Measuring the Rents from Public Employment: Evidence from Kenya *

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Abstract

A large literature demonstrates a wage premium for public employment, with particularly high premiums in many developing economies. The observed wage gap may be efficient – due to compensating differentials, efficiency wages, or selection of candidates into public sector jobs based on unobserved human capital – or an inefficient rent causing labor misallocation. To differentiate between these explanations, we use a regression discontinuity design that exploits the Kenyan government's decision to hire roughly eighteen-thousand new teachers in 2010 based on a simple algorithm ranking applicants within each district. Many unsuccessful candidates found employment as teachers in the private sector. Fuzzy regression discontinuity estimates yield a wage return to civil service employment of over 100% (not attributable to observable or unobservable skills), and a negative effect on teacher motivation (inconsistent with efficiency wage models).

JEL classification: H1; J3; O1
Keywords: civil servants, teachers, public sector wages, wage gap

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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).

The policy implications of these wage differentials hinge crucially on whether they are efficient rewards for talent and effort, or rather inefficient rents captured by public servants. Beyond rent seeking and clientelism, modern labor economics provides three main alternative explanations 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). While all have been shown to be empirically important phenomena in various contexts, our goal here is to isolate the role of rents.

To do so, we present evidence from a natural experiment in Kenya's education sector that allows us to measure the increase in wages caused by acquiring a civil service job. Compensating differentials and efficiency wages appear not be at work in this context, and we use an identification strategy that allows us to rule out both observed and unobserved human capital differences between public- and private-sector employees, giving us a uniquely clean measure of rents from public employment.

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. While teachers selected

[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.

for the civil service are initially more motivated, we also find that working in the civil service erodes teachers' motivation and public mindedness over time.

Our identification strategy is based on a regression discontinuity design in teacher hiring. In 2010, following the advent of free primary education in 2003 (Bold et al., 2015) 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 (66 positions in each of 250 constituencies, equivalent to almost one additional teacher per school). 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 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 this cut-off in a sample of districts, including their employment outcomes, income and self-reported motivation for teaching and public service.

To highlight how our approach isolates the role of economic rents, consider each alternative explanation in turn. First, one strand of efficiency wage models emphasizes an employer's need to overcome adverse selection, which results in paying above market wages to attract higher quality applicants (Krueger and Summers, 1988). Dal Bo et al. (2013) provide experimental evidence for this phenomenon in a developing-country civil service setting, showing that higher wages attract more able applicants. Observational studies instead rely on survey data to estimate public sector pay premia conditional on ability (see Ehrenberg

[2]This fuzziness may resolve any *prima facie* tension between our setup and the large literature demonstrating 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 uncorrelated with candidate characteristics related to earning potential.

and Schwarz, 1986, for a survey of the early literature). Still, some aspects of ability may not be observed in survey data. The key advantage of our regression discontinuity strategy is to remove the bias in the estimate of the public-sector wage premium due to either type of human capital, thus we can rule out this class of explanations.

The second and third explanations for public-sector wage premia – compensating differentials or efficiency wages based on moral hazard – share a common prediction: that public sector teachers endure more strenuous working conditions, or exert greater effort than their private-sector peers. Kenyan education has received disproportionate attention in the economics literature, and prior work provides strong evidence against this prediction. Bold et al. (2017) show in a nationally representative sample that public teachers in Kenya – and elsewhere – are found teaching in the classroom only half of the time they should be and are absent more often than teachers in private schools, implying that any difference in wages does not seem to compensate for greater work demands or to induce greater effort. Furthermore, Duflo et al. (2011) find in an experiment conducted in Western Kenya that the value-added in terms of pupil learning from non-civil service teachers hired on contract in Kenyan schools is higher than that of civil service teachers. Similarly, Bau and Das (2016) find no change in teacher value added following a policy that reduced teacher wages by 35% in Pakistan. Consistent with this, we find that working for the civil service leads teachers to report lower levels of motivation over time.

2 Sample and Data

The sample consists of 1,157 applicants for teaching vacancies in 36 constituencies interviewed 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.[3] 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.

Overall, 70% of applicants had been hired for a civil service teacher 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.

The average wage in the sample is 13,000 Kenyan Shillings (KSh), with a raw premium of KSh 4,000 for those working as civil service teachers (see Table 1).[4] 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 motivation for teaching and public service by responses to the following battery of questions. Motivation to work is based on respondents agreement with the statement, "These days I feel motivated to work as hard as I can." and disagreement with the statement "I only do my job so that I can get paid at the end of the month."[5] Public mindedness is

[3]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. Figure 1 shows 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. 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 by the confidence intervals in 1

[4]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.

[5]These question were only asked of those currently employed and are measured on a five-point Likert scale.

measured with two questions. First, "Do you believe that (A) it is possible to be successful on your own or (B) A large group is necessary to be successful?" Second, respondents were asked if they agree that "Money is important for happiness." From the answers, we construct indices of motivation on the job (agree with the first statement, do not agree with the second statement) and public-mindedness (agree with statement (B) and find money less important for happiness) following Kling et al. (2007).

Civil service teachers and other respondents look rather similar in Table 1 in terms of motivation on the job. For both groups, over 70% of the sample say that they are motivated to work as hard as they can, while roughly a third say that they only work to get paid at the end of the month.[6] Still, when combining the raw values in an index, a positive, but not significant, difference in job motivation opens up between those hired by the civil service and those engaged otherwise. Civil service teachers also appear more publicly-minded than others. They tend to agree less with the statements that money is important for happiness and that one can be successful on one's own, leading to a significant difference in the index of public-mindedness between the two groups.

3 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

[6]For the variables measured on a Likert scale, we create a dummy variable for the two values in strongest agreement with this statement. To create indices, we use the 'raw' values.

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.[7] 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).[8] 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.

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. The validity of this assumption 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 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, gender, marital status and number of children.

In the first stage, we estimate the predicted probability of being hired for the civil service (CS_i) with the following regression.

$$\text{CS}_i = \beta_0 + \beta_1 \text{I}_{\text{rank} \leq \text{ cut-off}} + \beta_2 \widetilde{\text{Rank}}_i + \beta_3 \widetilde{\text{Rank}}_i \times \text{I}_{\text{rank} \leq \text{cut-off}} + \gamma \mathbf{X_i} + \varepsilon_i \qquad (1)$$

[7] Since the hiring algorithm is constant across years, candidates not hired in 2010 should still have a higher probability of being hired in 2011 the higher their rank in 2010. Even if this were not the case, this would not invalidate identification, but could potentially weaken it. As it happens, the predictive power of the ranking is higher in 2011 than in 2010.

[8] 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 repeat all estimations using bootstrapped standard errors. While these are indeed slightly larger for the first-stage, all results remain intact.

where the rank variable has been re-centered at the hiring cut-off ($\widetilde{\text{Rank}}_i = \text{Rank}_i - \text{Cut-off}_i$). The interaction of the rank with the indicator variable allows for differential effects of the rank variable above and below the cut-off. $\mathbf{X}$ is a set of additional controls, namely age, age squared, a dummy for being married and the number of children.

In the second stage, we use this predicted probability of being hired and predicted interaction term to estimate the causal effect of civil service employment on wage income and measures related to job motivation and public mindedness,

$$Y_i = \beta_0 + \beta_1 \widehat{\text{CS}}_i + \beta_2 \widehat{\widetilde{\text{Rank}}}_i + \beta_3 \widehat{\widetilde{\text{Rank}}_i \times \text{CS}_i} + \gamma \mathbf{X_i} + \varepsilon_i \tag{2}$$

where hats denote predicted values and β_1 is the main coefficient of interest.

4 Results

4.1 Selection

The probability of being hired exhibits a large and significant jump (of roughly 25%) 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 local polynomial 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 30%. This first-stage regression has an F-statistic of 30.65, allaying any concerns about weak instruments due to favoritism in hiring.

4.2 Wage Gap

Regressing wages on civil service status using OLS (following the specification in Equation 2 but without instrumenting) 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 statistics and corresponds to a 50% increase in wages relative to the outside option (panel B).[9]

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 the local average treatment effects from instrumental variables estimation of Equation 2 in Table 3, columns (3)-(4). We find a large positive and significant effect of being hired as a civil service teacher (robust to the inclusion of controls), which we interpret as the local average treatment effect at the hiring cut-off. Being hired as a civil service teacher is predicted to increase wages by over KSh 10,000, equivalent to a 100% increase (panel B).

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, with an estimated wage increase of KSh 8,000 (both with and without controls), equivalent to a 160-220% increase. 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). Again, the results are stable and the wage increase is estimated to be around KSh 8,000.

In column (5)–(8), we also address non-response to the income question by some civil service teachers.[10] We follow two strategies here. In columns (5) and (6), we impute the missing wages from institutional knowledge about the teacher hiring program, namely that

[9] In the income regressions, we trim the top 1% of observations as they are implausibly large.
[10] We continue to assign zero wage income to the unemployed.

all posts were offered with a starting salary of KSh 10,000. Again, the results are unchanged. Finally, in columns (7) and (8), we follow Horowitz and Manski (2000) and estimate a worst-case bound on the treatment effect, under the assumption that non-respondents who were predicted to be hired by our instrument (i.e. ranked above the cut-off) received the lowest possible wage reported by civil service teachers (KSh 7,500), while those who were predicted not to be hired (i.e. ranked below the cut-off) received the highest possible wage 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 between KSh 3,000 and 5,500, or a 200% increase (Panel B), and significant in three of four specifications with a p-value of 0.2 in the fourth.

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

4.3 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 still be the case that the civil service pays higher wages in order to motivate teachers and thereby elicit more effort. In other words, the wage gap we estimate might be due to efficiency wages rather than rent-sharing.

We do not find evidence for this, however. Based on prior anecdotal evidence (Lindelow et al., 2006), we hypothesize (and find evidence that) working in the civil service causes teachers to become demotivated, but that this effect takes time to materialize.

We test the hypothesis in Table 5. In columns (5)–(6), we estimate the effect of being hired in 2010 (vs. 2011 or not at all) on our measures of job motivation and public mindedness

using the 2010 de-facto cut-off in the hiring rule as an instrument.[11] The effect is negative for both measures and significant in the case of public-mindedness. In column (7)–(8), we run the same regression, but now estimating the causal difference in motivation for those being hired in either 2010 or 2011 and those not hired at all. The effect is again negative for both measures and significant for on-the-job motivation in the regression without controls.

The patterns of coefficients are indeed consistent with the hypothesis that working in the public sector causes motivation to decline. They also suggest that this effect takes some time to take hold (but does so faster for on-the-job motivation than for public-mindedness).[12]

Interestingly, the OLS regression results in column (1)–(4), which conflate both the causal effect of civil service employment and the fact that candidates may be purposefully selected in deviations from the hiring rule, suggest that working in the civil service is associated with higher motivation. In all cases, the OLS coefficient is positive or effectively zero, but larger and significant only when comparing those hired in either 2010 or 11 with those never hired. Again, this is consistent with the hypothesis that teachers become more demotivated over time. In fact, based on the magnitude of the coefficients in columns (1) and (2), one might argue that after 15 months, the positive selection effect and the negative causal effect on motivation exactly outweigh each other.

This evidence of lower motivation and effort relies on self-reported data. However, the results align with prior studies which – although subject to endogenous selection of teachers into the civil service – find that Kenyan teachers working in the civil service exert lower effort

[11] 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).

[12] To see this consider a simple example in which motivation for those never hired is zero and for those hired in 2010 is $m < 0$, while those hired in 2011 lie somewhere between the two. Hence, the estimated negative effect of civil service employment on motivation will be larger in the 'Hired in 2010' regression than the 'Ever hired' regression if those hired in 2011 have motivation levels more similar to those never hired, i.e. if the demotivating effect is slow to materialize. The converse is true if those hired in 2011 have motivation levels more similar to those hired in 2010, i.e. demotivation happens quickly.

(through higher absence) than teachers who work in private schools or on non-government contracts (see Bold et al., 2017; Duflo et al., 2015)

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 an efficiency-wage equilibrium in which higher wages are traded off against higher motivation and effort. We therefore conclude that the evidence is most consistent with rent-sharing.

4.4 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 4, we present sensitivity checks for the OLS 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.

5 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 show that the lower motivation levels of public versus private teachers are largely a consequence of public employment: one and a half years later, civil service teachers are significantly less likely to say they are highly motivated to teach than otherwise identical applicants who were turned away.

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 using Horowitz and Manski's (2000) procedure. 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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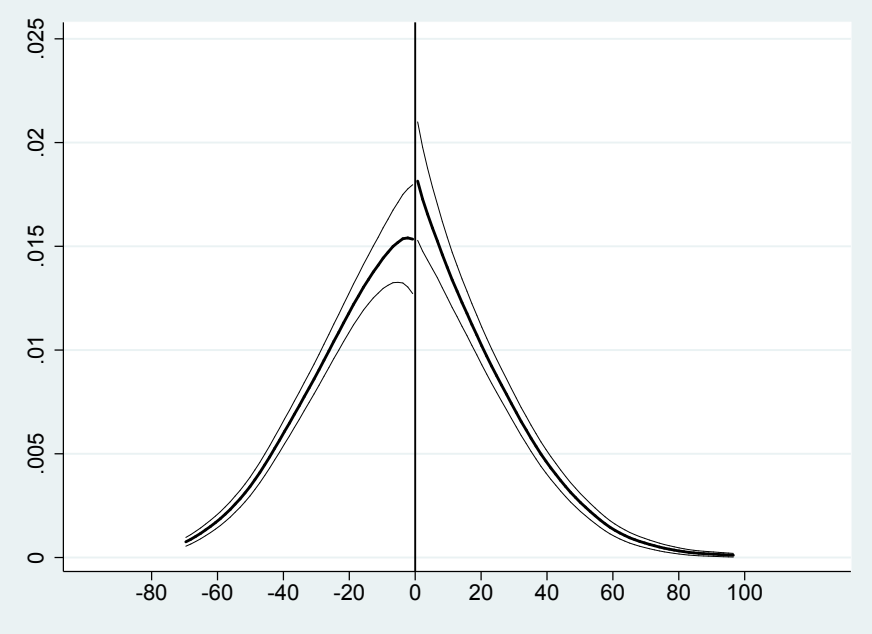
6 Tables and Figures

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



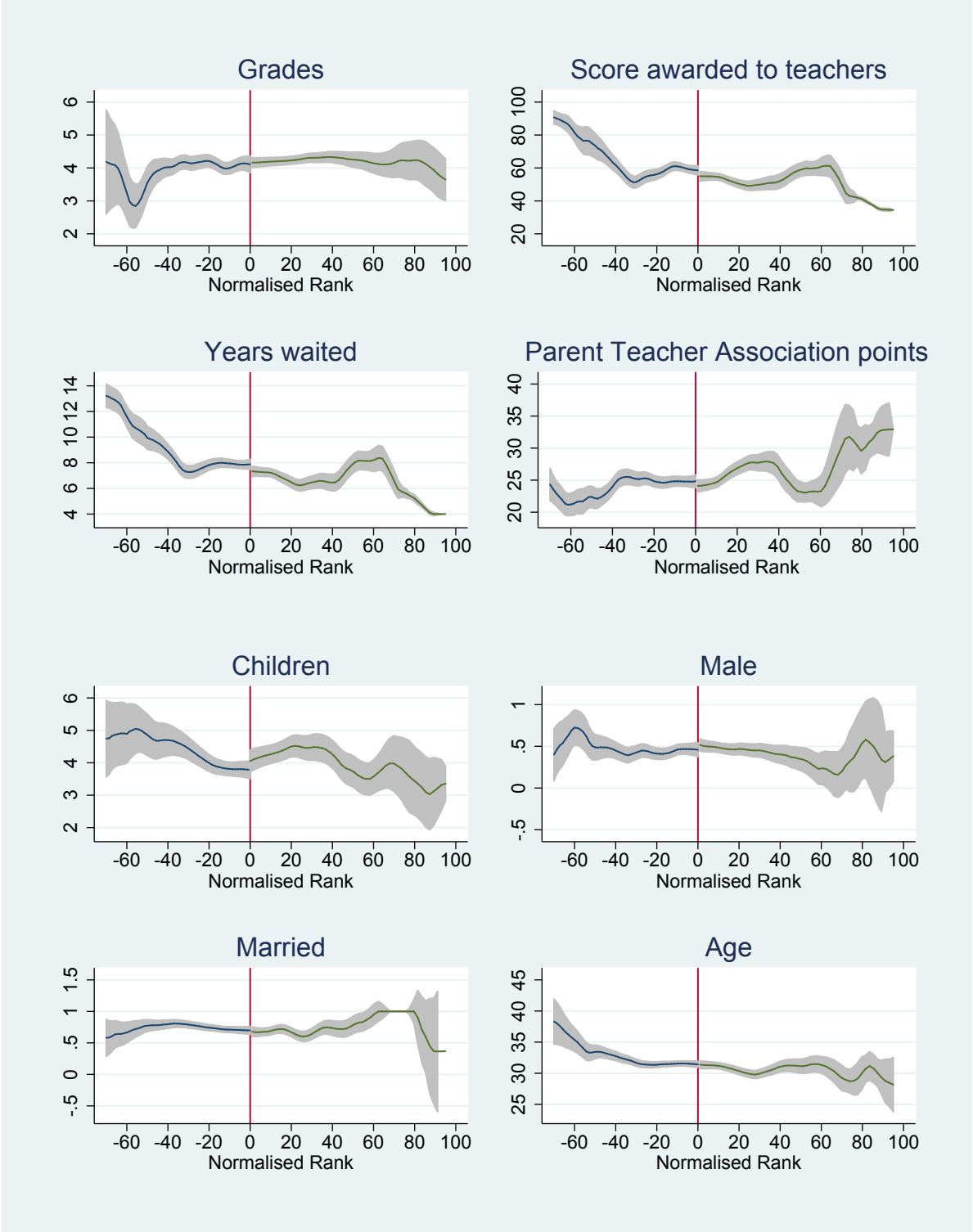
Note: The graph shows the density of individuals surveyed, which is bunched around the cut-off by design. The confidence intervals indicate that the null hypothesis that the density is the same on each side of the cut-off cannot be rejected.

Table 1: Descriptive Statistics

		Hired by civil service		
Panel A: Income and Motivation	All	Yes	No	Diff.
Monthly income (KSh)	12758.9	13705.2	9782.266	3922.929***
	(6851.449)	(5370.915)	(9654.065)	(710.214)
Log of income	9.319	9.424	8.987	0.437***
	(0.554)	(0.496)	(0.601)	(0.047)
Index: Job Motivation	-0.002	0.023	-0.068	0.091
	(1.532)	(1.520)	(1.564)	(0.115)
Motivated to work hard	0.722	0.725	0.710	0.015
	(0.448)	(0.447)	(0.455)	(0.034)
Work only to get paid at end of month	0.314	0.315	0.301	0.014
	(0.464)	(0.465)	(0.460)	(0.034)
Index: Public-mindedness	0.001	0.072	-0.154	0.226**
	(1.461)	(1.494)	(1.377)	(0.091)
Can depend on self	0.546	0.539	0.562	-0.023
	(0.498)	(0.499)	(0.497)	(0.032)
Money important for happiness	0.406	0.394	0.433	-0.039
	(0.491)	(0.489)	(0.496)	(0.032)
Panel B: Control variables				
Male	0.452	0.439	0.487	-0.048
	(0.498)	(0.497)	(0.501)	(0.032)
Age	31.391	31.648	30.828	0.819***
	(4.165)	(4.079)	(4.325)	(0.275)
Married	0.717	0.709	0.734	-0.025
	(0.45)	(0.455)	(0.443)	(0.029)
Household Size	4.184	4.232	4.078	0.154
	(2.413)	(2.492)	(2.236)	(0.154)
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.
"Can depend on self" was asked as a dichotomous question whether you can be successful on your own. "Money important for happiness", "Motivated to work hard", and "Work only to get paid at the end of the month" 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 indices for "Job motivation" and "Public-mindedness" were constructed by summing the standardized values of the two relevant variables (in their original form, rather than as a dummy variable). Specifically, the "Job motivation" index sums over "Motivated to work hard" and the negative of "Work only to get paid at the end of the month" such that a larger number indicates being more motivated, and the public mindedness index is then multiplied by -1 such that a larger number indicates being more publicly minded.

Figure 2: Possible discontinuities in control variables



Note: The graphs show the best polynomial 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 polynomial 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	0.31***	0.31***
	(0.041)	(0.041)
Rank	-0.00025	-0.00011
	(0.0012)	(0.0012)
Rank × Above cut-off	-0.0045***	-0.0045***
	(0.0017)	(0.0017)
Age		0.061**
		(0.031)
Age Squared		-0.00092**
		(0.00047)
Male		-0.0085
		(0.025)
Married		-0.040
		(0.031)
Household size		0.015**
		(0.0060)
Obs.	1031	1031
R-squared	0.19	0.20

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.

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

	(1) OLS	(2) OLS	(3) IV	(4) IV
Panel A: Income (KSh)				
Public Sector Job	5382.59***	5025.027***	11107.99***	12775.49***
	(376.61)	(408.075)	(3627.39)	(5177.77)
Rank × Public Sector Job	-1.58	-5.128	-386.99	-568.25
	(15.63)	(16.562)	(243.47)	(427.71)
Rank	-12.14	-8.735	314.57	427.48
	(13.79)	(14.715)	(258.08)	(349.40)
Const.	8419.75***	8780.419***	3474.13	1901.236
	(310.65)	(419.51)	(336.076)	(4696.295)
Panel B: log(Income)				
Public Sector Job	.530***	.510***	1.060***	1.267**
	(.038)	(.041)	(.337)	(.505)
Rank × Public Sector Job	-.00008	-.0006	-.031	-.054
	(.002)	(.002)	(.024)	(.046)
Rank	-.001	-.0009	.025	.044
	(.001)	(.001)	(.020)	(.037)
Const.	8.905***	8.927***	8.456***	8.258***
	(.031)	(.034)	(.286)	(.458)
Controls included		YES		YES
Obs.	840	765	840	765

Note: In panel A, the dependent variable in 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 simple OLS regressions of a dummy for working in a public sector job, along with the rank and an interaction term of the two, on the income variable. Columns (3) and (4) are IV regressions and use the predicted value of being hired from a first stage indicated in Table 2.
District 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 married, number of children in the household.

Table 4: Regression results for imputed income and log(income)

	Imputation A		Imputation B		Imputation C		Imputation D	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV	IV	IV	IV	IV	IV	IV	IV
Panel A: Income (KSh)								
Public Sector Job	7955.34***	7779.56***	8309.89***	8041.16***	9921.95***	8961.48***	3360.47	5280.52**
	(1719.83)	(1729.02)	(1813.15)	(1817.31)	(1898.94)	(1790.68)	(2592.55)	(2386.62)
Rank × Public Sector Job	-177.55***	-214.60***	-221.72***	-256.23***	-275.60***	-325.15***	-421.21***	-488.89***
	(67.93)	(81.70)	(71.62)	(85.87)	(91.48)	(112.50)	(124.89)	(149.94)
Rank	106.82**	132.73**	153.55***	178.6***	192.60***	223.17***	266.13***	327.20***
	(48.28)	(56.76)	(50.90)	(59.66)	(68.82)	(82.97)	(93.96)	(110.57)
Const.	5106.19***	5214.50***	5385.33***	5605.12***	3150.20**	3805.42***	8005.45***	6515.44***
	(1118.65)	(1134.45)	(1179.35)	(1192.38)	(1383.62)	(1330.09)	(1889.00)	(1772.74)
Panel B: log(Income)								
Public Sector Job	2.203**	1.662*	2.890***	2.132***	2.784***	2.469***	2.294**	2.181**
	(.962)	(.955)	(.813)	(.779)	(.904)	(.835)	(.947)	(.873)
Rank × Public Sector Job	-.046	-.073	-.101***	-.122***	-.045	-.077	-.059	-.092*
	(.038)	(.045)	(.032)	(.037)	(.044)	(.052)	(.046)	(.055)
Rank	.013	.027	.076***	.085***	.019	.039	.026	.049
	(.027)	(.031)	(.023)	(.026)	(.033)	(.039)	(.034)	(.040)
Const.	6.395***	6.694***	6.564***	7.054***	6.105***	6.272***	6.449***	6.465***
	(.626)	(.627)	(.529)	(.511)	(.659)	(.620)	(.690)	(.648)
Controls		YES		YES		YES		YES
Obs.	977	884	977	884	1141	1019	1141	1019

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 married, number of children in the household

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

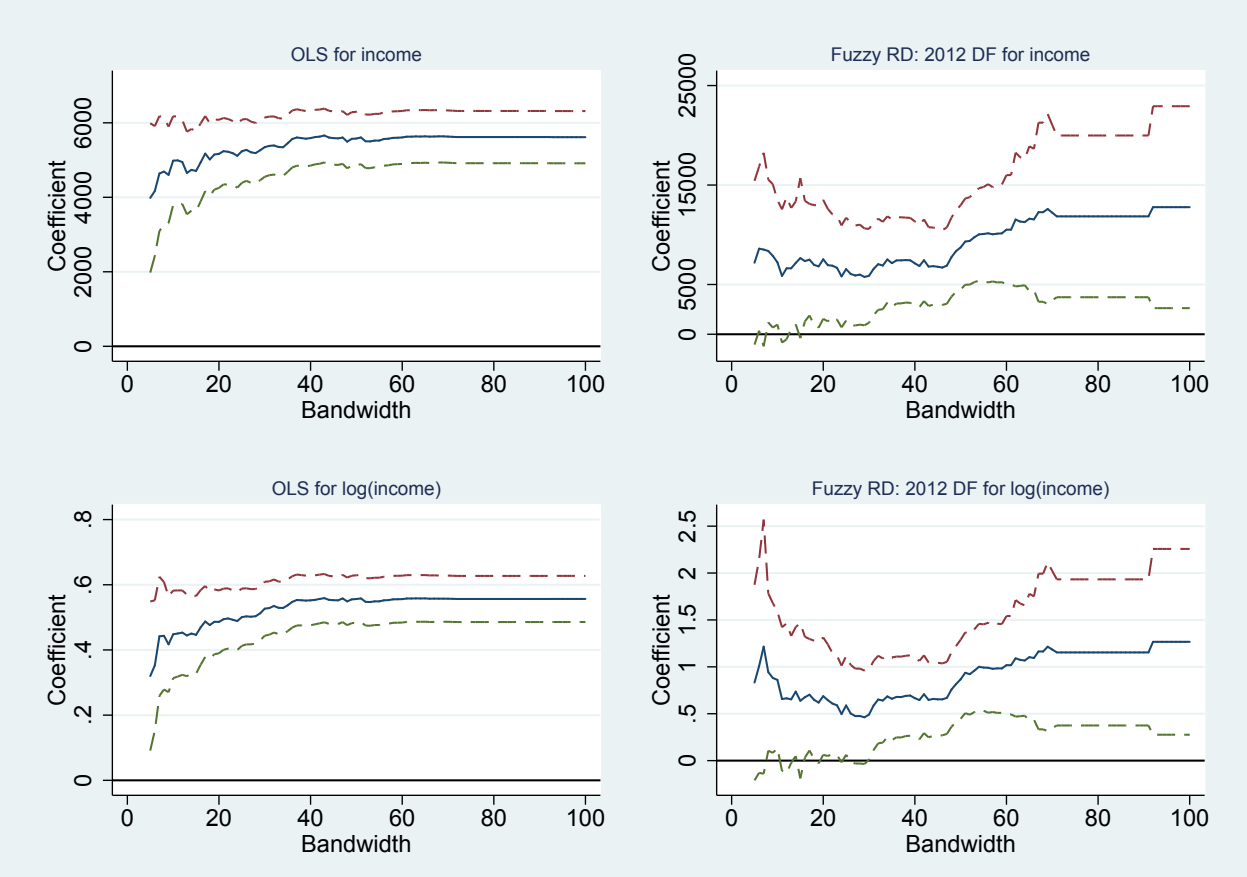
-Imputation D: we use a Manski-Horowitz worst case lower bound, assigning the lowest known income from those employed by the TSC and the highest value for those not working for the TSC who refuse to answer the income question.

Table 5: Regression results for Motivation

	Hired 2010		Ever hired		Hired 2010		Ever hired	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Panel A: On the job motivation								
Hired in 2010	-.02	.06			-.91	-.66		
	(.10)	(.11)			(.80)	(.72)		
Rank × Hired in 2010	.005	.004			.05***	.05**		
	(.004)	(.004)			(.02)	(.02)		
Rank (normalized wrt. 2010)	-.002	-.002			-.04***	-.03***		
	(.003)	(.003)			(.01)	(.01)		
Public Sector Job			.23**	.35***			-1.99*	-1.60
			(.11)	(.12)			(1.10)	(1.20)
Rank × Public Sector Job			.004	.002			.12**	.15*
			(.005)	(.005)			(.06)	(.08)
Rank (normalized wrt. 2010/11)			-.001	.0003			-.11**	-.13*
			(.004)	(.005)			(.05)	(.07)
Const.	.01	-.05	-.17*	-.28***	.71	.53	1.66*	1.41
	(.08)	(.09)	(.09)	(.10)	(.53)	(.47)	(.88)	(1.01)
Obs.	1025	912	1025	912	1025	912	1025	912
Controls		YES		YES		YES		YES
Panel B: Public Mindedness								
Hired in 2010	.04	.03			-1.93**	-1.55**		
	(.09)	(.11)			(.78)	(.70)		
Rank × Hired in 2010	-.002	-.004			-.01	-.009		
	(.003)	(.004)			(.02)	(.02)		
Rank (normalized wrt. 2010)	-.0006	.002			-.01	-.01		
	(.003)	(.003)			(.009)	(.008)		
Public Sector Job			.19**	.21**			-.14	-.06
			(.10)	(.10)			(.50)	(.44)
Rank × Public Sector Job			-.001	.0007			-.03	-.03
			(.004)	(.004)			(.02)	(.03)
Rank (normalized wrt. 2010/11)			.0003	-.0005			.02	.02
			(.003)	(.004)			(.02)	(.02)
Const.	-.02	.11	-.13*	-.08	1.18**	1.01**	.03	.04
	(.07)	(.09)	(.08)	(.08)	(.47)	(.42)	(.35)	(.32)
Obs.	1146	1020	1146	1020	1146	1020	1146	1020
Controls		YES		YES		YES		YES

Note: Regressions are for the indices of motivation (panel A) and public mindedness (panel B) as explained in the notes of Table 1.
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 married, number of children in the household

Figure 4: Alternative bandwidths



Note: The above graphs show how the coefficient of interest (blue solid line) changes as the bandwidth changes, with the 95% confidence interval plotted around the coefficient line (dashed red and green lines).

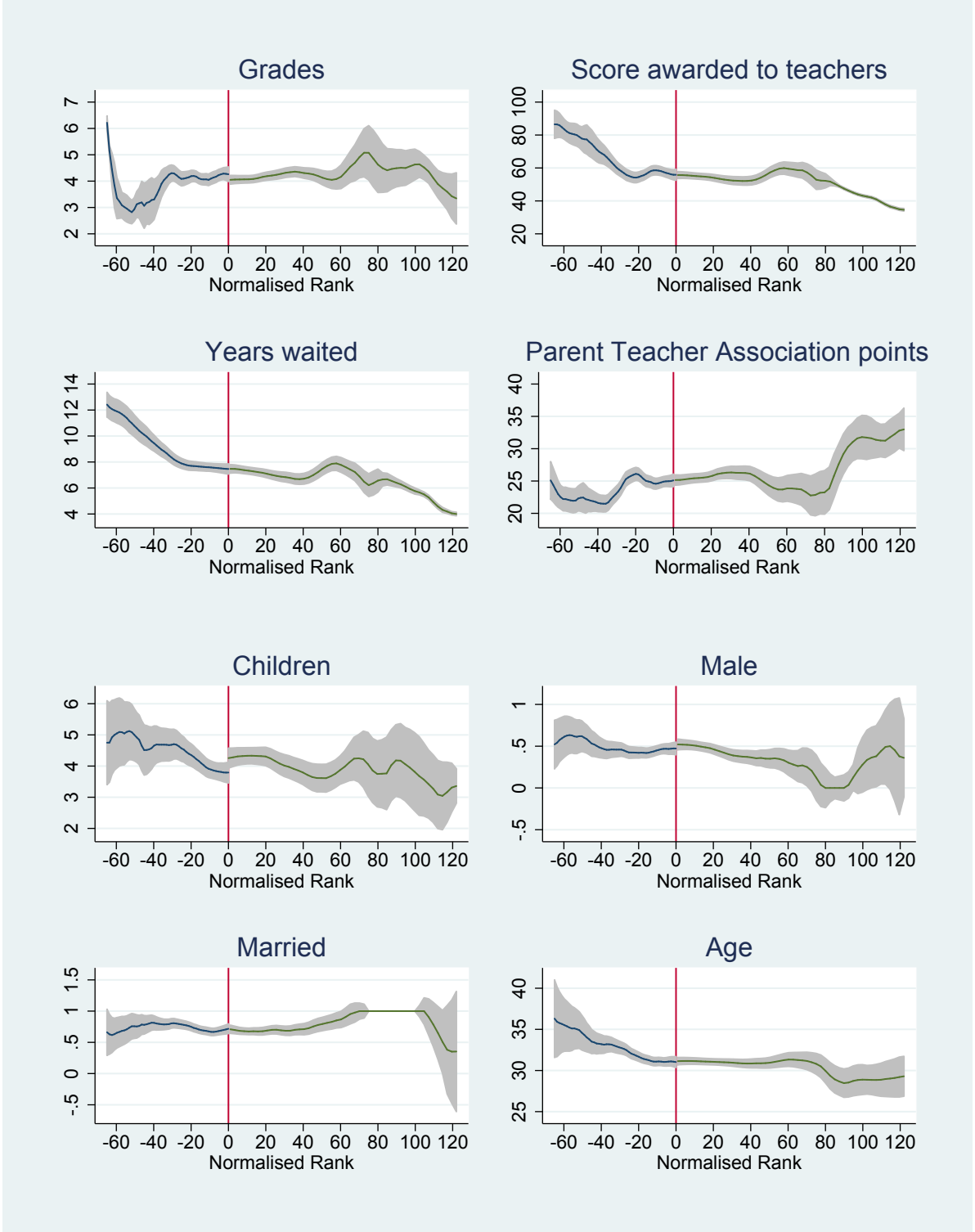
7 Online Appendix

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

	(1) Hiredin 2010	(2) Hired in 2010
Above cut-off	0.20***	0.23***
	(0.041)	(0.044)
Rank	-0.0050***	-0.0048***
	(0.0011)	(0.0012)
Rank × Above cut-off	0.000064	-0.000037
	(0.0018)	(0.0019)
Age		0.054
		(0.033)
Age Squared		-0.00082
		(0.00050)
Male		-0.023
		(0.027)
Married		-0.049
		(0.033)
Household size		0.013**
		(0.0064)
Obs.	1148	1022
R-squared	0.16	0.20

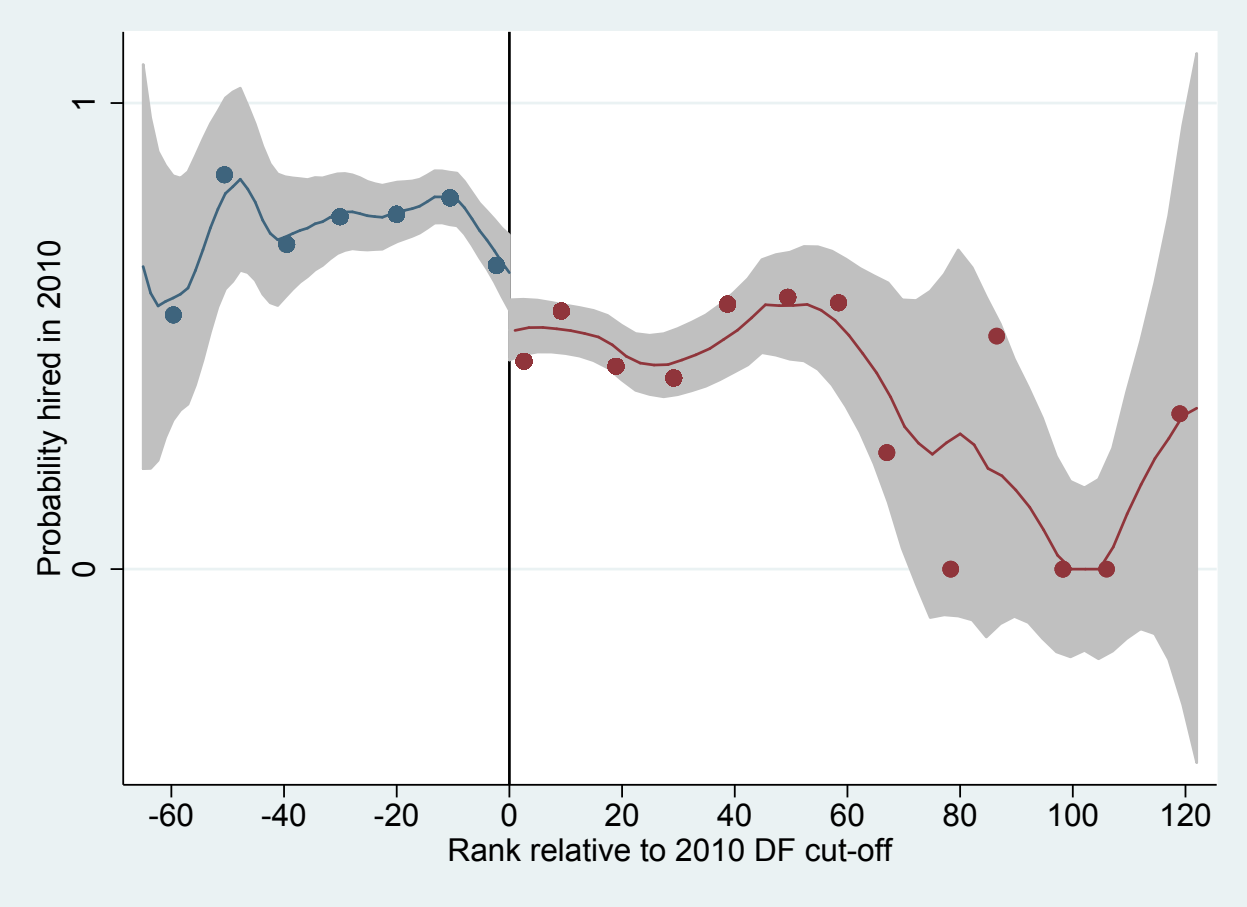
Note: The dependent variable is a dummy for being hired as a civil servant in 2010. "Above cut-off" is a dummy for being ranked at least as highly as the final rank to be hired by the civil service in 2010, and represents where the discontinuity is to be found. "Rank" is an individual's ranking in the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

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



Note: The above graphs indicate the best polynomial fit separately on each side of the cut-off for each of the named variables.

Figure 6: Discontinuity in treatment for 2010 de facto Cut-off



Note: The above graph indicates the best polynomial fit separately on each side of the cut-off for being hired in 2010.