, and so can be successfully expropriated. The lack of sequential rationality is a strong theoretical reason to reject this description of the process, but I can nonetheless test for it empirically. In this case, the selection agent should demand a bribe based on their expectation of applicant willingness to pay. This will be a positive function of \((W_j, \gamma_j, \alpha_j)\), but orthogonal to \((W_{j'}, \gamma_{j'}, \alpha_{j'})\), \( j' \neq j \), i.e. the characteristics of other competitors will not change bribe amounts.

\[47\] If there is a sufficiently high probability of a tie, such as if \( f(\cdot) \) is defined over a discrete set, with mass on a finite and small set of \( \alpha_o \), applicants may have an incentive to offer a bribe. The probability of a tie would have to be extremely large for bidders to offer as large bribes as observed in the data, so it is ignored here.

\[48\] Another option is that applicants are deceived about the nature of selection agent preferences, and mistakenly think that the selection agent has non-lexicographic preferences. This non-equilibrium outcome could occur if applicants are inexperienced in dealing with selection agents, unfamiliar with bribery for government positions, or it is not ex-post revealed that those making the highest bribe offers did not receive the position. Data on selected applicants suggests against this interpretation, since there are numerous cases where obviously inferior candidates are selected.
D Empirics: Application and Bribe Offers

D.1 Robustness Checks on Estimation of Selection Agent Preferences

A number of concerns are often raised about the estimation of selection agent preferences. First, agent preferences are limited to be simple substitutes over applicant characteristics, bribes, and political connections.\textsuperscript{49} There may also be complementarities between characteristics, such as if the selection agent places greater weight on bribe offers or connections of higher quality applicants. In appendix D.3, I introduce interactions between bribe value and quality measures into the estimation, but find no evidence for complementarities.

Second, political connections are modeled with a dummy variable for stated use of a connection. The coefficient on this variable represents the average benefit of use of a connection, but does not incorporate the power of a particular applicant’s connection or degree to which this connection exerts effort on an applicant’s behalf. From inspection of the data, this may explain some of the predictive failures. In one case, the selected supervisor is predicted to give lower utility to the selection agent than other applicants, but she has an immediate family member who is a politician in the region’s most powerful political party. Presumably the value of this connection was larger than average, and could explain the prediction failure. Given data limitations, it is infeasible to incorporate these factors without subjective and potentially arbitrary coding decisions.\textsuperscript{50}

Third, there may be variables unobserved to the econometrician that are part of the agent’s utility function. Given the small amount of unexplained variation, this could only be true if the unobserved factor were not play a large role in the observed selection decisions or were highly collinear with one of the selection variables. Variables with low explanatory power are irrelevant for the purposes of interpretation. For the second case to be true, such a variable would need to be implausibly highly correlated with one of the proposed selection factors.\textsuperscript{51} Thus omitted variable bias is unlikely to be a major problem.

Fourth, in cases where hires did not provide their bribe offers, secondary reports were used to create an estimated winning bribe offer. Although earlier robustness checks suggest a lack of systematic bias, I rerun the maximum likelihood estimation using only contests with primary reports of the winning bribe offer. As seen in column (1) of appendix table A15, the estimated coefficients on bribes and political connections are similar in magnitude and statistical significance. However, the coefficient on education shrinks towards

\textsuperscript{49}Jauregui (2014a)’s ethnographic account of bribery for police postings similarly suggests the substitutability of bribes and political connections.

\textsuperscript{50}The data contains information on the level at which the connection works, but not on their type of work (e.g., politician or bureaucrat) or the strength of their relationship with the applicant. For example, a province-level bureaucrat who worked within a health-related ministry would presumably have more sway than a national-level figure in an unrelated ministry. Similarly, a close family member may exert more costly effort than a more distant friend of the family.

\textsuperscript{51}For example, it might have a relatively low weight in the agent’s selection decision. It could also be the case that this factor has a high weight, but that all competitive applicants have similar values for this characteristic, and so it does not play a role in selection. Identification in the maximum likelihood estimation comes from relative differences between applicants on the margin of being selected, so these estimates miss the explanatory power of variables that do not vary around that margin. For the purposes of this paper, it does not matter, but it would be a problem for extrapolating this utility function into a setting where the relevant variable varies among competitive applicants.

\textsuperscript{52}How would a highly collinear variable affect the paper’s results? If it were a measure of quality and highly correlated with education, such as motivation, this does not change the interpretation of the process as mixed selection over bribes and applicant characteristics. On the other hand, it would affect the interpretation if it were a measure of quality that were highly correlated with bribery, such as if paying higher bribes was strongly correlated with motivation. In this case, the selection agent might be making their decision based on motivation, but the high correlation between the two gives the impression of selection on bribery.
zero and is no longer significant, perhaps due to reduced sample size. Regardless, use of secondary sources to infer winning bribe offers does not drive the result of bribery determining selection.

Fifth, and most seriously, unsuccessful applicants who refused to answer questions about bribes or claimed not to have offered a bribe are necessarily dropped from the estimation. If these individuals did not offer a bribe, this would have little effect on the estimation. Identification in the estimation procedure comes from those on the threshold of selection/non-selection, since marginal changes in parameter values will affect the probability that the observed winner is selected. For those who are far from the threshold of being selected, changes in the parameter values have little effect on their probability of selection, and thus the overall likelihood expression. If a missing individuals in fact did not offer a bribe, this would place them far from the threshold, and so their inclusion or exclusion makes little difference.

If they did offer bribes, then three cases of missingness are possible: 1) Missing at random; 2) Missing from applicants who would not be defined as competitive under the proposed evaluation metric; and 3) Missing from applicants who would be defined as competitive under the proposed evaluation metric. The first reduces the precision of the estimation, but is mostly irrelevant. The second also would not bias estimation, since these candidates are not on the margin of selection. The third case is the potentially troubling one. For example, if there were applicants that had offered larger bribes than the selected applicants, but these individuals systematically did not share this with the surveyors, then their inclusion might lead to substantially different parameter estimates, such as a variable other than bribery explaining selection.

This is unlikely for three reasons. First, it is unlikely that such a sizeable proportion of selection decisions would be explained by variables actually unrelated to selection. Suppose that selection were actually explained by other, unobserved variables, and bribery spuriously appeared correlated with selection because those offering high bribes systematically did not report them. If this were true, then it is unlikely that by chance, bribery would explain so many selection decisions. Second, among the set of hires, there is no statistically significant relationship between the decision not to report bribe amount and bribe amount. Third, even if unsuccessful candidates making high offers were less likely to report that offer, this relationship would have to be of an implausibly large magnitude to overturn the findings on selection. Nonetheless, I directly test this by imputing bribe offers using variables predictive of bribe amount (see section 4.2). As shown in column (2) of A15, including the imputed values has no effect on the estimates. Findings are robust to inflating missing bribe values by up to 1.75x of their predicted value. Given the implausibility of so many high bribes being omitted, the weight of the evidence is against missing bribe values creating meaningful bias.

D.2 Empirics: Selection on Quality

I first use a Wilcoxon signed-rank test\textsuperscript{53} to sign selection across these two margins for a large set of variables that are plausibly correlated with performance in the job. A univariate test is utilized because each quality measure may be a separate input into the future production of supervisor, so it is useful to know whether there is selection on each individually. For example, it may be the case that there is no

\textsuperscript{53}For each of the observed competitions, the test compares the median values for the groups being compared on the variable of interest. The competition is coded as positive if the median of the first group is greater than the median of the second, and negative if it is not. The test statistic depends on how far the number of positives/negatives deviates from those expected by chance, since if there were no pattern of selection, the true probability of positive/negative is 0.5.
statistically significant selection on health knowledge after controlling for education, but health knowledge enters the production function independently from education. As a result, it still matters whether selected applicants have better health knowledge, regardless of it being caused by education.

The first three columns give the overall mean of the three groupings of candidates, while the last three give the statistical significance of Wilcoxon signed rank tests comparing the groups. The pattern of selection seen here is replicated across almost all of the variables in the dataset: first, applicants are of a much higher quality than non-applicants, and second, those hired are of a higher quality than those that are not. While the second relationship is not always statistically significant, the first is strongly statistically significant in virtually every case.

In order to consider all of these relationships jointly, I run the joint significance test of Kling et al. (2007). This test normalizes each of the variables by their standard deviation, and combines them for a single test of joint significance. I find a statistically significant difference between applicants and non-applicants at p-value of less than .001 ($z = 10.54$), and between hires and non-hired applicants at a p-value of .001 ($z = 3.39$).
### Table A6: Characteristics of Non-Applicants, Unsuccessful Applicants, and Successful Applicants

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Non-Applicant Mean</th>
<th>Unsuccessful Applicant Mean</th>
<th>Successful Applicant Mean</th>
<th>1 vs 2</th>
<th>1 vs 3</th>
<th>2 vs 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health Knowledge</td>
<td>0.458</td>
<td>0.571</td>
<td>0.628</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Short Term Memory</td>
<td>4.323</td>
<td>4.561</td>
<td>4.879</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Intelligence (Raven’s)</td>
<td>2.486</td>
<td>3.658</td>
<td>4.606</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Education</td>
<td>8.828</td>
<td>11.48</td>
<td>12.68</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>Honesty (Dice Game)</td>
<td>0.505</td>
<td>0.539</td>
<td>0.540</td>
<td>***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pro-social (Donation)</td>
<td>0.230</td>
<td>0.223</td>
<td>0.236</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reading Skill</td>
<td>2.556</td>
<td>1.502</td>
<td>1.152</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Writing Skill</td>
<td>2.866</td>
<td>1.684</td>
<td>1.197</td>
<td>***</td>
<td>***</td>
<td>***</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

### Table A7: Psychometric Qualities of Non-Applicants, Unsuccessful Applicants, and Successful Applicants

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Non-Applicant Mean</th>
<th>Unsuccessful Applicant Mean</th>
<th>Successful Applicant Mean</th>
<th>1 vs 2</th>
<th>1 vs 3</th>
<th>2 vs 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public Service Motivation</td>
<td>2.262</td>
<td>2.153</td>
<td>2.057</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Intrinsic Motivation</td>
<td>2.655</td>
<td>2.443</td>
<td>2.358</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Extrinsic Motivation</td>
<td>3.069</td>
<td>3.068</td>
<td>3.089</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extroversion</td>
<td>2.304</td>
<td>2.257</td>
<td>2.212</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>2.684</td>
<td>2.549</td>
<td>2.409</td>
<td>**</td>
<td>***</td>
<td></td>
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<tr>
<td>Neuroticism</td>
<td>2.716</td>
<td>2.823</td>
<td>2.913</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>Openness</td>
<td>2.811</td>
<td>2.587</td>
<td>2.531</td>
<td>***</td>
<td>***</td>
<td></td>
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<tr>
<td>Agreeableness</td>
<td>2.746</td>
<td>2.854</td>
<td>2.750</td>
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<td></td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

### Table A8: CHW Performance of Non-Applicants, Unsuccessful Applicants, and Successful Applicants

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Non-Applicant Mean</th>
<th>Unsuccessful Applicant Mean</th>
<th>Successful Applicant Mean</th>
<th>1 vs 2</th>
<th>1 vs 3</th>
<th>2 vs 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOTS Patients</td>
<td>1.220</td>
<td>1.795</td>
<td>1.803</td>
<td>***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CHW Work Hours</td>
<td>13.66</td>
<td>15.83</td>
<td>19.09</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Tasks Performed at Client Visits</td>
<td>3.754</td>
<td>4.139</td>
<td>4.273</td>
<td>***</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>Medical Consultation Frequency</td>
<td>3.076</td>
<td>2.928</td>
<td>2.515</td>
<td>**</td>
<td>***</td>
<td>*</td>
</tr>
<tr>
<td>Contraception Work</td>
<td>2.044</td>
<td>2.350</td>
<td>2.924</td>
<td>**</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>Immunization Work</td>
<td>1.179</td>
<td>1.281</td>
<td>1.394</td>
<td>**</td>
<td>*</td>
<td></td>
</tr>
</tbody>
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* p < 0.10, ** p < 0.05, *** p < 0.01

Table A6: Characteristics of Non-Applicants, Unsuccessful Applicants, and Successful Applicants

Table A7: Psychometric Qualities of Non-Applicants, Unsuccessful Applicants, and Successful Applicants

Table A8: CHW Performance of Non-Applicants, Unsuccessful Applicants, and Successful Applicants
Table A9: Selection on Other Applicant Characteristics

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**Pairwise % Correct** | 0.87 | 0.88 | 0.90 | 0.88 | 0.89  
Pairwise GOF p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00  
Winner % Correct      | 0.83 | 0.85 | 0.88 | 0.85 | 0.86  
Winner GOF p-value    | 0.00 | 0.00 | 0.00 | 0.00 | 0.00  

***p < 0.01, **p < 0.05, *p < 0.1

D.3 Additional Tables for Selection Decision

In this section, I include additional tables from the selection decision estimation. I find that none of these additional variables are related to an applicant’s probability of selection. This includes variables that are typically unobserved by the econometrician, such as psychological profile or prosociality.

I also test for complementarities between the different components that are related to selection. Although the collinearity sometimes makes coefficients of the main effects statistically insignificant, the coefficient sizes remain the same.

Finally, as described in the paper, I run robustness checks with missing values. First, I only check for selection in those situations where the bribe amount is directly reported by the supervisor. Second, in cases where there is a missing secondary bribe information, I impute a bribe value and inflate it to check the effect on the selection coefficients.
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<th>Model 3</th>
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***p < 0.01, **p < 0.05, *p < 0.1

Table A10: Selection on Psych Characteristics

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***p < 0.01, **p < 0.05, *p < 0.1

Table A11: Selection on Big Five Index
### Table A12: Selection on Performance as CHW

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* ***p < 0.01, **p < 0.05, *p < 0.1 *

### Table A13: Selection on Other Applicant Characteristics

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* ***p < 0.01, **p < 0.05, *p < 0.1 *

Table A13: Selection on Other Applicant Characteristics
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***p < 0.01, **p < 0.05, *p < 0.1

Table A14: Selection on Other Applicant Characteristics

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***p < 0.01, **p < 0.05, *p < 0.1

Table A15: Selection Agent Utility Function Estimation- Missing Values Robustness
D.4 Using Pre-Supervisor Data to Measure the Impact of Supervisors

In the paper, I estimate the effect of the supervisor on changes in performance by their workers after the supervisor has begun their work. I do this because I was not able to access administrative data on worker outcomes from the government from the time period prior to the introduction of supervisors. This will only capture changes after the supervisor began their work, but there may be an immediate boost from the introduction of a supervisor that is not accounted for. Alternatively, it may be that the supervisors who have an immediate impact do not have any impact later, and so my estimation overestimates the impact of supervisors. I use data from the pre-supervisor period to determine the evidence for either case.

During the surveys, I collected data on a small set of indicators of CHW performance. Since one survey occurred prior to the start of the supervisors and the other was conducted after they had been working for six months, I can measures differences between the survey rounds and check if these are related to SPI. The outcomes measured in both rounds of surveys were: 1) number of pregnant women who they are currently serving; 2) days worked per week; 3) hours worked per week (not including time spent at trainings, mobilizing for immunization drives or monthly clinic days); 4) number of households mobilized for an immunization drive in the previous month; and 5) institutional deliveries assisted.

For the first four sets of outcomes, I calculate the average change between the pre and post survey, and then regress that on the SPI of their supervisor, clustering standard errors at the supervisor level. I find no evidence of an immediate change in performance related to the supervisors, other than an increase in hours worked per week. However, given that all the signs are positive, this suggests that if anything, I am underestimating the effect of the supervisor on performance.

For the fifth outcome, I use survey data on the number of institutional deliveries assisted by the CHW from the period six months prior to the start of the supervisors until after the supervisors had been working for six months. The data is at the monthly level, so I can run a differences-in-differences regression on deliveries assisted (first column). I can also check whether there are any pre-trends in deliveries assisted in the pre-period that are related to SPI (second column). I do not find any evidence for either an immediate boost in deliveries assisted related to the supervisor or for any pre-trend related to SPI.

<table>
<thead>
<tr>
<th>Pregnant Clients</th>
<th>Days Worked</th>
<th>Hours Worked</th>
<th>Immunization Mobilized</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supervisor SPI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.26</td>
<td>0.090</td>
<td>1.31***</td>
<td>0.16</td>
</tr>
<tr>
<td>(0.229)</td>
<td>(0.098)</td>
<td>(0.479)</td>
<td>(0.455)</td>
</tr>
</tbody>
</table>

Observations 280 284 284 232
Mean 11.6 3.98 14.62 25.54

For the fifth outcome, I use survey data on the number of institutional deliveries assisted by the CHW from the period six months prior to the start of the supervisors until after the supervisors had been working for six months. The data is at the monthly level, so I can run a differences-in-differences regression on deliveries assisted (first column). I can also check whether there are any pre-trends in deliveries assisted in the pre-period that are related to SPI (second column). I do not find any evidence for either an immediate boost in deliveries assisted related to the supervisor or for any pre-trend related to SPI.

<table>
<thead>
<tr>
<th>Deliveries</th>
<th>Deliveries (Pre-Period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post</td>
<td>0.78***</td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
</tr>
<tr>
<td>Post X Supervisor SPI</td>
<td>-0.056</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
</tr>
<tr>
<td>MonthXSPI</td>
<td>-0.021</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
</tr>
</tbody>
</table>

Observations 2903 1485
Mean 2.3 2.27
CHW and Month FE Yes Yes

Standard errors clustered at supervisor level
Taken together, there is little evidence that the supervisors have much immediate impact. Instead, they only seem to exert an impact over time, and so looking only at post-supervisor changes should not lead to inferential errors. The supervisor index is a significant predictor of pre-post changes in only one case, hours worked in a week, and in that case, those supervisors that have a positive later impact also have a positive immediate impact. Thus if anything, I am understating the impact of the supervisors on their workers.

D.5 Validations of the Administrative Data

A natural concern is that the supervisors might find a way to manipulate the administrative data and causes problems for estimating the effect of supervisors on their workers. This is unlikely for a few reasons. First, manipulation is only a problem if there are systematic differences in manipulation that are related to supervisor characteristics. If, for example, manipulation were consistent across all workers (e.g. all workers have overstated performance, but this is not related to their supervisor’s characteristics), then this would not affect measurement of the supervisor’s impact on their workers. Second, SPI lines up well with other measures of supervisor performance that are less subject to manipulation, such as performance evaluations by those who oversee the program (whose assessments are largely based on field visits) or information reported by the workers on their interactions with their supervisor. Third, there is little incentive to manipulate many of the outcomes, since doing so does not affect their financial compensation.

Nonetheless, in this section, I run three types of tests for manipulation of the data. I use features of the CHW program to check for manipulation of CHW services delivery score, but some of these details might be used to identify the area from which the data was collected. Interested individuals can email me directly for this section and agree not to disclose details that could lead to identification of the CHW program.

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54 This statement is slightly too strong, since there could be some non-linearities that cause this to happen, e.g. top censoring of measurement of a particular performance indicator might mean that overstating reduces variation at the top end of worker performance. But in this case, and most others that I have considered, this would, if anything, bias my estimates of supervisor impact towards zero.
E Counterfactual Appendix

This appendix section contains additional details about the counterfactual estimation.

E.1 Estimating $e_i$

In order to run the estimation, I construct bounds around the probability $e_i$ at which candidates are indifferent between entering/not entering. In order to do this, I split the candidates into three groups, with a different approach taken for each group.

**Group 1: Observed Bribe Offers** The first group is candidates whose bribe offers during the competition are observed. Using the estimated selection agent preferences from earlier in the paper, I devise a method following the intuition of Guerre et al. (2000). In the observed competition, there must exist some function that maps from $v, \alpha$ to bribe offer $b(v, \alpha)$. This can also be written in terms of the utility of the selection agent, $x$, where $x(v, \alpha) = b(v, \alpha) + \theta \alpha$. Since $\theta \alpha$ is fixed, it is simpler to write this as simply $\kappa = \theta \alpha$, where the weight $\theta$ is whatever the weights that the selection agent places on dimensions of $\alpha$ in the actual competition (positive weights on education and political connections). Under this formulation, the bidder can be thought of selecting score, rather than bribe.

To illustrate the intuition, I first solve ignoring the entry condition and presence of credit constraints, and suppose that they know the number of other entrants, $n$. This will result in their payoff function being:

$$\pi(v, \kappa) = (v - x + \kappa) H \left( \frac{x}{n} \right)^{n-1}$$

Where $H(x)$ is the distribution of scores that they expect to face. They will select a score $x$ so as to maximize their utility.

$$\frac{d\pi(v, \kappa)}{dx} = \left( v - x + \kappa \right) (n - 1) H(x)^{n-2} H_x(x) - H(x)^{n-1} = 0$$

$$(v - x + \kappa) (n - 1) H_x(x) - H(x) = 0$$

$$v = x - \kappa + \frac{H(x)}{(n - 1) H_x(x)}$$

Although it is difficult to recover the bidding function, I can use the data to empirically estimate $H(x)$ and differentiate that distribution to get $H_x(x)$. With that information, since $x$ and $\kappa$ are observed, the final equation recovers the valuation that must have produced their bid. In order to empirically estimate $H(x)$, I assume that it follows a normal distribution and use maximum likelihood to estimate the parameters of the

---

55Earlier drafts of the paper use a simpler process. Given that this group entered the bribery competition and made an offer, their offer $b_i$ must be a lower bound on $v_i$. All these applicants took part in at least one survey, for which they were paid $\frac{1}{30}$ of a month’s salary for at least 2 hours. None of the considered competitions require more than 20 hours of effort, so I select 20 hours as an upper bound on the time cost, and combine these figures to place an upper bound on $C_i$ of $C_i \geq 20 * \frac{1}{30}$, i.e. a half month’s salary. Based on the lower bound on $v_i$ and upper bound on $C_i$, this implies that they will enter if $p_i \geq \frac{20 \cdot \frac{1}{30}}{v_i}$. In the data, $5 \leq b_i \leq 30$, so individuals in this category will have an upper bound on $e_i$ of between .016 and .10. The bounds produced by this method are slightly less tight than those using the method described here, but results are virtually the same.
distribution based on the observed values of x for the competition. Separate parameters are estimated for each geographical regions in order to account for local level heterogeneity in scores. Inspection of the moments of the estimated and actual distribution of x suggest that the normal distribution provides a good fit.

However, under the independent private values assumption, the bidder doesn’t know the number of people that they are competing against - this will depend on whether competitors choose to enter given their valuation. Fortunately, this is relatively straightforward to deal with. Since this is an independent private values context, if I know the probability of non-entry, I can estimate the probability of facing a given number of competitors with a binomial distribution. Again, I use empirical estimates of non-entry to sidestep the problem of estimating the valuation at which there is a shift between entry and non-entry. Using the data, I estimate \( p_{ne} \), the probability of a given person not entering, separately for different geographical regions in order to account for local heterogeneity. Crucially, \( H(x) \) does not depend on the number of bidders, since that is not known at the time at which they place their bids, and so I can still estimate it via maximum likelihood using the observed distribution of scores (although I also estimate this separately for different regions). The profit function for a bidder will now be:

\[
\pi(v, \kappa, x) = (v - x + \kappa) \left[ \sum_{i=0}^{N-1} \left( \frac{N-1}{i} \right) (p_{ne})^{N-1-i} (1 - p_{ne})^i H[x]^i \right]
\]

Differentiating this with respect to \( x \):

\[
\pi_x(v, \kappa) = 0 = (v - x + \kappa) \left[ \sum_{i=0}^{N-1} \left( \frac{N-1}{i} \right) (p_{ne})^{N-1-i} (1 - p_{ne})^i (i - 1) H[x]^{min(i-1,0)} H_x(x) \right]
- \sum_{i=0}^{N-1} \left( \frac{N-1}{i} \right) (p_{ne})^{N-1-i} (1 - p_{ne})^i H[x]^i \]

And so rearranging to get this expression in terms of \( v \):

\[
v = x - \kappa + \frac{\sum_{i=0}^{N-1} \left( \frac{N-1}{i} \right) (p_{ne})^{N-1-i} (1 - p_{ne})^i H[x]^i}{H_x(x) \sum_{i=0}^{N-1} \left( \frac{N-1}{i} \right) (p_{ne})^{N-1-i} (1 - p_{ne})^i min (i - 1, 0) H[x]^{min(i-1,0)}}
\]

Finally, it remains to incorporate the presence of credit constraints. Because of the credit constraints, it may not be the case that the \( v \) recovered via this procedure is the true valuation of the bidder: they may have had a higher valuation, but been unable to bid as much as they would like, given that valuation, due to the credit constraints. As a result, this estimate of \( v \) is a lower bound on \( v \) for the credit constrained, although should be accurate for the non-constrained. Since I cannot identify who is or is not credit constrained without unreasonable assumptions, this is used as a lower bound on valuation.

Having recoved at least a lower bound on valuation, it remains to combine this with estimates of \( C_i \) in order to get bounds on \( e_i \). All these applicants took part in at least one survey, for which they were paid \( \frac{1}{20} \) of a month’s salary for at least 2 hours. None of the considered competitions require more than 20 hours of effort, so I select 20 hours as an upper bound on the time cost, and combine these figures to place

\[56\]Given the estimated weights, \( x = b + 1.64 \times \text{education} + 4.68 \times \text{connection.}\]
an upper bound on $C_i$ of $C_i \geq 20 \cdot \frac{1}{10}$, i.e. a half month’s salary. Based on the lower bound on $v_i$ and upper bound on $C_i$, this implies that they will enter if $p_i \geq \frac{20}{v_i}$. In the data, the recovered value of $v_i$ is between 7.16 and 67.26, so individuals in this category will have an upper bound on $e_i$ of between .16 and .0074.

**Group 2: Entrants, No Observation of Bribe Offer**  Second, take those that previously entered the competition, but did not reveal a bribe offer. I want to show that if their probability of entry is greater than 0.1, they will enter, meaning that an upper bound on $e_i$ is 0.1. First, consider those candidates who had a probability of less than 0.1 of winning the bribery competition. These candidates will certainly enter this alternative competition, since their probability of winning is higher and there is no longer a cost of winning (i.e. paying a bribe). Next, consider those candidates with a probability of greater than .10 of winning the bribery competition. No competition was won with a bribe of less than 8 months salary and no bribes were for less than 5 months salary. Thus for a candidate to have such a high probability, they must have offered a bribe of at least 5 months’ salary. Under the same logic as the previous paragraph, if a candidate entered the bribery competition and did not offer a bribe, they will enter an alternative competition for $p_i > \frac{5}{5} = .10$.

It is also possible to solve for a non-zero lower bound for this group. Using the recovered selection rule, these individuals must have a lower score, in terms of the selection agent’s utility over selecting them, than the person who was selected. This gives an upper bound on the bribe offer that they could have made, and, using the method of the previous paragraph, that can be used to recover an upper bound on their valuation. I also take a lower bound on the cost of applying in order to generate a lower bound on their entry cutoff. For this lower bound, I assume a very low time cost of one hour, with their opportunity cost of time being equal to the daily prevailing wage.

**Group 3: Non-Entrants**  The previous two cases used application decisions to infer bounds on willingness to pay, but this is not possible for non-applicants. To deal with their counterfactual entry decisions, the survey of CHWs included questions on whether they would have applied for the job under different probabilities of being hired. CHWs were first asked to “think back to the time when you were deciding to apply [for the job as Supervisor] or not. If you knew for sure that you would be made CHW Supervisor without giving anything, would you apply for the job?”. Answering no implies that even when $p_i = 1$, $p_i v_i < C_i$, i.e. $v_i < C_i$, and so these women would never apply.

Many CHWs do not have sufficient schooling to understand mathematical statements of probability. They were instead asked in the following way: “Think back again to the time when you were deciding whether to apply [for the job as supervisor] or not. Suppose that you knew the process would happen without any giving anything. If you knew that one(two/three) other women in your area were applying to become supervisor, and you thought that you each had an equal chance, would you apply for the job?”. This gives their entry decision under subjective probabilities of 0.5, 0.33 and 0.25 in a manner easily intelligible to respondents. A wider range of probabilities would give more precision in the estimation, but this proved sufficient for reasonably tight bounds.
E.2 Estimating \( g(\kappa, e) \)

In order to get estimates of \( p_i = p(\kappa_i) \) for each of the candidates, it is necessary to estimate the joint distribution of \( g(\kappa, e) \) from which they and their competitors are drawn. However, there are some entrants for which \( \frac{v_i}{C_i} > 1 \), meaning that the valuation is greater than the cost of entry, and so they would never enter even if they have probability 1 of being selected. These are identified in my data as those who indicate that they would never apply for the supervisor position even if they were guaranteed to get it. I omit these from the estimation of \( g(\kappa, e) \), instead using their frequency in the population as an estimate for \( p_{ne} \), the probability of never wishing to enter. \( p_{ne} \) will be used later in the estimation of \( p(\kappa) \).

I assume that this distribution \( g(\kappa, e) \) has a beta-bivariate distribution \(^{[\text{Olkin and Liu 2003}]}\) for the set of individuals with \( e \leq 1 \). This distribution is selected due to its extreme flexibility in shape and allowance of a broad set of correlations between the dimensions (see pg 410-411 of Olkin and Liu (2003) for examples of this). Its probability density function takes the form:

\[
g(\kappa, e) = \frac{\kappa^{a-1}e^{b-1}(1-\kappa)^{b+c-1}(1-e)^{a+c-1}}{B(a, b, c)(1-\kappa e)^{a+b+c}}
\]

where \( B(a, b, c) = \frac{\Gamma(a)\Gamma(b)\Gamma(c)}{\Gamma(a+b+c)} \). The function is defined over \( 0 \leq \kappa \leq 1, 0 \leq e \leq 1 \), and so it is necessary to redefine \( \kappa \) as \( \hat{\kappa} = \frac{\max(v_i) - \kappa}{\max(v_i) - \min(v_i)} \). I split the competitions into geographically based clusters of 6-12 supervisors in order to incorporate possible differences in distributions over space. I then estimate the parameters \( (a, b, c) \) using maximum likelihood. Since \( e \) is not point identified, during the estimation, I integrate over the set of values from which \( e \) could be drawn for each of the \( (a, b, c) \). This produces separate estimates of \( (a, b, c) \) for each competition. Inspection of the moments of the estimated distributions indicates that they well approximate the actual distribution of \( \kappa \) and \( e \).

E.3 Robustness Checks

Predicted counterfactuals may differ from the true counterfactual because: 1) estimates of \( e_i \) based on survey questions are inaccurate; 2) respondent perceptions of \( p_i(E) \) differ from the bootstrapped estimates; or 3) \( C_i \) varies greatly across competitions. I run five robustness checks related to these concerns.

Validation 1: Testing Simulation against Reported Entry Behavior in an Additional Competition

As an internal validation, survey respondents were directly asked about their application decision if hiring were conducted via a health knowledge-based exam similar to that taken as part of the survey. I can thus compare their reported entry decision against the entry decision predicted by the counterfactual method. Doing so addresses two concerns: whether the proposed counterfactual method is satisfactory in predicting behavior, and whether \( C_i \) is relatively constant across competitions. \(^{[57]}\) Using the counterfactual method, I estimate the set of certain entrants, possible entrants, and certain non-entrants, and then compare to their stated entry decision. In 92% of cases, the winner predicted under reported entry is correctly predicted as a possible entrant by the counterfactual method. Predictive accuracy is also quite high (88%) for the entire set, but the accuracy for winners is really what matters; even if predictions were completely

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\(^{[57]}\)This type of competition should have a relatively high value of \( C_i \), i.e. studying and taking the exam. Thus if individual-specific variation in cost across competitions causes a problem, this is one in which it is most likely to occur.
off for non-winners, that would not affect the counterfactual comparisons. Although the method is not quite perfect, it appears to closely approximate the entry decisions of candidates.

**Validation 2: Hypothetical vs. Observed Behavior** Hypothetical statements about $e_i$ may be inaccurate if respondents do not take survey questions seriously or answer differently than they would behave in practice. I collected data on CHW’s perceived likelihood of being hired at the time of applying, including for those who chose not to apply. Since I observe their application decision, I can compare their hypothetical statements on entry behavior to their perceived likelihood of selection, and determine if actual behavior matches hypothetical. For example, a candidate’s observed behavior would be inconsistent with their hypothetical statements if they reported that they would only apply if $p_{it} > .5$, felt that they had a very low probability of being selected, and still choose to apply.

The hypothetical questions do not quite match the observational data, so it is only possible to run this check for a subset of potential applicants. In particular, the hypothetical questions ask about the decision to enter if bribe-paying were not required, but in the real competition, bribes were paid. Thus an applicant may have felt certain of winning, report that they would apply if $p_{it} > .33$ in the case when no bribe is required, but still not have entered due to the required bribe payment. The hypothetical questions do not apply, since they only state that the applicant would apply if $(.33) WTP_i > C_i$; if $b_{it}$ is large, then it might be that $(.33)(WTP_i - b_{it}) < C_i$.

I can still test consistency for those that the hypothetical data predicts should not apply, since if they would not apply without paying a bribe, they certainly should not apply if they would also have to pay a bribe. This yields a sample of 417 testable cases whose ex ante subjective probability of winning was lower than the threshold at which they would stated they would have applied. The hypothetical data matches observed behavior in 97.1% of cases, suggesting that respondents accurately responded to the hypothetical questions.

**Validation 3: Accuracy of Probability Estimates** This procedure relies on accurately approximating respondents’ perceptions of $p_i(E)$. Inaccurate approximations cause a problem only if higher probability respondents significantly underestimate their true probability of winning. In this case, the method may incorrectly predict that they enter and win with a high probability, but their misperception in fact causes them not to enter. If they overestimate their probability, they will still enter in the predicted fashion; overestimation does not change this. Lower probability applicants may either overestimate or underestimate of $p_i(E)$, but since they are unlikely to win even if they do enter, their entry/non-entry has little effect on the final estimates.

I thus check whether applicants overestimate, underestimate or are approximately correct in their ranking of themselves. As part of the survey, respondents were asked to create rankings of CHWs who live geographically proximate to them on a series of metrics (health knowledge, motivation for CHW work, overall quality of CHW work, and wealth). For each metric, they first ranked the top two CHWs other than themselves, and then added themselves to the ranking, producing a ranked list of three individuals. For health knowledge, I can observe the ranking based on the administered knowledge test, and can thus compare actual to perceived ranking (see table A16).

Around 85% of the top two CHWs in health knowledge accurately gauge themselves as being top performers within the comparison group. Even in those cases where top applicants are underconfident,
Table A16: Perceived and Actual Rank: Health Knowledge

<table>
<thead>
<tr>
<th>Actual Rank</th>
<th>Perceived Rank</th>
<th>Perceived Rank</th>
<th>Perceived Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Perceived 1st</td>
<td>Perceived 2nd</td>
<td>Perceived 3rd or Below</td>
</tr>
<tr>
<td>Rank 1</td>
<td>48.8</td>
<td>35.6</td>
<td>15.6</td>
</tr>
<tr>
<td>Rank 2</td>
<td>43.4</td>
<td>42.7</td>
<td>14.0</td>
</tr>
<tr>
<td>Rank 3</td>
<td>36.6</td>
<td>35.2</td>
<td>28.2</td>
</tr>
<tr>
<td>Rank 4</td>
<td>31.9</td>
<td>40.3</td>
<td>27.7</td>
</tr>
<tr>
<td>Rank &lt;= 5</td>
<td>26.5</td>
<td>36.7</td>
<td>36.7</td>
</tr>
<tr>
<td>All Ranks/Total</td>
<td>36.0</td>
<td>37.8</td>
<td>26.2</td>
</tr>
</tbody>
</table>

this will not noticeably affect predictions, since practically all would either apply even at low probabilities of winning or never apply regardless of probability of winning. Therefore, even if their probability estimates were somewhat lower than the predictions, the predicted behavior will be the same, and so the counterfactual predictions would be accurate.

**Validation 4: Errors in Probability Estimates** A second robustness test is to see how the results change if the estimated probabilities were systematically wrong in a predictable fashion, such as if applicants overestimate their probability of being selected. Expected probability of being selected directly affects their entry decision, and so, if, for example, applicants were systematically overconfident about their probability of being selected (as the data in validation 3 suggest), this would lead to larger numbers of individuals entering the competition. On the other hand, it may be that the patterns are more complicated: perhaps the highest probability individuals are underconfident, while the lowest probability are underconfident.

This section investigates each of these cases by re-running the model with changes in expected probability of selection.

I run four manipulations: 1) uniformly increase the anticipated probability of being hired (systematic overestimation of their odds); 2) uniformly decrease the anticipated probability of being hired (systematically underestimating their odds); 3) increase the expected hiring probability of low probability applicants and decrease it for high probability applicants (low probability are overconfident and high probability are underconfident); and 4) decrease the expected hiring probability of low probability applicants and increase it for high probability applicants (low probability are underconfident and high probability are overconfident). This is done for the Raven’s Matrices and the health knowledge test counterfactual, and the resulting upper and lower bounds on SPI are given in table A17. The factors by which the estimated probabilities are increased or decreased are given in the table for the first two cases. For case 3, expected probability is regressed towards the mean according to \( \hat{p} = \bar{p} + 0.3(p - \bar{p}) \), and for case 4, expected probability is regressed away from the mean according to \( \hat{p} = p + 0.3(p - \bar{p}) \), with bounds to ensure that it does not fall outside of \([0, 1]\).

Although the manipulations do move around the upper and lower bounds of SPI, the qualitative results of the study remain the same: selection via the Raven’s matrices produces slightly better hires, while selection via the health knowledge test does somewhat worse. This is because those who are most likely to get hired typically have high valuations for the job; thus even if they had a much higher or lower anticipated probability, their entry cutoff is sufficiently low that this has little effect on their decision.
Table A17: Manipulation of Expected Probability of Selection

<table>
<thead>
<tr>
<th></th>
<th>Raven’s Matrices</th>
<th>Health Knowledge Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Manipulation</td>
<td>0.01 / 0.42</td>
<td>-0.53 / -0.34</td>
</tr>
<tr>
<td>Case 1 (x2)</td>
<td>0.20 / 0.38</td>
<td>-0.52 / -0.39</td>
</tr>
<tr>
<td>Case 1 (x3)</td>
<td>0.11 / 0.34</td>
<td>-0.52 / -0.31</td>
</tr>
<tr>
<td>Case 2 (x0.5)</td>
<td>0.03 / 0.58</td>
<td>-0.61 / -0.20</td>
</tr>
<tr>
<td>Case 2 (x0.33)</td>
<td>-0.09 / 0.67</td>
<td>-0.71 / -0.16</td>
</tr>
<tr>
<td>Case 3</td>
<td>0.06 / 0.37</td>
<td>-0.47 / -0.39</td>
</tr>
<tr>
<td>Case 4</td>
<td>0.17 / 0.46</td>
<td>-0.57 / -0.39</td>
</tr>
</tbody>
</table>

Table A18: Percent of Estimated First Best SPI

<table>
<thead>
<tr>
<th></th>
<th>With Entry</th>
<th>Without Entry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health Knowledge</td>
<td>81.2-84.0%</td>
<td>80.2%</td>
</tr>
<tr>
<td>Raven’s Matrices</td>
<td>89.8-95.5%</td>
<td>93.2%</td>
</tr>
<tr>
<td>Government System</td>
<td>84.5-88.6%</td>
<td>86.7%</td>
</tr>
</tbody>
</table>

Validation 5: Full Entry  As a final robustness check, I investigate what happens when there is full, rather than strategic entry. This can be thought of as: 1) checking how much the estimation process drives the final results; and 2) considering the screening role of strategic entry. For this, all whose valuation of the position exceeds their cost of entry are considered as applicants. The winners are those with the highest value on the relevant selection metric among this group. Rerunning the estimation for each of the main counterfactuals, estimated SPI is not terribly different under full entry. In general, this suggests that the entry decision does not have a major screening value for final SPI of supervisors, and that specific decisions about modeling of entry are not driving the outcomes. Instead, outcomes are due to the relative correlations of each of these measures with the final outcome of performance as a supervisor.

E.4 Standardized Testing with Bribery

Set-up  This appendix section discusses hiring systems in which N slots are supposed to be based on standardized testing, but applicants can offer a bribe to the tester to have their score altered and be selected for a slot. Each applicant has a test score \( t_i \) and valuation \( v_i \) draw from a joint distribution \( r(t, v) \). Let \( Q(t) \) be the cumulative density functions of test scores, i.e. \( Q(t) = \int_0^t \int_0^{v_i} r(t, v) dv_i dt \). Applicants know the total number of other applicants \( I \) and their own score, but not the scores and valuations of others (independent private values context). They must decide whether to make a bribe offer prior to the scores of others being realized, and knowing whether or not they would be selected without paying a bribe.

The selection agent administering the test can sell as many slots as they would like, but has a fixed cost \( b \) of allocating each slot. They will thus refuse to accept a bribe lower than \( b \), and \( b \) is common knowledge, so no bribe less than that will be offered. This cost \( b \) can be thought of as their risk of being caught/punished due to monitoring, and will vary depending on the monitoring environment. If \( b \) is sufficiently high, fewer than \( N \) of the applicants will have a willingness to pay that exceeds \( b \), and so not

\[ 58 \] This is defined based on a hypothetical question on willingness to enter if guaranteed the position without making a payment

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all the slots will be allocated corruptly. This is visualized in the supply and demand graphs in figure 12.

In the context of my project, the solution strategy remains the same, but $N = 1$, where each competition is for only slot. However, I observe multiple competitions, which will be helpful for estimation. Although there is an entry decision in my context, for the purposes of this estimation, I will assume that there is no entry choice. Furthermore, I will need to use estimated valuations for candidates. This is done in appendix section E using a modified version of Guerre et al. (2000), but I only recover valuations for those whose bribe offers are observed. Thus I will restrict attention to this set of individuals, which may lead to inaccurate results, but still provides the key insight into how these systems work.

**Solution** Solving this problem proceeds in three steps. First, I solve for the boundary in $(t, v)$ that splits individuals between being willing and unwilling to offer a bribe. This boundary will be the set of individuals who are indifferent between offering and not offering a bribe. Note that if they do not offer a bribe, they will only be selected if: 1) they have the highest test score; and 2) no one else offers a bribe. The set of individuals who switch between offering and not offering a bribe will offer the lowest possible successful bribe offer, $b$, and thus only be hired if no one else offers a bribe. This indifference condition is equal to:

$$Q(t)^{I-1} \Psi^{I-1} v = \Psi^{I-1} (v - b)$$

where $\Psi$ is equal to the probability that no one else offers a bribe. This will be solved for explicitly later. Here, it cancels out, and the equation rearranges to:

$$v = \frac{b}{1 - Q(t)^{I-1}} = v_c(t)$$

The boundary is thus equal to the set of points $(t, v_c(t))$. Having solved for this, we can derive $\Psi$:

$$\Psi = \int_{\frac{v_c(t)}{b}}^{1} \int_{v'}^{v_c(t)} r(t, v) dv dt$$

Second, having characterized the boundary, I explicitly solve for it. In order to do this, I need an empirical estimates of $Q(t)$ and $r(t, v)$. To estimate $Q(t)$, I take the distribution of test scores in the data and fit a non-parametric distribution over it. For $r(t, v)$, I estimate a beta-bivariate distribution over the estimated valuations from section E.1 and observed test scores. This can be done for any of the testing systems used.

Third, I recover the function that maps from $(t, v)$ into bribe amounts for those that offer bribes. Note that for those that offer bribes, their test scores is irrelevant: they will be selected if they offer the largest bribe amount, including if no one else offers a bribe. As a result, this becomes a simple first-price auction among the pool of individuals for whom $v_i > v_c(t_i)$. Let $S(v)$ be the cumulative density of valuation over those individuals, i.e.

$$S(v) = \int_{\frac{v_c(t)}{b}}^{v} \int_{v_c(t)}^{v'} r(t, v') dv' dt$$

Using this, their probability of being selected, $\Lambda(v)$, will be equal to:
\[ \Lambda(v) = (\Psi + (1 - \Psi) S(v))^{I-1} \]

The bid function can be derived from the standard first order conditions using:

\[
\max_x (v - b(x)) \Lambda(x)
\]

where \( b(x) \geq b \). The bid function will thus be equal to:

\[
b(t, v) = \begin{cases} 
0 & v < v_c(t) \\
\frac{1}{\Lambda(v)} \int_v^\infty x\Lambda'(x) + b & v \geq v_c(t)
\end{cases}
\]

This procedure is implemented in R, and the results are shown in the body of the paper.

F  Counterfactual Estimation Method #2

In the main text of the paper, I carry out a counterfactual estimation under the assumption that individuals make independent, private draws from a common distribution \( G(v, C, \alpha) \) for their valuation, cost of entry, and additional characteristics. The independent private values assumption is standard in the entry literature, but requires possibly undesirable assumptions. First, I assume a bivariate beta distribution for the distribution \( g(e, \kappa) \). While this distribution is quite flexible, it is possible that it does not adequately approximate the true joint distribution of \( e \) and \( \kappa \). Second, I do not allow for any noise in the realization of \( \kappa \) by the selection agent. For many types of counterfactual contests, such as testing, we might expect that an individual’s performance would vary across different administrations of that instrument, and so it may not always be that the individual with the highest underlying \( \kappa \) will be selected. In a sense, this is still fine in an independent private values context, since the noise in who they expect to face is similar to the noise due to their variation in performance, but it might underestimate the actual amount of noise. In this section, I make a stronger assumption on the information available to applicants and leverage that to relax the two assumptions. Results are qualitatively similar, but predict somewhat better performance by the actual hires relative to the counterfactual ones.

F.1 Model

In order to allow estimation, I maintain the structure of the main theoretical model, but make a few simplifying or complicating assumptions to deal with the reality of data. First, in the theoretical model, I assumed that cost of applying was the same across all applicants. This is probably false, so in the estimation, I allow cost of application \( C_i \) to vary by individual. Next, I change the information structure so that there is complete information about \( \zeta_i \) among applicants. The selection agent, on the other hand, receives a signal of each individual’s characteristics that may be noisy. Specifically, they observe \( \hat{\alpha}_i \), where \( \hat{\alpha}_i = \alpha_i + \epsilon_i \), \( \epsilon_i \sim z(.) \), where the distribution \( z(.) \) is common knowledge, and applicants cannot observe any \( \epsilon_i \). \( \epsilon_i \) is a vector, but may equal zero for some of the diagonal entries, i.e. the selection agent may observe some characteristics without any noise. Finally, in the counterfactuals that I examine, there is no weight placed on bribery, and so the selection agent will pick the applicant with the highest signal on

\(^{59}\)\( \zeta_i \) contains the valuation \( v_i \) of \( i \) for the job, their individual specific cost of applying \( C_i \), and their set of characteristics \( \alpha_i \).
the characteristics that they value, incorporating the relative weight placed on each in $\theta$. The set-up is otherwise identical to the above.

As a result of the common knowledge, individuals know exactly the set of opponents that they will face when making their application decisions. Despite this, individuals with low values of the selected characteristics may still have a chance of winning due to the noise in signal. In the paper, I take an alternative approach, assuming independent private values. The complete information approach is similar, but more explicitly models the probability of selection that each individual expects to face.

Under complete information, the entry decision of an individual $i$ will depend on the set $E$ of other candidates who they expect to face. Let $p_i(E)$ denote the probability of candidate $i$ winning the position where a set $E$ of applicants enter. A candidate $i$ will enter if their expected benefit is greater than their expected cost, i.e. $p_i(E)v_i > C_i$. Although simple, this model is quite general, with each term is allowed to vary at the individual level. The only notable restriction is that cost of entry $C_i$ is held fixed across competition types. This may not strictly hold across some types of competition, such as if some contests impose a higher time-cost of application than others. Fortunately, robustness checks confirm that this is approximately true for the counterfactual competitions considered here.

Empirically identifying entry decisions based on this framework presents two challenges. First, it is difficult to empirically estimate $C_i$, $v_i$, and $p_i(E)$ for all possible sets $E$. Second, although an equilibria is guaranteed in mixed strategies, there may be no or multiple pure strategy Nash equilibria.

F.2 Candidate Elimination and Winner Selection

Rather than estimating $C_i$ and $v_i$ individually, I focus on the cutoff probability of entry $e_i$, where the candidate will enter if and only if $p_i(E) > e_i$. For all of the applicants, I establish bounds on $e_i$ using behavior in the observed contest as well as a small set of hypothetical questions (see appendix E for details). By comparing $p_i(E)$ to the bounds on $e_i$ for a given competition and set of entrants, it is possible to determine whether applicants prefer to enter. For example, if for an applicant $i$, I determine a lower bound of $e_i > .5$ and $p_i(E) = .24$ for a given $E$, then the applicant would prefer not to enter: $e_i > .5 > .24 = p_i(E)$. Similarly, if I find that $.25 > e_i$, and $p_i(E) = .34$, then applicant $i$ will enter, since $p_i(E) = .34 > .25 > e_i$. As a result of data limitations, it is sometimes not possible to determine if a given candidate would prefer to enter. For example, if I only know that $.25 > e_i$, it is not possible to state with certainty whether candidate $i$ would enter for $p_i(E) = .15$ or any other $p_i(E) < .25$. Fortunately, this data limitation proves simple to deal with.

Having established bounds, I develop a resampling method to estimate $p_i(E)$ for any set of entrants $E$ under each of the considered counterfactual competitions. To do this, I take 2000 draws of $\hat{\alpha}_i$ for each $i \in E$, using variation in the data to generate the noise term. Each draw can be thought of as a competition, so $p_i(E)$ is equal to the percent of competitions in which an applicant $i$ has the highest value of $\theta \hat{\alpha}_j$ among all $j \in E$.

In order to generate draws of $\hat{\alpha}_i$, I take advantage of the fact that in all of the counterfactual systems, there is some points-based measure on which applicants are evaluated, where the applicant with the highest number of points is the winner. Applicant points may across different realizations of the contest for two

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60: For example, I observe two rounds of health knowledge test so use this to estimate variation across rounds of the competition.
reasons: variation in the scoring system, i.e. the formula by which applicant score is computed, and variation in performance, where applicant performance may vary across iterations, even if the scoring system is held fixed.

To account for variation in the scoring system, I resample over each of the individual components of scoring. Under the Raven’s and health knowledge test, this is a resampling of the questions asked, whereas under the government points system, this is a resampling over the categories by which one could accrue points. In the case of testing, this accounts for tests of varying content or difficulty, whereas under the government points system, different hiring procedures may differentially favor certain accomplishments or background. Taking the health knowledge test as a concrete example, I resample 2000 sets of 30 questions from the 30 question health knowledge test; this is done with replacement such that in some sets questions are repeated, whereas on others, a question may be entirely absent. This will approximate the distribution of possible tests under the assumption that the testing instrument has good coverage of the set of possible knowledge categories.

When calculating the applicant’s performance on each of the resampled tests, I also incorporate variation in performance. This requires calculating the probability of receiving/not receiving a given point in another iteration of the contest based on whether they received a point in the current iteration and other relevant factors. For the Raven’s matrices, I use previous studies of re-test reliability, while for the health knowledge test, I use stability on questions that were used across both rounds of the survey. In the case of the government points method, I do not incorporate these transitions, since the points are earned for fixed attributes. For each method, the value of $p_i(E)$ is the proportion of resampled cases in which applicant $i$ has the highest score in $E$ for that contest.

Next, I apply these components to the data to determine the entrants for each competition and candidate pool. Data limitations preclude point identification of this set, so I instead establish a “best” and “worst” set of possible entrants for the competition to bound the predicted supervisor performance under this counterfactual. I first establish the set of candidates who will never wish to enter the competition and the set of those who can be shown to definitely enter. The process of elimination is most easily visualized with an example. Suppose that there are 12 candidates for the position, as visualized in figure 17. In Panel 1, each candidate is denoted as a circle containing their cutoff probability $e_i$. Those that would not enter even under $p_i(E) = 1$ are colored in orange to indicate their elimination. In the second panel, the eliminated candidates are placed in a separate box, while the six non-eliminated candidates are listed with their value of $p_i(E)$, where $E$ is the set of six non-eliminated. This is the lowest possible $p_i(E)$ that they could face, since they are facing the maximal possible set of competitors. Despite this, the upper two have $e_i > p_i(E)$. Thus, regardless of who they face, they will prefer to enter the competition, and are denoted in green as “always entrants”.

61 Probability of getting a question right on a new iteration of the test is estimated as a function of getting the question right on this iteration, the overall probability of receiving a correct mark on that question, and the performance profile of that individual. Due to the highly non-linear nature of this prediction problem, I use a regression tree to partition the space.
Figure 17: Example of Counterfactual Method
In the third panel and fourth panels, I begin to eliminate other competitors. For each of the non-always entrants, I check they would prefer to enter even if they were only facing the always entrants, which is the highest possible $p_i(E)$ for them in any equilibrium. In the third panel, this does not hold, since $p_i(E) = .32$ is less than the minimum of the range in which their $e_i$ falls. In the fourth panel, $p_i(E) = .05$, which is greater than their cutoff of .04, and so they would be willing to enter against the always entrants. While they still may not enter in the end, it means that they cannot yet be eliminated.

This process is repeated until it results in a stable set of always and possible entrants (Panel 5). In this example, neither of the grey applicants would prefer to enter if the other entered, implying that there are multiple equilibria. Using predicted supervisor scores, I construct the pools of entrants that yield the highest and lowest expected supervisor score (labeled as “best” and “worst” case). These are then used to construct bounds on the how far the applicants selected under each system deviate from the first best allocations.

More formally, let $E_1$ be the set of all candidates in a cluster for whom $v_i > C_i$. I iteratively eliminate those candidates in $E_1$ that can be shown never to enter the competition. To do this, I check if any candidates in the cluster would be willing to enter in all cases, i.e. even if $E = E_1$, under which they have the lowest possible probability of being selected. I iteratively add these candidates to a set $E_2$, beginning with those who have the highest probability, checking at each addition if there are any candidates $j \in E_1$ s.t. $p_j\{j,E_2\} < e_i$, i.e. who would always prefer to exit against a set of competitors $E$ that contains $E_2$. If this is true, then they will never place any positive probability on entering, since those in $E_2$ will always enter. At each drop-out, I repeat the process from the beginning, having removed $j$ from $E_1$, and continue until either there are no more drop-outs or additions to $E_2$. In each of the competitions, this process reduces the set of possible entrants substantially.

At the end of this process, one is left with a set of candidates who cannot be eliminated. Always entrants in this set will be present in any possible equilibrium, but possible entrants may not be. Since I cannot further eliminate candidates, I solve for the worst and best possible set of entrants according to predicted SPI. Each of these sets must include all of the always entrants, and possible entrants are included/excluded based on whether they bring down(up) the expected supervisor rating of the set, i.e. $\sum_{i \in E} p_i(E) S_i$, where $S_i$ is the predicted SPI for $i$. Having done this, I can calculate the expected SPI for each contest and percentage of first best predicted SPI.

This method obviates the need to check for or select among possible multiple equilibria and is implementable with the collected data. One could make assumptions on the entry process in order to narrow the bounds (e.g. sequential entry, where first entrants are those with the highest probability of winning, second entrants have the second highest, etc.), but this may not be tenable assumptions. When considering the worst/best set of entrants, I also do not restrict attention to pure strategy Nash equilibria. Although this widens the bounds, it is more conservative than any possible mixed strategy equilibria, so eliminates the need to search for mixed strategy equilibria. That is necessary since pure strategy Nash equilibria may not exist, but data limitations make it impossible to solve explicitly for mixed strategy equilibria.

F.3 Counterfactual Comparisons

As previously, I evaluate the relative performance of each counterfactual system based on the deviation in predicted SPI for selected candidates from the predicted first best allocation. This is depicted visually in
Figure 18: Predicted Supervisor Rank under Counterfactual Competitions

Figure 18, which plots the cumulative density functions for percent of first best supervisor score realized under each counterfactual. The dashed gold line gives the first best outcome, i.e. the top predicted supervisor is selected with a probability of one in each competition. The solid black line is the cumulative density function for those supervisors who are actually selected. The solid colored lines are the upper/lower bounds for the weighted cumulative density function under a particular counterfactual systems. The weights incorporate the probability of each member of the set being selected, e.g. if there were two candidates who might be selected in a given competition with win probabilities of .34 and .66, they would have associated weights of .34 and .66.

The graphs demonstrate a striking and clear pattern: the selected supervisors are closer to first best than those who would have been hired under the counterfactual systems. While the selected supervisors capture 78.2% of the predicted first best SPI, the intended government system captures 68-71.9%, a health knowledge test captures 67.2-75.3%, and the Raven’s matrices capture 72.5-75.8%. Although this is still not at the predicted first best, the corrupted hiring system typically picks one of the three best possible supervisors and does better than any of the other systems, a striking contrast to what previous work would suggest.