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Measuring Rents from Public Employment: Regression Discontinuity Evidence from Kenya

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Measuring Rents from Public Employment:

Regression Discontinuity Evidence from Kenya

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Abstract

Public employees in many developing economies earn much higher wages than similar private-sector workers. These wage premia may reflect an efficient return to effort or unobserved skills, or an inefficient rent causing labor misallocation. To distinguish these explanations, we exploit the Kenyan government's algorithm for hiring eighteen-thousand new teachers in 2010 in a regression discontinuity design. Fuzzy regression discontinuity estimates yield a civil-service wage premium of over 100 percent (not attributable to observed or unobserved skills), but no effect on motivation, suggesting rent-sharing as the most plausible explanation for the wage premium.

Keywords: civil servants, teachers, public sector wages, wage gap, motivation

JEL Codes: H1; J3; O1

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1 Introduction

A large literature documents a significant wage gap between public and private sector workers across many countries, particularly in the developing world.[1] These wage differentials – which are often interpreted as rents accruing to public employees – have been central to economists understanding of wages, unemployment, migration, and state capacity in the developing world (Harris and Todaro, 1970; Fields, 1975; Finan et al., 2015) as well as development itself (Acemoglu, 1995; Robinson and Verdier, 2013).

How to judge these wage differentials hinges crucially on whether they are efficient rewards for talent or effort, rather than inefficient rents captured by public servants. Beyond rent seeking and clientelism, modern labor economics provides three main rationales for sectoral wage differentials: compensating differentials, efficiency wages, or selection of candidates into public-sector jobs based on unobserved human capital (see Katz, 1986, and Katz and Summers, 1989 for reviews).

We empirically separate the role of economic rents from the various efficiency based theories by exploiting data from a natural experiment in Kenya's education sector. Our identification strategy is based on a regression discontinuity design in teacher hiring. In 2010, following the advent of free primary education in 2003, the Kenyan government ended a multi-year hiring freeze and significantly expanded the number of civil service teaching posts, hiring 18,000 new civil service teachers. In most districts, hundreds of qualified applicants competed for these new teaching jobs. Applicants were ranked according to an algorithm designed by the central government, based on time since graduation as well as grades received during teacher

[1] For instance, the average raw differential is positive in favor of the public sector in Zambia at 38%-45% (Skyt-Nielsen and Rosholm, 2001), Tanzania at 51% (Lindauer and Sabot, 1983), a range of countries in Latin America, from 40% in Chile to 111% in Colombia (Mizala et al., 2011), and Pakistan at roughly 50% (Aslam and Kingdon, 2009; Hyder and Reilly, 2005). Ehrenberg and Schwarz (1986) provide a summary of the early literature using a Mincerian earnings function, while Finan et al. (2015) provide up-to-date estimates for a larger set of countries.

training and secondary school exam results, and in principle, teachers were hired from the top of the list down, until all vacancies in the district were filled. In practice, deviations from the rule occurred, creating a "fuzzy" discontinuity, which we employ as an instrumental variable.[2] Our study is based on surveys of applicants above and below the cut- off in a sample of districts, including their employment outcomes, income and self-reported motivation for work.

We find that becoming a civil service teacher in Kenya yields a wage a premium of over 100% relative to applicants with otherwise identical characteristics, without increasing either motivation or effort. This finding is inconsistent with standard efficiency wage models emphasizing an employer's need to overcome adverse selection, which results in paying above market wages to attract higher quality applicants (Krueger and Summers, 1988), as applicants around the threshold are in expectation of the same type.[3]

The finding is also difficult to reconcile with several other explanations for public-sector wage premia - compensating differentials (Rosen, 1986) or efficiency wages based on moral hazard (Shapiro and Stiglitz, 1984) or reciprocity (Akerlof, 1982), all of which share a common prediction: that public sector teachers endure more strenuous working conditions, or exert greater effort than their private-sector peers. In contrast, we find that working for the civil service leads teachers to report the same or lower levels of motivation and effort than applicants with otherwise identical characteristics, who also in most cases worked as teachers in private schools or on short-term contracts in public schools. This result suggests that neither efficiency wages nor

[2]This fuzziness may resolve any *prima facie* tension between our setup and the large literature demonstarting ethnic favoritism in the allocation of public services and rents in Kenya (Barkan and Chege, 1989; Burgess et al., 2015; Jablonski, 2014; Nellis, 1974) including in the education sector (Kramon and Posner, 2016). Roughly a third of teaching posts in our natural experiment were misallocated, i.e., district education officials deviated from the algorithm to favor certain applicants. We require that some, not all, hiring was determined by a candidate's ranking in the hiring algorithm.

[3] Our result does not rule out that higher wages attract a more able or larger applicant pool, a result that has received empirical support in a number of recent studies (see for example (see for example Dal Bo et al., 2013; Bold et al., 2013).

compensating differentials are likely to be the source of the wage gap.

Such an interpretation is further supported by Duflo et al.'s (2015) experimental findings from Western Kenya that the value-added in terms of pupil learning from (low paid) non- civil service teachers hired on contract in government schools is higher than that of (high paid) civil service teachers, and research by de Ree et al. (2016) and Bau and Das (2016) who estimate zero effects from wage increases on student learning. Thus, we argue that rent-sharing is the most plausible explanation for the large wage a premium we identify.

Although our findings originate from a particular setting – teachers in Kenya – we would argue that they likely apply across a variety of contexts in Sub-Saharan Africa. First, civil service teachers are by far the most common public sector position in most low income countries; second, we exploit data from national large scale multi-year hiring process; and third, Kenyan civil service teachers are paid wages that are close to the average among a larger group of developing countries; i.e. about twice GDP per capita (see Chaudhury et al., 2006) and at the lower end of teacher in Sub-Saharan Africa (see Bold et al., 2017a), all of which speak in favor of the portability of our results.

The findings on motivation and effort are also of independent interest, as there is scant evidence on the causal effect of working for the civil service on these dimensions. Moreover, by showing that intermediate inputs into the education production function are not affected by wages, we can shed light on why the wage elasticity of teacher productivity appears so low.

Most previous work on the public sector premium in both developed and developing countries relies on controls for observable worker characteristics to distinguish rents from returns to human capital, often in the framework of a Mincerian wage equation (for a summary of the early literature, see Ehrenberg and Schwarz, 1986).[4] Even with a rich set of controls and a flexible specification, estimates may still be biased due to the non-random sector selection. Authors have attempted to correct for this by using a two-step sample selection correction (à la Heckman, 1979) or by estimating a structural switching model to simultaneously model the wage equations and which sector a worker chooses to work in.[5] Modelling the sector selection can be challenging as for identification it requires the use of variables to predict the sector choice without having any impact on wages. Alternative approaches to estimating the private-public wage gap include the use of time series data to exploit changes in the sector an individual is working in or attempting to calculate lifetime income, thus taking unemployment risk and other benefits into account.[6] The general finding in both developed and developing countries is that the public sector earns a positive wage premium for comparable individuals, and this is more pronounced for those at the lower end of the wage distribution, in some cases even becoming negative for those at the upper end of the distribution.

[4] More recently this approach has been used by Giordano et al. (2015) for 10 EU countries, and Teal (1996) in Ghana. A slightly more flexible approach, allowing differential returns to observable characteristics across sectors, is applied in a number of studies: Chatterji et al. (2011) in Great Britain, Depalo et al. (2015) in 10 EU countries, Gunderson (1979) in Canada, Lindauer and Sabot (1983) in Tanzania, Lucifora and Meurs (2004) in France, Italy and Great Britain, Melly (2005) in Germany, Mueller (1998) in Canada, Poterba and Rueben (1994) in the USA, Robinson and Tomes (1984) in Canada, and Skyt-Nielsen and Rosholm (2001) in Zambia.

[5] Work attempting to account for selection includes: Adamchik and Bedi (2000) in Poland, Assaad (1997) in Egypt, Boudarbat (2004) in Morocco, Casero and Seshan (2006) in Djibouti, Christofides and Pashardes (2002) in Cyprus, Dickson et al. (2014) for 5 EU countries, Glinskaya and Lokshin (2007) in India, Gyourko and Tracy (1988) in the USA, Hartog and Oosterbeck (1993) in the Netherlands, Heitmueller (2004) in Scotland, Hou (1993) in Taiwan, Hyder and Reilly (2005) in Pakistan, Imbert (2013) in Vietnam, Mengistae (1999) in Ethiopia, Mizala et al. (2011) in 12 Latin American countries, Ramoni-Perazzi and Bellante (2007) in the USA, Ramos et al. (2014) in Spain, Seshan (2013) in Malaysia, Tansel (2005) in Turkey, Terrell (1993) in Haiti, and van der Gaag and Vijverberg (1988) in Côte d'Ivoire.

[6] These include: Borjas (2002) for the USA, Danzer and Dolton (2012) for Great Britain, Disney and Gosling (1998) for Great Britain, Hospido and Moral-Benito (2014) for Spain, and Postel-Vinay and Turon (2007) for Great Britain.

2 Context

The labor market for teachers in Kenya is highly segmented. The formal sector consists of civil service public school teachers who are employed centrally by the Teacher Service Com- mission (TSC) on “permanent and pensionable” contracts. The sector is strongly unionized and teachers are represented by the Kenyan National Union of Teachers (KNUT), which has roughly 200,000 members. TSC and KNUT jointly negotiate the terms and conditions of service for teachers, which are binding for the employer. Applicants for TSC positions are required to be fully qualified to teach in primary school and are ranked according to a well- defined algorithm that rewards seniority (i.e., years since graduation from teacher training) and merit (qualifications and grades in teacher training) with the larger weight put on the former.

While all teachers should in principle be employed as civil service teachers, this system of hiring came under increasing pressure during the Structural Adjustment Programs in the 1990s and the Education for All movement in the 2000s. In January 2003, the government of Kenya introduced the Free Primary Education (FPE) act, which abolished fees in all primary schools. This led to an influx of students into primary schools (UNESCO, 2011), which together with a hiring freeze on new civil service teachers in place since 1998 led to large increases in pupil-teacher ratios (47:1 in 2009). In 2011, the government of Kenya estimated a shortfall of 61,000 teachers.

Alongside the formal labor market, there exists an informal sector with free entry and low wages that grew rapidly in size in the 2000s. In government schools, many parent-teacher associations raise funds to employ teachers on short-term contracts at wages below the civil service pay scale (in 2012, just under 20% of teachers were employed on such contracts, Bold et al., 2017a). Simultaneously, the private school sector has tripled in size from 3 to 9%(Bold et al., 2015). Candidates for either of these positions are often drawn from the pool of recent graduates who were queueing for civil service positions.

In 2010, the government of Kenya stepped in and lifted the hiring freeze on civil service teachers - partly in an attempt to regularize the hiring of teachers on short-term contracts - and hired 18,000 new civil service teachers (66 positions in each of 250 constituencies equivalent to almost one additional teacher per school) offering a starting salary of 10,000 KSh (123.75 USD in September 2010) per month.[7] These teachers were initially employed on fixed-term contracts, all of which were converted to permanent and pensionable contracts within two years.

The district education officers in each constituency were tasked with conducting the hiring process using the TSC algorithm described above to rank candidates. Most of the vacancies were filled in 2010, with some additional hiring taking place in 2011.

3 Sample and Data

The sample consists of 1,157 applicants for teaching vacancies in 36 constituencies inter- viewed at the beginning of 2012 (15 months after the hiring initiative). In each constituency, enumerators were instructed to interview between 20-40 candidates, half directly above and half directly below the hiring cut-off.[8] For each interviewee, we use the scores and ranking from the applicant list, and collected data on their socio-economic background, employment outcomes, income and self-reported motivation for teaching and public service.

The segmentation of the Kenyan labor market for teachers is mirrored also in our sample: Overall, 70% of sampled applicants had been hired for a civil service teacher

[7]In some cases, constituencies were split into two parts, with the sum of vacancies adding up to 66.

[8]Where an individual was not reached, the next applicant away from the cut-off on the list was interviewed until up to 40 applicants had been interviewed in each district. More than two thirds of candidates lie within 20 ranks above or below it. If individuals without a civil service job had been harder to reach and these individuals were systematically different from those reached, this could cause a bias in our results. This is not the case, which is confirmed by a McCrary test as shown in Figure 1.

position at the beginning of 2012, the large majority (almost 90%) in 2010. Of those not hired by the civil service, more than half were working as teachers either in private schools or on short-term PTA contracts, while most others were unemployed.

Beyond the large number of applicants in each district, the attractiveness of civil service teaching positions is revealed by two additional features of the sample: (i) candidates have spent a long-time queuing for them (25% of the teachers applying in 2010 had waited 8 years or longer after graduation); (ii) once hired by the teacher service commission, civil service employment becomes an absorbing state (only 8 teachers left civil service employment).

3.1 Measurement

Income measurements are based on survey participants' self-reported earnings in the previous four weeks. If respondents were unwilling to report their income, we asked them to select their income band (starting at zero and rising in steps of KSh 5,000 up to KSh 20,000), and use the mid-point of the band in our estimation. A small number of respondents (mainly civil-service teachers) refused to respond to either of the two income questions. In addition, the income variable is naturally censored for those who are unemployed. We present results from various treatments of this missing data in the estimation below.

We measure the determinants of motivation using two constructs, general motivation (consisting of intrinsic and extrinsic motivation) and job satisfaction, and how they translate into outcomes, namely effort (see Michaelowa and Wittman, 2007). The constructs used are grounded in Deci and Ryan's (1985) theory of self-determination and Herzberg's (1966) two factor model of motivation.[9] The items have been

[9] Deci and Ryan's theory of self-determination posits that motivation can be either intrinsic/autonomous, which refers to doing something because it is 'inherently interesting or enjoyable', or extrinsic, which refers to doing something because 'it leads to a separable outcome'. According to the authors,it is the former that is particularly desirable and should be fostered if organizations, especially in the public sector, want to achieve good outcomes. Extrinsic motivation on the other hand is associated with less positive attitudes and behavior. Herzberg posits that motivation

specifically developed to measure these constructs among endline service providers, such as teachers and health workers, in Sub-Saharan Africa (see Mbindyo et al. (2009), Prytherch et al. (2012) and Leonard and Maestad (2016) for more details on the instrument).

To measure general motivation and the extent to which applicants are intrinsically motivated, we ask for agreement with the following statement: "These days I feel motivated to work as hard as I can".[10] To measure extrinsic motivation, we ask how much applicants are motivated by job security and high pay, desires which are generally seen as incompatible with autonomous motivation, because they imply external control over the incentive structure (Chen and Hsieh, 2015). Specifically, we ask for agreement with the following two statements: "I only do my job so that I get paid at the end of the month" and "I do my job as it provides long term security for me". To capture both satisfaction and dissatisfaction with one's job, we ask for agreement with the statement "Overall, I am very satisfied with my job." and "I feel emotionally drained at the end of every day."

Turning from determinants to outcomes, we focus on attendance, which has been shown to be positively related to productivity in a number of experimental and non-experimental studies (including Duflo et al., 2012; Bold et al., 2017b). Specifically, we ask candidates to report the number of days they were absent from work in the last four weeks. Two caveats remain: given our interest in 'motivation to work' and how this is shaped by working in the public sector, the questions are only applicable to those currently working, not the whole sample.[11] Second, the data is a self-reported

is positively affected by job satisfaction, which is the consequence of motivators, such as having responsibility, being recognized for one's achievement or doing a meaningful job. Motivators are separate from 'hygiene factors', such as adequate pay and security, the absence of which can lead to dissatisfaction.

[10] For this and all following questions, agreement is measured on a five point Likert scale.

[11] The questionnaire is purposefully kept short and simple, which has been noted to be important for validity by Mbindyo et al. (2009) and Prytherch et al. (2012). As such, we also focus on intrinsic motivation more generally, rather than specifically on public service motivation. The latter is often measured by the Perry scale (1996), but we deemed this tool too complex and not quite appropriate for junior teachers. Within the questionnaire developed by Mbindyo et al. (2009) and Prytherch et al. (2012) we focus on those items related to individual aspects of motivation rather than organizational or institutional ones, since our focus

measure of an intermediate outcome, motivation, that may (or may not) be positively related to the final outcome of interest that wages ought to operate on, namely productivity.

Bearing these caveats in mind, we use our measures of general motivation, job satisfaction and effort to construct an index of motivation, aggregating items after standardizing relative to the unsuccessful applicants (see Kling et al., 2007). We present two versions of this index: (i) a simple average into which items measuring intrinsic/autonomous motivation, job satisfaction and attendance enter positively while the measures of extrinsic motivation and dissatisfaction are reversed following the recommendation by Mbindyo et al. (2009), (ii) an average constructed using factor analysis to first reduce the items to groups of interrelated variables and then aggregate over these groups.

The two different aggregation methods yield similar conclusions with the two indices highly correlated. Also at a conceptual level, the index based on factor analysis accords well with the theory of motivation by reducing the data to three latent factors: one that captures positive determinants of motivation, one related to negative determinants of motivation and one linked to outcomes. More specifically, the first factor has high loadings for being motivated to work hard and job satisfaction and enters the index with a positive sign. The second has high loadings for being driven by money and symptoms of burnout and the last is most correlated with absence. The second and third factor are reversed in the index.

The index constructed with factor analysis also mirrors an inherent ambiguity in the theoretical literature where some researchers have argued that the desire for job security – far from being a component of extrinsic motivation – may in fact crowd in intrinsic motivation because individuals do not see job security as external control but rather as support (Chen and Hsieh, 2015). Consistent with this, we find that being motivated by job security is most predictive of the first factor, but also has

here is on the former, not the latter.

moderately high loadings for the other two.

3.2 Descriptive results

Based on the summary statistics in Table 1, neither the stereotype of the underpaid nor demotivated teacher appear to apply in our sample (see Michaelowa and Wittman, 2007 and Bennell and Akyeampong, 2007 for similar findings). The average wage is 14,000 Kenyan Shillings (KSh), with a raw premium of KSh 4,000 for those working as civil service teach- ers (see Table 1). Hence, teachers working for the civil service earn almost twice annual GDP/capita, a higher ratio than in developed countries.[12]

Consistent with evidence showing that higher wages would attract more able and motivated candidates to the public sector, we find that motivation levels among the sample of applicants and in particular those currently working as civil service teachers are relatively high. Over two thirds of applicants report that they feel motivated to work as hard as they can, and only around a third agree with the statement that they only do their job to get paid at the end of the month. When it comes to satisfaction and well-being, 60% report that they are overall satisfied with their job, though one in three report feeling emotion- ally drained.[13] Regarding effort, absence is low with an average one and half days absence in the last four weeks.[14] These numbers are consistent with self-reported absence rates in other African countries (Michaelowa and Wittman, 2007), but lower than absence measured through direct observation (Chaudhury et al., 2006; Bold et al., 2017a).

There are also significant differences between those working for the TSC and those who were not successful in their application. The former are more motivated to work

[12] In February 2012. the prevailing exchange rate was approximately 84 Kenyan Shillings to the U.S. dollar, and the Shilling was relatively stable over the period considered here. Kenyan GDP/capita was USD 1024 per annum in 2012.

[13] For the variables measured on a five point Likert scale, we create a dummy variable equal to one for the two values in strongest agreement with this statement.

[14] A small number of teachers reported absence numbers exceeding the number of working days in the last four weeks, we drop these observations.

hard, put higher value on job security and are more satisfied with their job. They also report higher levels of absence. The latter two findings are consistent with other research which shows that increases in effort are correlated with lower job satisfaction, if those increases come about through increased external control (Michaelowa and Wittman, 2007). Of course, there may also be systematic differences in reporting absence if those working on private sector contracts are less comfortable reporting unauthorized absences. However, the sign of the difference is consistent with measures based on direct observation that show that Kenyan teachers in private schools and on short-term contracts in public school are absent significantly less often than teachers in government schools (Bold et al., 2017b).

Aggregating the different dimensions of motivation and effort, we find no difference in overall motivation for the simple average index, and a small positive difference when con- structing the index using factor analysis. That is, civil service teachers report – if anything – higher levels of motivations than their counterparts.

4 Estimation Strategy

Our estimation strategy differs from a textbook regression discontinuity design (see Angrist and Pischke, 2009; Hahn et al., 2001; Imbens and Lemieux, 2008; Lee and Lemieux, 2010) in two respects. First, in practice, hiring deviated from the ranking generated by the selection algorithm in some cases, for reasons potentially related to potential earnings and job motivation. Nevertheless, the probability of being hired jumps discontinuously at the cut-off defined by the running variable, and we employ this cut-off in an instrumental variables framework.

Second, inspection of the data shows that the biggest jump in the probability of being hired does not always occur at the official cut-off (i.e. 66 vacancies for most constituencies), due to district education officers having some discretion over how many vacancies to fill and because of additional hiring in 2011.[15] We therefore follow Urquiola (2006) and Card et al. (2008) and define de-facto cut-offs in each district at the rank where the R^2 in a regression of the probability of being hired on being above or below this rank is maximized (see Hansen, 2000).[16]The official and the de-facto cut-off are highly correlated with the mode of the former 66 and the mode of the latter 69, where the difference is equal to the average number of additional people hired in each district in 2011.[17]

Our instrumental variables strategy will yield an unbiased estimate of the causal effect if other variables that affect both outcomes and hiring change smoothly around the hiring cut- off. Importantly, it does not require either the official or the de-facto cut-off in the district to be endogenous to district conditions (including characteristics of applicants in the district), but only that these conditions do not change discontinuously at the cut-off. This assumption might be violated if cut-offs are mechanically located at ranks where there are gaps in the sample, for example because applicants working as civil service teachers are easier to contact for interview than those who were not hired, or if district education officers endogenously hire up to ranks at which some unobservable changes discontinuously.

While we cannot directly test for the validity of the identifying assumption, it is supported by Figure 2, which shows smooth changes at the cut-off for the applicants' overall score and its constituent parts, years waited since graduation and secondary school

[15] Since the hiring algorithm is constant across years, candidates not hired in 2010 still have a higher probability of being hired in 2011 the higher their rank in 2010.

[16] As noted by Card et al. (2008), the fact that the same data is used to estimate the location of the hiring cut-off and its impact on hiring may result in standard errors that are too small. We therefore show two set of robustness checks of the main results in Tables 10, 11 and 12 in the Online Appendix. First (and again following Card et al., 2008), we split the sample in two halves, using one half to estimate the location of the hiring cut-off and the other half to estimate its effect on the outcomes of interest. Second, we repeat all estimations using bootstrapped standard errors. While the standard errors are slightly larger for both procedures, all results remain intact.

[17] Not only does the de-facto cut-off deliver a stronger instrument for the first stage regression, but given the fact that individuals were hired beyond the official cut-off, the LATE we seek is not at the official cut-off. If there is hiring beyond the official cut-off, then the applicants on both sides of the official cut-off will be hired by design (and not just in deviation from the hiring rule) and so the estimated wage differential would be downward biased.

grades, the points awarded to the candidate by the parent-teacher association (which are not part of the selection algorithm) and other socio-economic indicators, such as age and gender. Similarly, a McCrary test determines that the distribution of the candidates' rank in our sample changes smoothly around the cut-off and more than two thirds of candidates lie within 20 ranks above or below it (see Figure 1).

In the first stage, we estimate the predicted probability of being hired for the civil service (CS_i) as a function of being ranked above the hiring-cutoff in each constituency

$$\mathrm{CS}_i = \alpha_0 + \alpha_1 \mathrm{I}_{\text{rank} \leq \text{cut-off}} + \alpha_2 \widetilde{\mathrm{Rank}}_i + \alpha_3 \widetilde{\mathrm{Rank}}_i \times \mathrm{I}_{\text{rank} \leq \text{cut-off}} + \gamma \mathbf{X_i} + \varepsilon_i \qquad (1)$$

where the rank variable has been re-centered at the hiring cut-off

$(\widetilde{\mathrm{Rank}}_i = \mathrm{Rank}_i - \text{Cut-off}_i)$. The specification is equivalent to a linear control function with different slopes on either side of the cut-off.

To estimate the effect of becoming a civil-service teacher on wage income and job motivation, we present three specifications. First, a 'naive' OLS regression,

$$Y_i = \beta_{0,\mathrm{OLS}} + \beta_{1,\mathrm{OLS}} \mathrm{CS}_i + \beta_{2,\mathrm{OLS}} \widetilde{\mathrm{Rank}}_i + \beta_{3,\mathrm{OLS}} \widetilde{\mathrm{Rank}}_i \times CS_i + \gamma \mathbf{X_i} + \varepsilon_i \qquad (2)$$

where $\beta_{1,OLS}$ is the main coefficient of interest and **X** is a set of additional controls, namely age, age squared and gender. Second, we present an ITT specification,

$$Y_i = \beta_{0,\mathrm{ITT}} + \beta_{1,\mathrm{ITT}} \mathrm{I}_{\text{rank} \leq \text{cut-off}} + \beta_{2,\mathrm{ITT}} \widetilde{\mathrm{Rank}}_i + \beta_{3,\mathrm{ITT}} \widetilde{\mathrm{Rank}}_i \times \mathrm{I}_{\text{rank} \leq \text{cut-off}} + \gamma \mathbf{X_i} + \varepsilon_i \quad (3)$$

which estimates the reduced-form effect of being ranked above the hiring cut-off on the outcomes of interest. Third, we use the predicted probability of being hired and predicted interaction term from the first stage (Equation 1) to estimate the causal effect of civil service employment on wage income and job motivation,

$$Y_i = \beta_{0,\text{LATE}} + \beta_{1,\text{LATE}}\widehat{\text{CS}_i} + \beta_{2,\text{LATE}}\widetilde{\text{Rank}_i} + \beta_{3,\text{LATE}}\widehat{\widetilde{\text{Rank}_i} \times \text{CS}_i} + \gamma\mathbf{X_i} + \varepsilon_i. \tag{4}$$

We control for a full set of constituency fixed effects in all specifications.[18] For the main part of the analysis, we use the whole sample of applicants, which corresponds to a bandwidth of 66 (on average) and a linear control function. In Section 6.1, we show robustness of the results with respect to bandwidth and functional form.

5 Results

5.1 Selection

The probability of being hired exhibits a large and significant jump (of roughly 20%) where the candidate's rank crosses the hiring cut-off. This can be seen graphically in Figure 3, which displays the probability of being hired as a linear function of the candidates rank centered at the cut-off. The result is confirmed in Table 2, based on estimates of Equation 1, which shows that being ranked higher than the cut-off increases the probability of being hired by 26%. This first-stage regression has an F-statistic of 71, allaying any concerns about weak instruments due to favoritism in hiring.

5.2 Wage Gap

Regressing wages on civil service status using OLS shows a civil service premium of KSh 5,000 in columns (1) and (2) of Table 3, panel A. This is in line with the descriptive

[18] We do not cluster standard-errors as our treatment varies within clusters and the intra-cluster correlation of residuals is close to zero.

statistics and corresponds to a 50% increase in wages relative to the outside option (panel B).[19]

OLS results are likely biased by endogenous selection into the civil service, both through favoritism on the hiring side and private-sector job search by candidates. We present in- tention to treat effects and instrumental variable estimates of civil-service status in columns (3)-(6) of Table 3. Being ranked above the hiring cut-off on the hiring list increases wages by roughly KSh 2,000, a positive and significant effect. The local average treatment effect at the cut-off is even larger: being hired as a civil service teacher is predicted to increase wages by over KSh 10,000, equivalent to a more than 100% increase (from column 5 in panel B, see also Figure 4). That the LATE estimate exceeds the OLS coefficient is consistent with negative selection into the public sector, possibly because successful applicants with large private sector returns may decide not to take up the job offer or because those in charge of hiring engage in favoritism rather than finding the most qualified applicants.

In Table 4, we repeat the IV estimation to show that the finding of a large causal public sector wage premium is robust to various methods addressing censoring and non-response in the outcome variable. In columns (1)–(2) we follow Angrist and Pischke (2009, p.100) and set the wage of the unemployed to zero. The effect is still large and significant both in levels and in logs, with an estimated wage increase of KSh 8,000 (both with and without controls), equivalent to a 4-fold increase.[20] In columns (3)–(4), we instead estimate reservation wages for those who are unemployed on the basis of salary earned in their last known job (Falk et al., 2006, show that reservation wages are affected by previously earned wages). Again, the results are stable and the wage increase is estimated to be around KSh 8,000.

In column (5)–(10), we also address non-response to the income question by some

[19] In the income regressions, we trim the top 1% of observations as they are implausibly large.

[20] The results from the log regression are somewhat sensitive to the $log(x + 1)$ transformation we use to deal with zero wages. However, the results remain intact even with different transformations such as taking square roots or a hyperbolic spline.

civil service teachers.[21] We follow three strategies here. In columns (5) and (6), we impute the missing wages from institutional knowledge about the teacher hiring program, namely that all posts were offered with a starting salary of KSh 10,000. Again, the results are qualitatively unchanged. In columns (7) and (8), we estimate a worst-case bound on the treatment effect (similar to Horowitz and Manski, 2000). That is, we assume that non-respondents who were predicted to be hired by our instrument (i.e. ranked above the cut-off) received the wage equivalent to the tenth percentile of the wage distribution for civil service teachers, namely KSh 8,000, while those who ranked below the cut-off received the wage equivalent to the 90th percentile reported by civil service teachers (KSh 21,000). Even in this most conservative specification, the income effect of a public sector job is still estimated to be around KSh 4,000 (Panel A), with a p-value of .13 in levels and significant in the log specification (Panel B). Finally, in columns (9) and (10), we account for non-random missingness by trimming the top percentiles of the income distribution for those predicted to be hired by the algorithm (see Lee, 2009).[22] Again, the results are robust with an estimated effect of civil service employment on wages of over KSh 8,000 or a 100% wage increase.

We conclude that civil service teachers in Kenya benefit from a large public sector pay premium that cannot be explained by unobserved applicant characteristics.

5.3 Motivation

Our identification strategy allows us to rule out that either observable or unobservable human capital differences explain the wage premium civil service teachers receive. However, it may be the case that the civil service pays higher wages in order to motivate teachers and thereby elicit more effort. We now examine whether such an

[21] We continue to assign zero wage income to the unemployed.

[22] The lower-bound on the ITT effect estimated with Lee bounds (Tauchmann, 2014) is KSh 800 or 14% and significant. To estimate the IV, we trim income of the top $(q_T - q_C)/q_T$ percent of those predicted to be hired by the algorithm, where q_T is the proportion of individuals above the cut-off whose income is observed and q_C is the proportion of individuals below the cut-off whose income is observed. We then estimate the IV regression with this trimmed income variable in the second stage.

efficiency wage mechanism is at work here.

In Table 5, we examine how motivation is affected by being hired as a civil service teacher in 2010 (vs. later or not at all), using the 2010 de-facto cut-off in hiring as an instrument.[23] The implicit assumption here is that – in contrast to income – effects on motivation are not instantaneous.

Overall, we do not find evidence that working in the civil service leads people to be more motivated, but neither does it measurably decrease motivation levels compared to others working as teachers on short-term contracts or in private schools, or in the private sector.

Based on the IV estimates in column (5) and (6) of the bottom panel of Table 5, we see small negative, but insignificant, effects on the motivation index constructed with factor analysis and a zero effect on the simple average over all standardized items. Together with the income estimates, this suggests that higher wages in the civil service do not serve to motivate people to work harder (above and beyond possible selection effects at the application stage, which are already netted out in our sample).

Looking beyond the average, we see that working for the civil service either has no or a negative effect on most of the determinants of motivation and outcomes. Those predicted to work in the civil service by the hiring algorithm are less motivated to work hard and more likely to report that they only do their job to get paid at the end of the month. The only component of motivation that goes into the opposite direction is job security, which becomes a less important motivator for those predicted to work in the civil service. However, as noted in Section 3, there is some disagreement whether being motivated by the desire for job security crowds in or crowds out intrinsic

[23] The 2010 de-facto cut-off is found by searching for the rank that maximizes the R^2 of the regression of the probability of being hired in 2010 on being above or below that rank. As seen in Table 6 of the Online Appendix, the first stage coefficient is positive and significant, while other variables change smoothly also at this cut-off (see Figure 5 in the Online Appendix).

motivation.

In sum, we find little evidence that civil service employment (and the higher wages it entails) increases either effort or motivation. On the upside, working as a teacher in the civil service system does not appear to have a demotivating effect either. This is an important finding given the large literature that documents the often dysfunctional institutions and surroundings in which teachers operate. Of course, we do not observe the counterfactual, perhaps there are additional insalubrious factors associated with working as a civil service teachers that would demotivate teachers even further if wages were lower. However, the evidence on the performance of contract and civil service teachers working side by side in the same school casts doubt on this.

Given that working for the civil service at a higher wage does not appear to motivate candidates per se, and might even have a slightly demotivating effect, it is interesting to examine to what extent deviations from the hiring rule by district education officers counteract this. We can gain some insights into this by comparing the OLS results in column and (2) to the IV coefficients. Inasmuch as controlling for the forcing variable in the regressions adequately captures the fact that candidates with a higher rank are likely also more motivated, we can interpret the OLS coefficient as the sum of the causal effect of civil service status and the selection effect. Based on this, it would appear that district education officers select candidates who are more motivated to work hard, care less about money, and more about security than the average candidate situated on either side of the hiring cut-off. No selection seems to take place on job satisfaction and the likelihood of burnout (i.e., feeling drained). There is, however, negative selection in terms of effort (i.e., being present in school). Overall, the picture is mixed with a bias towards more motivated candidates emerging in the motivation index constructed with factor analysis, but not in the simple average.[24]

[24] The difference between the two indices is due to the fact that the simple average index rates 'job security' as a negative determinant of motivation, while it is predictive of both positive and negative determinants of motivation in the index constructed with factor analysis.

6 Discussion

Taken together, our results show that even when controlling for unobserved human capital differences, there is a large wage premium for civil service teachers. We find no evidence that this is due to compensating differentials or that higher wages are traded off against higher motivation and effort as predicted by the shirking version of efficiency wage models (Shapiro and Stiglitz, 1984). We therefore conclude that the evidence is most consistent with rent-sharing.

To be able to categorically rule out efficiency wages, we would have to be able to compare productivity of those ranked above and below the cut-off. Although it is in general difficult to compare productivity across sectors, one advantage here is that a large majority of the sample works as teachers either in the civil service or under private sector conditions making student achievement a natural productivity measure to use. While we do not have such a measure in our data, we can draw on both experimental and observational studies from Kenya, which show that teachers who work on private sector contracts with lower wages produce higher test scores than their civil service counterparts (see Duflo et al., 2015; Bold et al., 2017b).

Similarly, Bold et al. (2013) find in an experimental setting which randomizes contract structures across teachers that those with contracts similar to civil service teachers (higher wages and recruited and paid through the district education officer) do not perform significantly better than teachers with contracts similar to PTA and private school teachers (lower wages and recruited and paid through the school). Finally, an interpretation of rent-sharing is also consistent with findings by de Ree et al. (2016), Bau and Das (2016) and Gagliarducci and Nannicini (2013) who estimate zero effects from wage increases (or decreases) on teachers' and politicians' productivity.

It is also important to acknowledge that the argument that rent-sharing with its implied inefficiencies which is at play here is essentially a static one. That is, we cannot rule out that longer-term efficiency considerations are important where higher wages (at least in expectation) induce higher ability individuals to apply for civil service positions or enter the teaching profession in the first place. Such a mechanism may indeed be important: Dal Bo et al. (2013) provide experimental evidence showing that higher wages attract more able applicants in the context of public service workers in Mexico and Bold et al. (2013) show in the experiment described above that higher wages increase the likelihood of filling teacher vacancies in Kenya. On the other hand, the effect of higher wages on the quality of the applicant pool is by no means unambiguous as studied theoretically by Delfgaauw and Dur (2007) and experimentally by Deserranno (2016).

Finally, we point out that although our results do not imply that it would be possible to lower all teachers' wages permanently to the level of the outside option estimated here, they do show that teachers are willing to work for lower wages, often for many years, while waiting or hoping for eventual civil service employment, suggesting the potential for efficiency gains. Indeed, both Muralidharan and Sundararaman (2010) and Duflo et al. (2015) argue based on calibration exercises that substantial cost-savings could be achieved without sacrificing student learning if more teachers were employed for longer on contracts and salary levels outside of the civil-service.

6.1 Robustness

Regression discontinuity results may be sensitive to the bandwidth of the running variable used in estimation. In the main regressions, we use all the available data. In Figure 6 in the Online Appendix, we present sensitivity checks for the OLS, ITT and LATE specification with control variables, using different bandwidths around the cut-off. The main results do not appear to be an artifact of a specific bandwidth, though the magnitude of the coefficient on civil service employment falls somewhat as the bandwidth narrows. The confidence interval expands slightly as the bandwidth narrows and the sample size falls, rendering it impossible to reject a null result with a bandwidth of less than roughly ten applicants per district. Among the alternative bandwidth choices are those calculated as the “optimal bandwidth” by three different techniques, namely 69 for Cross Validation (Ludwig and Miller, 2007), 30 for IK (Imbens and Kalyanaraman, 2012), and 22 for CCT (Calonico et al., 2014b). The results of the regressions for income using these bandwidths can be found in Table 7, with the effect remaining uniformly positive and significant. The values of these cut-offs are also indicated in Figure 6.

In order to ensure that our results are not a result of the functional form we also repeat our main regressions of interest including a quadratic polynomial term, though not for higher order polynomials (as argued in Gelman and Imbens, 2014). The first stage remains significant as can be seen in Table 8 and the effect on income continues to be positive and significant (see Table 9 in the Online Appendix).

7 Conclusions

While wage differentials between observably similar workers in the public and private sector have been widely documented in many labor markets, previous research has largely been unable to discern whether these wage gaps reflect inefficient economic rents, or efficient rewards for unobserved skills and effort. We study this question in a context where working conditions appear to be more favorable, and effort levels appear to be lower, in the public sector compared to the private. We rely on a natural experiment in teacher hiring in Kenya in 2010 and 2011 that allows us to rule out both observed and unobserved human capital as explanations for wage differentials, and measure the quantity of economic rents in civil service salaries.

Estimates based on a regression discontinuity design using the civil service hiring algorithm suggest public teachers earn a premium of over 100% above their colleagues in the private sector. Furthermore, we find no evidence of an increase in motivation levels for public sector teachers above those not hired by the civil service.

Two key caveats to our results bear highlighting. First, we calculate rents as the gap between civil service wages and labor market outcomes for an ostensibly identical applicant who was rejected. We implicitly assume these unsuccessful applicants take the best job available to them in a relatively competitive informal labor market, and do not sacrifice earnings opportunities by remaining in the queue for a civil service job. Officially, the government hiring algorithm provides no reason to forego other earning opportunities while queuing, but future research might address the possibility that candidates feel the need (rightly or wrongly) to signal neediness and desert, or to expend effort being visible to local education officials.

A second caveat is the potential for non-response bias in the sampling of our teacher survey. We take a fairly conservative approach to addressing non-response, placing bounds on the potential bias either through imputation or trimming. While this solution is not perfect, the bounds suggest our finding of significant rents from public-sector employment are robust to even very perverse patterns of non-response to the income questions.

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Measuring Rents from Public Employment:

Regression Discontinuity Evidence from Kenya

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Abstract

Public employees in many developing economies earn much higher wages than similar private-sector workers. These wage premia may reflect an efficient return to effort or unobserved skills, or an inefficient rent causing labor misallocation. To distinguish these explanations, we exploit the Kenyan government's algorithm for hiring eighteen-thousand new teachers in 2010 in a regression discontinuity design. Fuzzy regression discontinuity estimates yield a civil-service wage premium of over 100 percent (not attributable to observed or unobserved skills), but no effect on motivation, suggesting rent-sharing as the most plausible explanation for the wage premium.

Keywords: civil servants, teachers, public sector wages, wage gap, motivation

JEL Codes: H1; J3; O1

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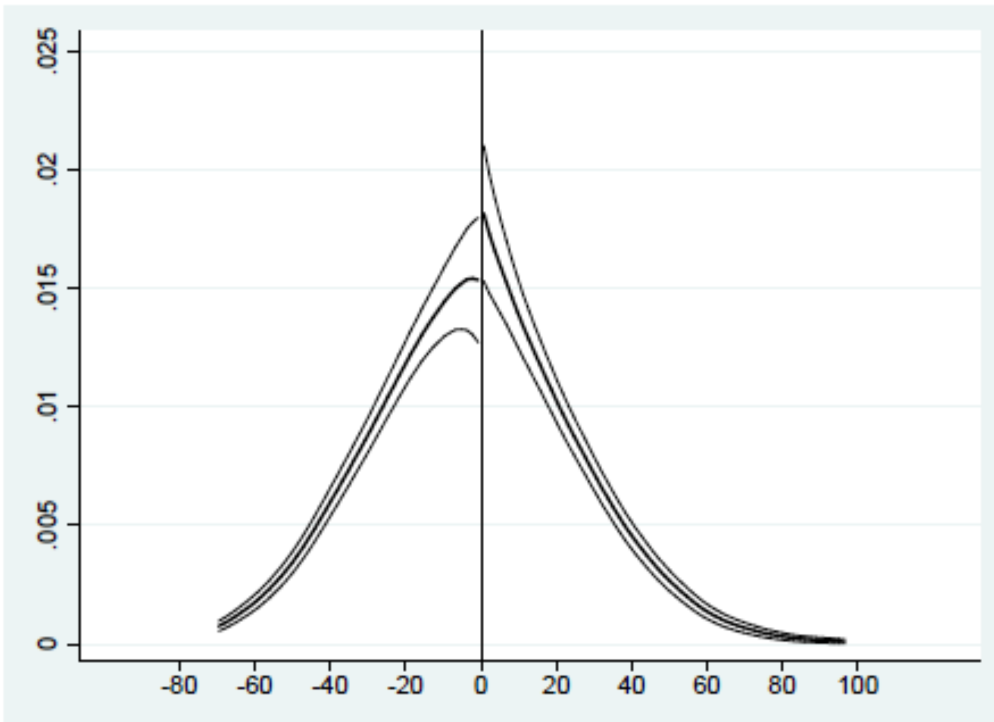
Tables and Figures

Figure 1: Density of Adjusted Rank (Adjusted for the de Facto Cut-off)



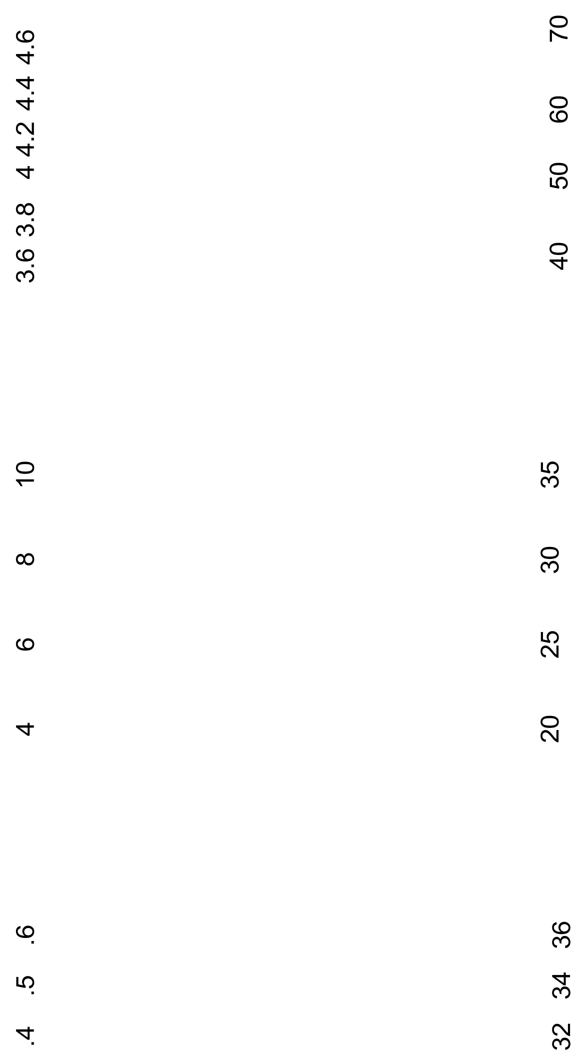
Note: The graph shows the density of individuals surveyed, which is bunched around the cut-off by design. The confidence intervals indicate that the null hypothesis that the density is the same on each side of the cut-off cannot be rejected.

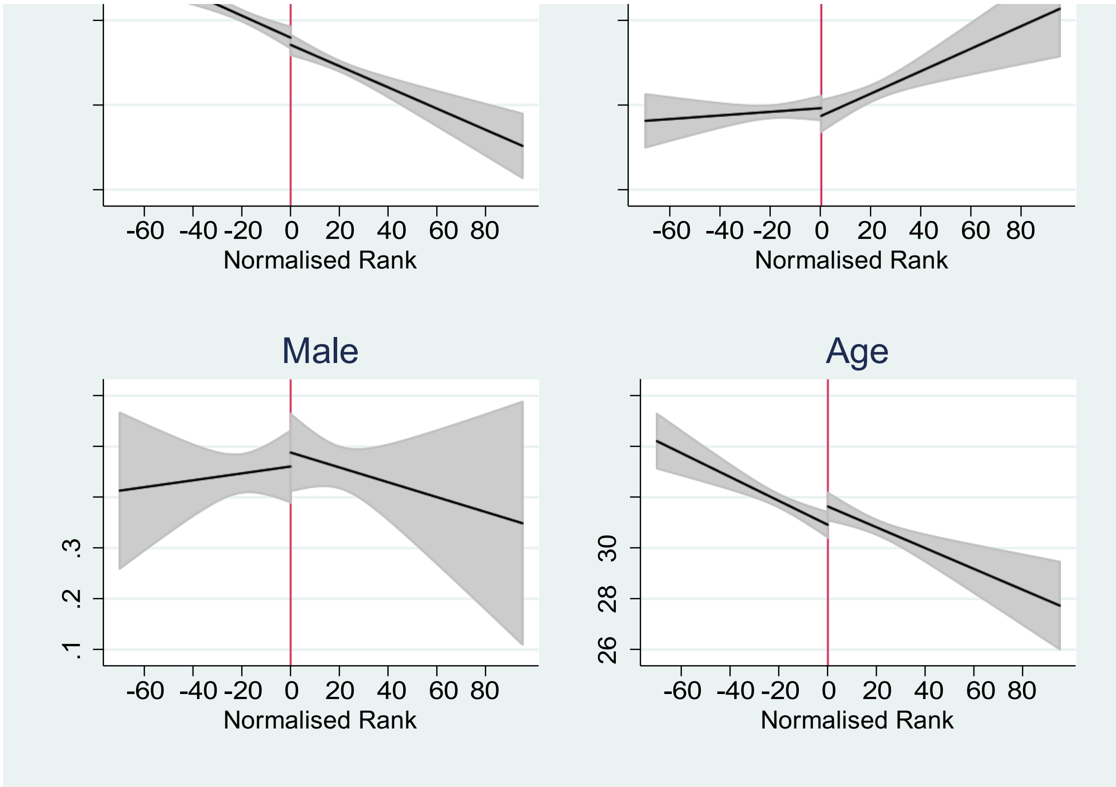
Table 1: Descriptive Statistics

		Hired by civil service		
Panel A: Income and Motivation	All	Yes	No	Diff.
Monthly income (KSh)	12759	13705	9782	3923***
	(6851.45)	(5370.92)	(9654.07)	(710.21)
Log of income	9.32	9.42	8.99	0.44***
	(0.55)	(0.50)	(0.60)	(0.05)
These days I feel motivated to work as hard as I can	0.72	0.73	0.68	0.05
	(0.45)	(0.45)	(0.47)	(0.04)
I only do my job so that I get paid at the end of the month*	0.31	0.32	0.30	0.01
	(0.46)	(0.46)	(0.46)	(0.04)
I do my job as it provides long-term security for me*	0.56	0.59	0.47	0.11**
	(0.50)	(0.49)	(0.50)	(0.04)
I feel emotionally drained at the end of every day*	0.36	0.35	0.38	-0.02
	(0.48)	(0.48)	(0.49)	(0.04)
Overall, I am satisfied with my job	0.61	0.63	0.50	0.14**
	(0.49)	(0.48)	(0.50)	(0.04)
Days absent in last 4 weeks*	1.51	1.57	1.32	0.25
	(2.28)	(2.22)	(2.44)	(0.18)
Motivation Index (PCA)	-0.10	-0.06	-0.20	0.14*
	(0.97)	(0.96)	(1.00)	(0.00)
Motivation Index (simple average)	-0.08	-0.07	-0.08	0.01
	(0.98)	(0.99)	(0.91)	(0.05)
Panel B: Control variables				
Male	0.452	0.439	0.487	-0.048
	(0.498)	(0.497)	(0.501)	(0.032)
Age	31.39	31.65	30.83	0.82***
	(4.17)	(4.08)	(4.33)	(0.28)
N	1157	801	356	

Note: In panel A income and motivation variables are shown first for the whole sample and then split by civil service status. The fourth column shows the difference between the groups and the results of a t-test of equality of each variable for the two groups. Panel B displays the demographic control variables.
All motivation variables (except days absent) were measured on a 5-point Likert scale. We create a dummy variable for the two values in strongest agreement with the statement given. The first motivation index is created using principal component analysis (PCA). The second index averages over standardized values of the variables (in their original form, rather than as a dummy variable) with items measuring intrinsic/autonomous motivation, job satisfaction and attendance entering positively and the measures of extrinsic motivation and dissatisfaction being reversed (indicated with an asterisk). Both indices are standardized with respect to the group not hired as civil service teachers.

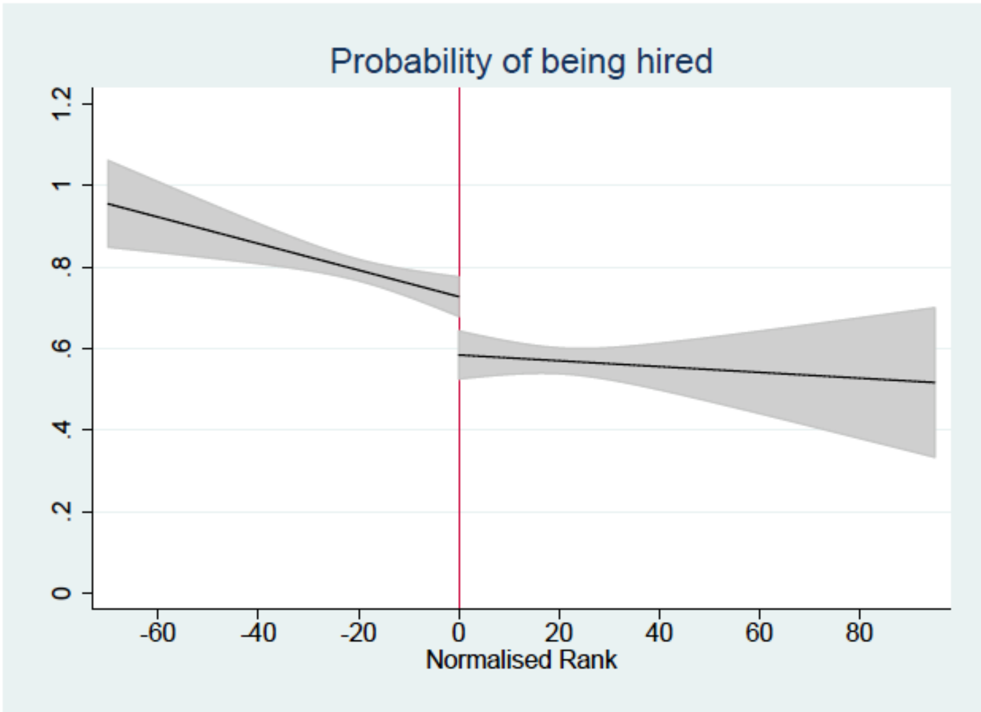
Figure 2: Possible discontinuities in control variables





Note: The graphs show the best linear fit separately on each side of the cut-off for each of the named variables.

Figure 3: Discontinuity in treatment



Note: The graph shows the best linear fit separately on each side of the cut-off for being hired as a civil servant in either 2010 or 2011.

Table 2: First-stage regressions

	(1) Hired	(2) Hired
Above cut-off	0.26***	0.27***
	(0.039)	(0.039)
Rank	-0.0006	-0.0011
	(0.0012)	(0.0012)
Rank × Above cut-off	-0.0037**	-0.0035**
	(0.0016)	(0.0016)
Age		0.062**
Age Squared		-0.00091**
Male		-0.010
		(0.024)
Obs.	1157	1123
R-squared	0.16	0.17
		(0.030)
		(0.00045)

Note: The dependent variable is a dummy for being hired as a civil servant in either 2010 or 2011.
"Above cut-off" is a dummy for being ranked at least as highly as the final rank to be hired by the civil service, and represents where the discontinuity is to be found. "Rank" is an individual's normalized ranking in the district in which they applied. Both columns include constituency fixed effects. Column two also includes additional variables controlling for demographic characteristics of the applicant as indicated. Stan- dard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 4: Intention to Treat for Income

Income

18000
16000
14000
12000
10000

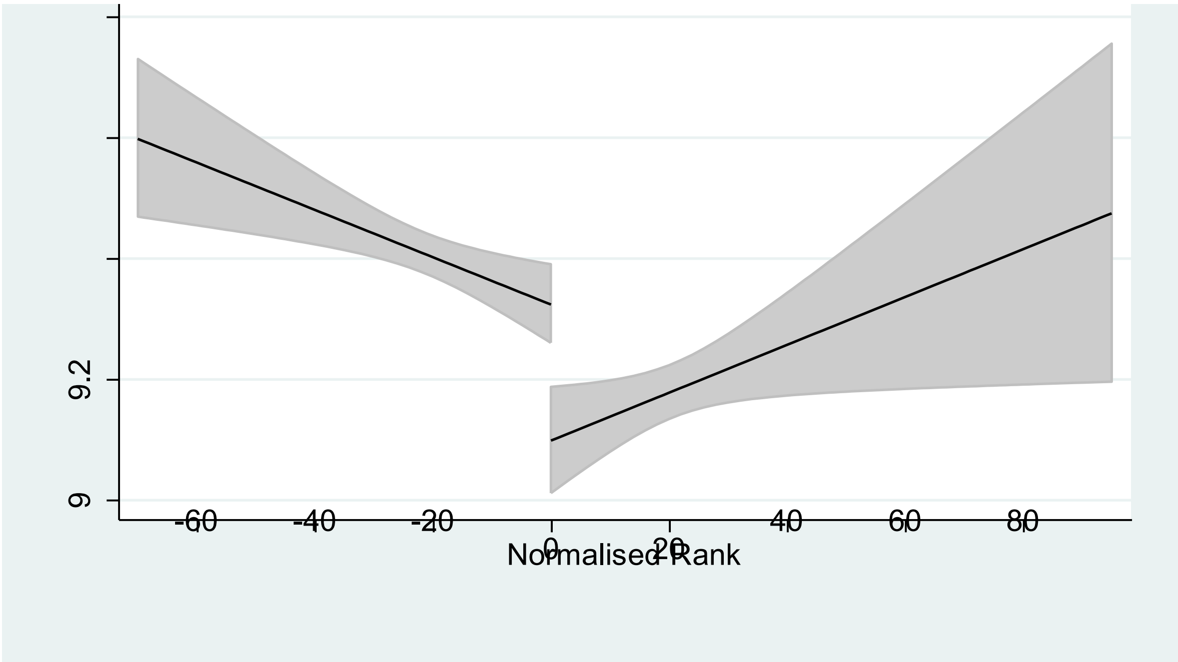
0 20

9.8
9.6
9.4

-60 -40 -20 40 60 80

Normalised Rank

Log income



Note: The graph shows the best linear fit separately on each side of the cut-off for income in KSh and log(income) using the de facto cut-off for being hired in either 2010 or 2011.

Table 3: Regression results for income and log(income)

	OLS		ITT		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income (KSh)						
Public Sector Job	5381.1***	5159.0***			11052.4***	11479.3***
	(376.9)	(389.8)			(3630.5)	(3992.2)
Rank × Public Sector Job	-.08	-1.8			-371.8	-449.2
	(15.7)	(16.0)			(246.3)	(297.7)
Above cut-off			1861.9***	1960.2***		
			(542.2)	(548.6)		
Rank × Above cut-off			-66.1***	-69.8***		
			(22.0)	(22.3)		
Rank	-13.3	-10.3	22.1	28.8*	301.0	364.8
	(13.8)	(14.2)	(17.3)	(17.5)	(204.1)	(245.0)
Const.	8427.9***	8685.8***	10731.9***	10753.0***	3522.7	3078.0
	(311.8)	(322.7)	(411.4)	(412.6)	(3080.3)	(3489.6)
Panel B: log(Income)						
Public Sector Job	.53***	.51***			1.04***	1.10***
	(.04)	(.04)			(.34)	(.37)
Rank × Public Sector Job	.0001	-.0002			-.03	-.04
	(.002)	(.002)			(.02)	(.03)
Above cut-off			.20***	.20***		
			(.05)	(.05)		
Rank × Above cut-off			-.006***	-.006***		
			(.002)	(.002)		
Rank	-.002	-.001	.002	.002	.02	.03
	(.001)	(.001)	(.002)	(.002)	(.02)	(.02)
Const.	8.91***	8.92***	9.13***	9.13***	8.47***	8.41***
	(.03)	(.03)	(.04)	(.04)	(.28)	(.33)
Controls included		YES		YES		YES
Obs.	840	813	840	813	840	813

Note: In panel A, the dependent variable is income in Kenyan Shillings (KSh), where 1 US Dollar was approximately equal to 84 KSh. In panel B we use the natural logarithm of the income. Columns (1) and (2) are OLS regressions of income on a dummy for working in a public sector job, along with the rank and an interaction term of the two. Columns (3) and (4) are ITT regressions which include a dummy variable equal to one when ranked higher than the cut-off as well as rank and an interaction of rank with the aforementioned dummy. Columns (5) and (6) are IV regressions and use the predicted value of being hired from a first stage indicated in Table 2.
Constituency fixed effects are included in all regressions.
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Controls are standardized and include: Age, age^2 and a dummy for being male.

Table 4: Regression results for income and log(income) correcting for non-response and censoring

	Imputation A		Imputation B		Imputation C		Imputation D		Trimming	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Income (KSh)										
Public Sector Job	8094***	7939***	8684***	8596***	10241***	10187***	3766	3914	8266**	
		8978**	(1714)	(1693)	(1800)	(1767)	(1940)	(1930)	(2521)	
		(2496)	(3444)	(3977)						
Rank × Public Sector Job	-178.8***	-199.0***	-215.1***	-228.5***	-285.0***	-315.0***	-395.1***	-425.2***	-247.9	-340.3
	(67.1)	(69.5)	(70.5)	(72.6)	(91.0)	(96.7)	(118.4)	(125.1)	(226.6)	(296.1)
Rank	108.0**	121.9**	151.1***	162.1***	200.3***	222.2***	248.8***	272.5***	210.1	285.4
	(47.9)	(49.3)	(50.3)	(51.5)	(68.8)	(72.6)	(89.5)	(93.9)	(188.1)	(243.7)
Const.	5013***	5084***	5158***	5228***	2901**	2890**	7809***	7667***	5287*	4630
	(1124)	(1115)	(1181)	(1163)	(1423)	(1425)	(1850)	(1843)	(2872)	
		(3437)								
Panel B: log(Income)										
Public Sector Job	3.75**	3.48**	3.26***	3.16***	2.98***	2.93***	2.51***	2.48***	.90**	.98**
	(1.69)	(1.65)	(.81)	(.78)	(.91)	(.89)	(.95)	(.93)	(.37)	
		(.43)								
Rank × Public Sector Job	-.08	-.10	-.10***	-.10***	-.05	-.07	-.06	-.08	-.02	-.04
	(.07)	(.07)	(.03)	(.03)	(.04)	(.04)	(.04)	(.05)	(.02)	(.03)
Rank	.02	.03	.08***	.08***	.02	.03	.03	.04	.02	.03
	(.05)	(.05)	(.02)	(.02)	(.03)	(.03)	(.03)	(.04)	(.02)	(.03)
Const.	4.29***	4.36***	6.33***	6.38***	5.96***	5.93***	6.30***	6.27***	8.55***	8.47***
	(1.11)	(1.09)	(.53)	(.51)	(.67)	(.66)	(.70)	(.69)	(.31)	(.37)
Controls		YES		YES		YES		YES		YES
Obs.	977	948	977	948	1141	1108	1141	1108	771	744

See notes for Table 3.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls are standardized and include: Age, age^2, a dummy for being male
A number of individuals did not report their income, some by survey design and some due to question non-response. If the respondent answered that they were currently not working, they were not asked their current income but were asked if they were working in October 2010 and their wage at the time. For those working in the TSC, we know the official starting wage of a civil service teacher.
-Imputation A: Those without a job are assigned a zero income.
-Imputation B: Those reporting an income in 2010 but not 2012 are assigned their last known income as a proxy for their reservation wage
-Imputation C: Zero is assigned to those with no job and 10,000 KSh to those working for the TSC who did not respond to the income question
-Imputation D: we use a 'worst-case' scenario similar to Horowitz and Manski (2000), where we assign the 10th percentile

(8,000 KSh) of the income distribution of civil service teachers to non-respondents above the cut-off and the 90th percentile (21,000 KSh) of this income distribution to those below the cut-off.
-Trimming: Following Lee (2009) we trim the upper 16% of the income distribution for those above the hiring cut-off.

Table 5: Regression results for Motivation

	OLS		ITT		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
These days I feel motivated to work as hard as I can	.07	.12	-.10	-.10	-.40	-.35
	(.08)	(.08)	(.10)	(.10)	(.47)	(.45)
Mean in Comparison Group	3.77	3.74	3.93	3.93	4.15	4.13
I only do my job so that I get paid at the end of the month*	.05	.03	.15	.19*	.65	.75
	(.07)	(.08)	(.10)	(.10)	(.49)	(.47)
Mean in Comparison Group	2.71	2.72	2.54	2.52	2.18	2.10
I do my job as it provides long-term security for me	.41***	.40***	-.15	-.13	-.64	-.54
	(.07)	(.07)	(.10)	(.10)	(.45)	(.42)
Mean in Comparison Group	3.16	3.17	3.53	3.53	3.91	3.84
I feel emotionally drained at the end of every day*	-.03	.002	.02	.01	.04	.01
	(.07)	(.07)	(.09)	(.10)	(.42)	(.41)
Mean in Comparison Group	3.11	3.09	3.04	3.02	3.03	3.03
Overall, I am satisfied with my job	.16**	.19**	.06	.06	.23	.20
	(.08)	(.08)	(.11)	(.11)	(.52)	(.49)
Mean in Comparison Group	.50	.50	.63	.63	.53	.59
Days absent in last 4 weeks*	.44**	.45**	.0004	-.10	.02	-.39
	(.18)	(.19)	(.24)	(.25)	(1.03)	(.98)
Mean in Comparison Group	1.18	1.17	1.53	1.54	1.51	1.77
Indices						
Motivation Index (PCA)	.04	.04	-.07	-.08	-.32	-.37
	(.07)	(.08)	(.10)	(.10)	(.51)	(.50)
Motivation Index (average)	-.15*	-.16**	.008	.005	.03	.003
	(.08)	(.08)	(.10)	(.10)	(.53)	(.52)
Obs.	971	940	971	940	971	940
Controls		YES		YES		YES

Each entry presents the effect of a public sector job on the outcome listed on the left. For the specification, see notes for Table 3. Standard errors in parentheses for the coefficient of interest. Standard errors are excluded for the "Mean in Comparison Group" (the constant term).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The first and second motivation index are created using principal component analysis (PCA), first with absence in logs and then levels. The third and fourth indices average over standardized values of the variables with items measuring intrinsic/autonomous motivation, job satisfaction and attendance entering positively and the measures of extrinsic motivation and dissatisfaction being reversed (indicated with an asterisk). Indices are standardized with respect to the group not hired as civil service teachers.

Online Appendix

Table 6: First-stage regressions for the 2010 de facto cut-off

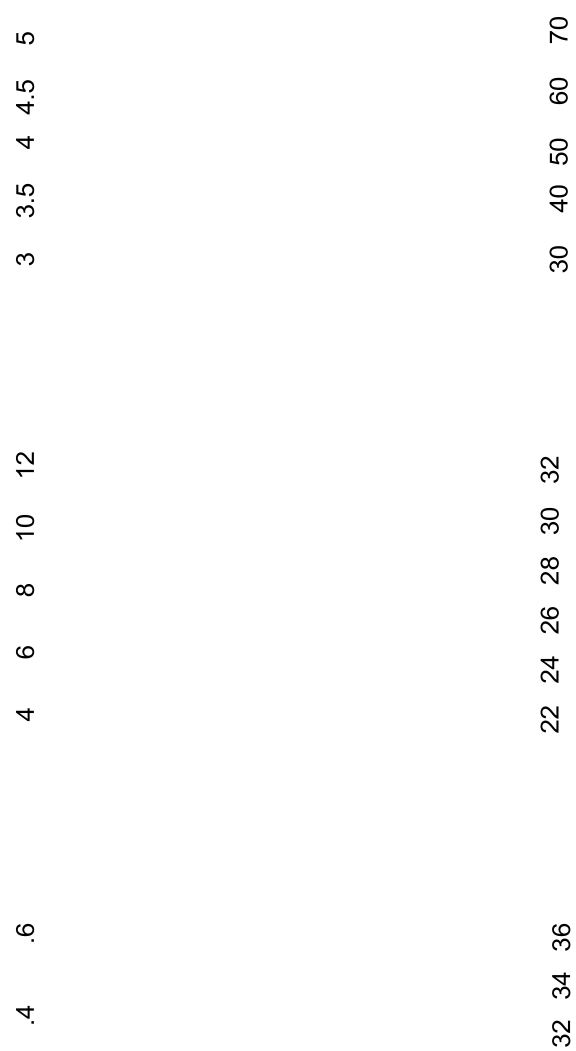
	(1) Hired in 2010	(2) Hired in 2010
Above cut-off	0.20***	0.21***
	(0.041)	(0.042)
Rank	-0.0049***	-0.0048***
	(0.0011)	(0.0012)
Rank × Above cut-off	-0.00011	0.0000095
	(0.0018)	(0.0018)
Age		0.060*
Age Squared		-0.00088*
Male		-0.029
		(0.026)
Obs.	1148	1114
R-squared	0.16	0.17

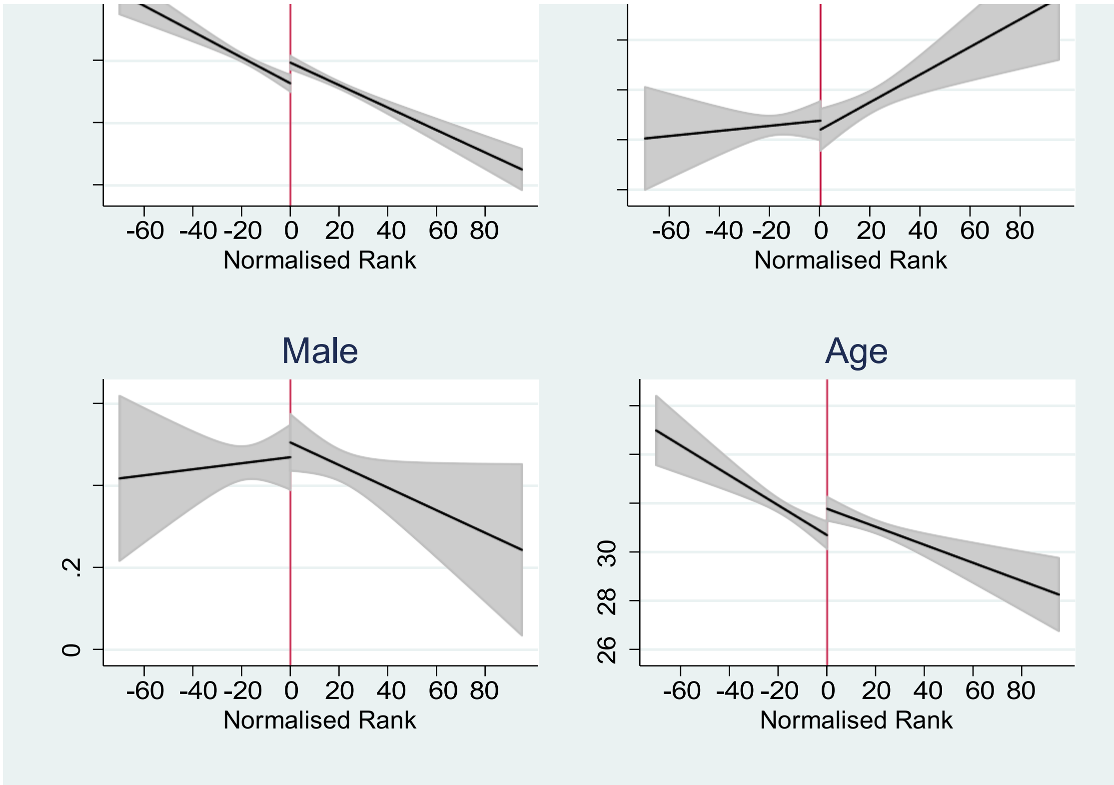
(0.032)

(0.00048)

Note: The dependent variable is a dummy for being hired as a civil servant in 2010. “Above cut-off” is a dummy for being ranked at least as highly as the final rank to be hired by the civil service in 2010, and represents where the discontinuity is to be found. “Rank” is an individual’s ranking in the district in which they applied. Both columns include constituency fixed effects. Column two also includes additional variables controlling for demographic characteristics of the applicant. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 5: Possible discontinuities in control variables for 2010 de facto Cut-off





Note: The above graphs indicate the best linear fit separately on each side of the cut-off for being hired in 2010 for each of the named variables.

Table 7: Treatment Regressions for Optimal Bandwidth

	OLS			ITT			IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Income (KSh)									
Public Sector Job	4587.4***	4851.6***	5145.8***				5183.1*	5815.6*	11649.5***
	(466.0)	(534.0)	(391.2)				(2737.6)	(3221.1)	(4134.6)
Rank × Public Sector Job	29.41	1.481	-4.273				-279.7*	-354.7	-522.5
	(33.85)	(51.17)	(16.14)				(157.4)	(220.7)	(321.8)
Above cut-off				1167.3	1384.8	1869.6***			
				(736.1)	(862.0)	(554.5)			
Rank × Above cut-off				-102.1*	-151.0*	-75.28***			
				(56.06)	(83.97)	(22.89)			
Rank	-53.43*	-22.92	-10.37	5.07	40.13	28.22	156.1	225.2	415.9
	(27.77)	(41.89)	(14.19)	(43.24)	(64.48)	(18.11)	(117.6)	(158.7)	(261.0)
Constant	9413.7***	9064.0***	8690.1***	11448.3***	11152.2***	10748.4***	8440.1***	7867.9***	2794.2
	(388.8)	(450.3)	(323.0)	(578.0)	(676.6)	(418.6)	(2080.6)	(2386.5)	(3621.1)
Panel B: log(Income)									
Public Sector Job	0.442***	0.464***	0.513***				0.442	0.518	1.082***
	(0.0478)	(0.0562)	(0.0393)				(0.271)	(0.336)	(0.373)
Rank × Public Sector Job	0.00172	-0.00105	-0.000454				-0.0205	-0.0347	-0.0432
	(0.00347)	(0.00539)	(0.00162)				(0.0156)	(0.0230)	(0.0291)
Above cut-off				0.103	0.122	0.193***			
				(0.0748)	(0.0893)	(0.0557)			
Rank × Above cut-off				-0.00755	-0.0146*	-0.00664***			
				(0.00570)	(0.00870)	(0.00230)			
Rank	-0.00558*	-0.00281	-0.00122	-0.00220	0.00209	0.00222	0.00901	0.0201	0.0342
	(0.00285)	(0.00441)	(0.00142)	(0.00439)	(0.00668)	(0.00182)	(0.0116)	(0.0165)	(0.0236)
Constant	9.004***	8.975***	8.925***	9.220***	9.181***	9.135***	8.964***	8.888***	8.415***
	(0.0399)	(0.0474)	(0.0324)	(0.0587)	(0.0701)	(0.0420)	(0.206)	(0.249)	(0.327)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	546	431	809	546	431	809	546	431	809
Selector	IK	CCT	CV	IK	CCT	CV	IK	CCT	CV
Bandwidth	27	20	69	27	20	69	27	20	69

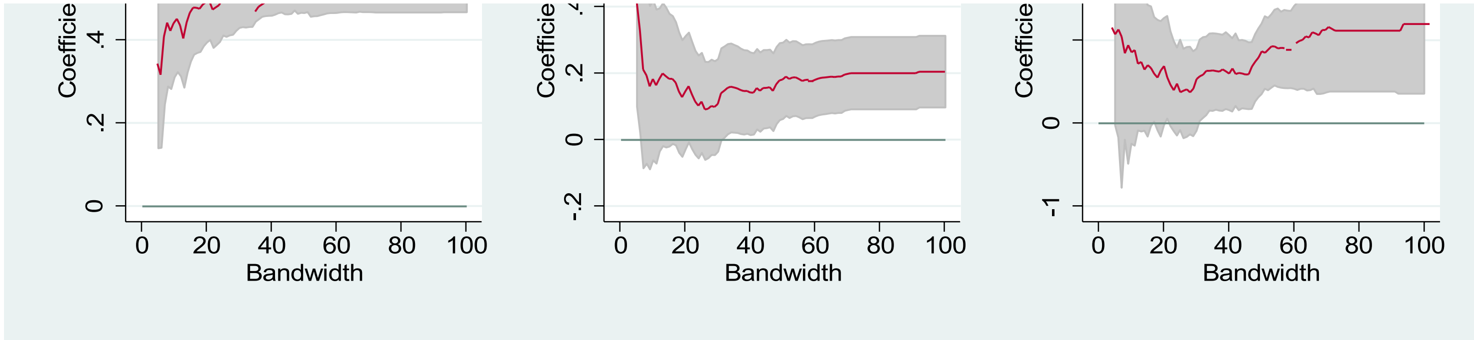
*** p<0.01, ** p<0.05, * p<0.1. See notes for Table 3.
Controls are standardized and include: Age, age^2, a dummy for being male
Columns 1, 4 and 7 use the optimal bandwidth as calculated in Imbens and Kalyanaraman (2012), columns 2, 5 and 8 use the method of Calonico et al. (2014b), while 3, 6 and 9 use the Cross Validation method of Ludwig and Miller (2007) as calculated by the *rdbwselect* command in Stata (Calonico et al., 2014a).

Figure 6: Alternative bandwidths

Coefficient
2000 4000 6000
.6 .8

Coefficient
-2000 0 2000 4000 6000
.6 .8

Coefficient
0 5000 15000 25000
2 3



Note: The above graphs show how the coefficient of interest (darker red solid line running from left to right) changes as the bandwidth changes, with the 95% confidence interval plotted around the coefficient line (the grey area).
The vertical lines indicate the values of the “optimal bandwidth” according to Ludwig and Miller (2007, the green line at 69), Imbens and Kalyanaraman (2012, the blue line at 27), and Calonico et al. (2014a, the red line at 20).

Table 8: First-stage regressions including quadratic terms

	(1) Hired	(2) Hired
Above cut-off	0.21***	0.22***
	(0.050)	(0.051)
Rank	-0.0033	-0.0038
	(0.0029)	(0.0029)
Rank × Above cut-off	-0.0059	-0.0048
	(0.0044)	(0.0044)
Rank^2	0.000036	0.000046
	(0.000045)	(0.000045)
Rank^2 × Above cut-off	-0.00013*	-0.00013*
	(0.000076)	(0.000077)
Age		0.058*
		(0.030)
Age Squared		-0.00085*
		(0.00046)
Male		-0.010
		(0.024)
Obs.	1157	1123
R-squared	0.16	0.18

Note: The dependent variable is a dummy for being hired as a civil servant in either 2010 or 2011.
"Above cut-off" is a dummy for being ranked at least as highly as the final rank to be hired by the civil service, and represents where the discontinuity is to be found. "Rank" is an individual's ranking in the district in which they applied. Both columns include constituency fixed effects. Column two also includes additional variables controlling for demographic characteristics of the applicant.

Table 9: Regression results for income and log(income) including quadratic terms

	OLS		ITT		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income (KSh)						
Public Sector Job	5188.5***	4955.8***			6610.2***	6634.2***
	(442.5)	(458.4)			(2218.2)	(2154.4)
Rank × Public Sector Job	2.4	.6			-125.9	-147.1
	(16.1)	(16.5)			(103.332)	(105.053)
Rank^2 × Public Sector Job	.3	.3			2.4	2.5
	(.4)	(.4)			(2.2)	(2.1)
Above cut-off			887.3	1026.7		
			(707.9)	(712.0)		
Rank × Above cut-off			-68.2	-77.8		
			(62.6)	(63.4)		
Rank^2 × Above cut-off			-2.3**	-2.3**		
			(1.1)	(1.1)		
Rank	-13.2	-10.0	-37.5	-26.6	97.1	116.2
	(14.1)	(14.6)	(46.1)	(46.6)	(85.6)	(86.9)
Rank^2	.1	.1	1.1	1.0	-1.7	-1.7
	(.4)	(.4)	(.8)	(.8)	(1.9)	(1.8)
Const.	8357.0***	8604.0***	11234.0***	11209.2***	7141.1***	7134.4***
	(376.3)	(389.8)	(547.4)	(548.2)	(1702.9)	(1674.4)
Panel B: log(Income)						
Public Sector Job	.503***	.481***			.617***	.675***
	(.045)	(.048)			(.214)	(.208)
Rank × Public Sector Job	.0005	-.0002			-.006	-.011
	(.002)	(.002)			(.010)	(.010)
Rank^2 × Public Sector Job	.00004	.00004			.0002	.0002
	(.00004)	(.00005)			(.0002)	(.0002)
Above cut-off			.093	.097		
			(.071)	(.071)		
Rank × Above cut-off			-.002	-.004		
			(.006)	(.006)		
Rank^2 × Above cut-off			-.0002**	-.0003**		
			(.0001)	(.0001)		
Rank	-.002	-.001	-.006	-.005	.004	.008
	(.001)	(.002)	(.005)	(.005)	(.008)	(.009)
Rank^2	-3.02e-06	9.20e-06	.0002*	.0001*	-.0002	-.0002
	(.00004)	(.00004)	(.00008)	(.00008)	(.0002)	(.0002)
Const.	8.906***	8.923***	9.200***	9.196***	8.817***	8.764***
	(.038)	(.041)	(.055)	(.055)	(.165)	(.162)
Controls included		YES		YES		YES
Obs.	840	813	840	813	840	813

Note: In panel A, the dependent variable is income in Kenyan Shillings (KSh), where 1 US Dollar was approximately equal to 84 KSh. In panel B we use the natural logarithm of the income. Columns (1) and (2) are OLS regressions of income on a dummy for working in a public sector job, along with the rank, rank squared and an interaction term of each of the rank variables with the dummy. Columns (3) and (4) are ITT regressions which include a dummy variable equal to one when better than the cut-off as well as rank, rank squared and an interaction of rank variables with the aforementioned dummy. Columns (5) and (6) are IV regressions and use the predicted value of being hired from a first stage indicated in Table 7. Constituency fixed effects are included in all regressions.

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Controls are standardized and include: Age, age^2, a dummy for being male.

Table 10: First-stage regressions for the split sample

	(1) Hired	(2) Hired
Above cut-off	0.11*	0.12**
	(0.057)	(0.057)
Rank	-0.0058***	-0.0055***
	(0.0017)	(0.0018)
Rank × Above cut-off	-0.00089	-0.0012
	(0.0023)	(0.0024)
Age		0.022
Age Squared		-0.00031
Male		-0.064*
		(0.035)
Obs.	594	571
R-squared	0.16	0.17

(0.042)

(0.00063)

Note: The dependent variable is a dummy for being hired as a civil servant in either 2010 or 2011.
"Above cut-off" is a dummy for being ranked at least as highly as the final rank to be hired by the civil service, and represents where the discontinuity is to be found. "Rank" is an individual's ranking in the district in which they applied. Both columns include district fixed effects. Column two also includes additional variables controlling for demographic characteristics of the applicant.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
These results are for half of the sample, with the other half being used to find estimate where the cut-off is found, as suggested in Card et al. (2008)

Table 11: Regression results for income and log(income) for the split sample

	OLS		ITT		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income (KSh)						
Public Sector Job	6690.1***	6787.4***			7316.4	7153.1*
	(515.2)	(540.4)			(4667.5)	(4306.3)
Rank × Public Sector Job	9.7	6.5			-153.1	-174.5
	(18.7)	(19.5)			(147.8)	(139.7)
Above cut-off			986.0	1027.8		
			(807.9)	(833.7)		
Rank × Above cut-off			-30.4	-40.3		
			(31.2)	(32.1)		
Rank	-16.9	-11.4	-19.2	-11.0	107.8	124.1
	(16.9)	(17.6)	(24.3)	(25.4)	(123.2)	(114.9)
Const.	7383.5***	7496.7***	11481.2***	11538.7***	6564.8*	6782.7**
	(425.7)	(447.1)	(582.0)	(599.2)	(3574.1)	(3303.3)
Panel B: log(Income)						
Public Sector Job	.66***	.68***			1.08**	1.02**
	(.05)	(.06)			(.54)	(.48)
Rank × Public Sector Job	.0008	.0002			-.02	-.02
	(.002)	(.002)			(.02)	(.02)
Above cut-off			.15*	.15*		
			(.08)	(.09)		
Rank × Above cut-off			-.004	-.005		
			(.003)	(.003)		
Rank	-.002	-.001	-.0005	.0001	.02	.02
	(.002)	(.002)	(.003)	(.003)	(.01)	(.01)
Const.	8.80***	8.80***	9.16***	9.17***	8.44***	8.50***
	(.05)	(.05)	(.06)	(.06)	(.42)	(.36)
Controls included		YES		YES		YES
Obs.	431	413	431	413	431	413

Note: In panel A, the dependent variable is income in Kenyan Shillings (KSh), where 1 US Dollar was approximately equal to 84 KSh. In panel B we use the natural logarithm of the income. Columns (1) and
(1) are OLS regressions of income on a dummy for working in a public sector job, along with the rank and an interaction term of the two. Columns (3) and (4) are ITT regressions which include a dummy variable equal to one when ranked higher than the cut-off as well as rank and an interaction of rank with the aforementioned dummy. Columns (5) and (6) are IV regressions and use the predicted value of being hired from a first stage indicated in Table 10.
Constituency fixed effects are included in all regressions.
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Controls are standardized and include: Age, age^2 and a dummy for being male.

Table 12: First stage and main regression results with bootstrapped standard errors

First Stage		
	Hired	Hired
Above cut-off	0.26*** (0.072)	0.27*** (0.073)
Intention to Treat		
	Income	Income
Above cut-off	1861.9*** (681.4)	1960.2*** (685.1)
	log(Income)	log(Income)
Above cut-off	0.20** (0.078) (0.079)	0.20**
Second Stage		
	Income	Income
Public Sector Job	11052.4** (5092.1)	11479.3*** (3937.3)
	log(Income)	log(Income)
Public Sector Job	1.04* (0.578)	1.10** (0.454)
Controls		YES

Note: The above are the results as found in Tables 2 and 3 with bootstrapped standard errors. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1