The Long Term Effects of Teacher Wage Differentials*

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Abstract

The algorithm used for nationwide teacher recruitment in Costa Rica randomly selects candidates for offers, which may include an unconditional bonus pay for positions in hard-to-staff schools. We find that teachers who receive the bonus tend to leave these schools quickly, yet they achieve higher future earnings and experience faster career progression into principal appointments. Leveraging administrative data on wage offers, we show that teachers seek rent extraction by considering outside offers. The steeper career trajectories depend on the initial higher salary resulting from the bonus pay, which reduces the pressure to accept outside offers. This reduced pressure leads to more focused job searches, lower forgone earnings from accepting an offer, and dynamic transitions towards principal positions. Furthermore, relatively less effective teachers before receiving the initial bonus pay may become even less effective principals in the longer term.

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1 Introduction

The body of research exploring the impact of teacher salary increases on short-term and long-term student outcomes has significantly expanded. This paper shifts the focus to teacher outcomes and investigates the lasting effects of an unconditional pay raise on their later career trajectories. We use experimental variation in the pay of a significant portion of the Costa Rican public sector workforce, aligning with efforts to improve public spending efficiency.[1] We consider randomized offers from schools where teachers receive a bonus payment, irrespective of performance, to supplement a base salary determined by seniority. Schools paying the bonus are hard-to-staff, have facilities of relatively poorer quality, and are located in disadvantaged areas. By leveraging longitudinal administrative data, we study the employment and earnings paths of teachers who initially received the bonus payment.

The randomness in pay arises from the algorithm employed in the nationwide centralized recruitment, as we explain in Section 2. We consider multiple recruitment drives spanning a decade, leveraging the randomness of offers generated by the algorithm. Our research design compares teachers receiving an offer *with* the bonus to teachers receiving an offer *without* the bonus, tracking the outcomes of both groups over time. We study the *dynamic effects* of being appointed with higher salaries for up to six years post-appointment. Several event study graphs rule out any pre-appointment differential trends between the groups.

Teachers starting with the bonus consistently earn more, over the six-year period following their appointment, compared to what they would have earned without the bonus. The treatment effect on earnings, as shown in Figure 7, is estimated at $1,000$ USD or 5.3% of the sample average. Compared to the average teacher in the sample, teachers accepting the initial offer from a school with bonus are younger, without tenure (i.e., an open-ended contract) in the public sector, but with above-average teaching experience in the private sector.

Teachers receiving the bonus are comparable to other teachers in terms of our measure of value-added derived as explained in Section 5. This suggests that a salary increase in hard-to-staff schools does not succeed in attracting higher-quality teachers to those schools.[2] Additionally, we

[1]Public salaries in the country account for about half of total revenues. This share is the largest in OECD countries, and this fiscal burden constrains the public expenditure on educational inputs (OECD, 2020).

[2]The evidence on teacher sorting induced by the availability of monetary incentives varies across countries and institutional contexts. For example, teachers applying and accepting offers for pay-for-performance contracts in Rwanda (Leaver et al., 2021) have lower intrinsic motivation but are not different in terms of other measurable

find no evidence of higher salaries at entry leading to improved future performance. This finding echoes the results in Kube et al. (2013), Jayaraman et al. (2016) and Krueger and Friebel (2022), among others: while wage cuts are found to damage work morale, an equivalent pay raise does not necessarily fosters productivity or effort. Importantly, we do find that this average effect on teacher quality masks important non-linear effects that depend on the value-added prior to receiving the offer. Specifically, we show that teachers with lower value-added become even less effective as teachers and principals after receiving the bonus.

We show that experimentally induced pay raises yield steeper trajectories of accomplishment for teachers with lower value-added before receiving the offer. For example, six years after receiving the offer with the bonus, the treatment effect on earnings for teachers with lower value-added (bottom two quartiles) at baseline is about 6.6%. This effect is 3.9% for teachers with higher value-added at baseline, as showed in Figure 10. These effects on accomplishment are likely to persist beyond the six-year window considered in our study. For example, other work demonstrated that labor market conditions have long-term effects on life-time earnings trajectories and the size of these effects depends on when in a person's life the conditions change (Oreopoulos et al., 2012, Schwandt and von Wachter, 2019, and Rinz, 2022). Besides, de Ree et al. (2018) show that higher earnings for teachers increase job satisfaction and lower the occurrence of financial problems and stress.

However, higher long-term earnings are not explained by longer employment spells at hard-to-staff schools. We show, in Panel A of Figure 6, that the bonus pay is not effective at retaining teachers once they have arrived at the school: teachers appointed with the bonus pay experience higher turnover rates in the six years after the offer, about 60% more than what they would have experienced by starting without the bonus. We interpret this finding in Section 3 by using institutional features of the recruiting process. We explain that individuals who accept offers for a tenured position enjoy enhanced job security through open-ended contracts, which are not tied to a particular school. In particular, teachers can take leave from one school and temporarily work at another, fostering flexibility in the labor market and contributing to considerable turnover post-tenure (about one third of teachers in our data take leave).

skills. Instead, these contracts induce positive sorting among teachers with higher value-added in Pakistan (Brown and Andrabi, 2021). Dal Bó et al. (2013) find that higher base salaries can attract skilled and motivated applicants for civil service jobs in Mexico.

We show that teachers engage in rent extraction by considering external offers for temporary positions. In particular, we show that the turnover rates are explained by increased employment in temporary positions after commencing with higher salaries. Drawing from the institutional features of the teacher labor market, we explain why there are incentives to seek better conditions at another school. First, schools cannot prevent tenured teachers from taking leaves, and teachers on leave retain the option to return to their original school at any time. Second, there are no obvious costs, whether monetary, reputational, or in terms of time, associated with applying for temporary positions. Furthermore, the system entirely bears the cost of declining potential offers, with no consequences for candidates, who remain eligible for future offers.

We use administrative records on the wages offered to teachers to demonstrate that higher starting salaries alleviate the pressure to accept temporary job offers, which usually come with tight deadlines. This reduced pressure leads to more focused job searches, lower forgone earnings from accepting offers, and enables teachers to progress towards more managerial and better-paid roles. Specifically, Figure 12 shows the unpredictability of the timing and attractiveness of offers for temporary jobs. This unpredictability stems from two aspects of the Costa Rican teaching market. There is no regulation determining the order in terms of how and when temporary positions need to be filled. Additionally, unlike offers made for tenured positions, the process for publishing and filling newly available temporary positions is decentralized to regional offices of the Department of Education, which act and make offers independently. This suggests limited ability to anticipate trends regarding which positions and job profiles will become available or whether these opportunities will arise early or late in the process.

Drawing on this evidence, we compare teachers who start with the bonus to those without it, adjusting for their ex-ante risk of receiving subsequent offers for temporary positions. Our research design exploits the unpredictability of future offers for groups of teachers equally at risk of receiving these offers. The analysis from risk-adjusted regressions, similar to studies on centralized assignment (such as Abdulkadroglu et al., 2017), reveals in Figure 15 that teachers with higher initial salaries because of the bonus exhibit more patience in job searches, leading to a slower rate of offer acceptance compared to those with standard compensation. This finding explains the positive effects of higher entrance salaries on the transition to managerial positions and sorting into schools with higher-achieving students (Hanushek et al., 2004, Boyd et al., 2013, Bonhomme et al., 2016 and Johnston, 2020). The forgone earnings resulting from starting with a lower salary are estimated to be approximately 38% of the current salary.

In conclusion, wage differentials resulting from unconditional bonus payments yield private returns for teachers in terms of future earnings and career progression but perpetuate inequalities in access to quality education at hard-to-staff schools paying the bonus (Evans and Mendez Acosta, 2023). Our findings speak to the literature on the effects of pay raises and contract types on teacher selection and performance. Experimental evidence from developing countries, including Kenya (Glewwe et al., 2010), India (Muralidharan and Sundararaman, 2011), Pakistan (Barrera-Osorio and Raju, 2017, and Brown and Andrabi, 2021) and Rwanda (Leaver et al., 2021), points to positive effects, in general, of *performance-based* pay raises on student learning (Jackson et al., 2014, and Pham et al., 2021, review findings in the literature). A growing body of research in development economics considers the effects of *unconditional* pay raises for teachers, finding little to no impact on student learning. Experimental evidence from Indonesia on this matter is in de Ree et al. (2018) – see also Biasi (2021) for the US. Recent RD studies are for Peru (Castro and Esposito, 2017, and Bobba et al., 2021), the Gambia (Pugatch and Schroeder, 2018), Uruguay (Cabrera and Webbink, 2019), Zambia (Chelwa et al., 2019), and Brazil (Camelo and Ponczek, 2021). Like us, these studies consider interventions offering pay raises to teachers employed at less desirable schools in disadvantaged or rural areas.

Our research design addresses a significant identification problem in these non-experimental studies, which use policy-induced discontinuities in the eligibility to receive the pay raise depending on an underlying index of poverty or rurality. However, the causal effects of eligibility of subsequent outcomes cannot separate the effects of teacher sorting across jobs from the effects of teacher compensations. Our empirical approach, based on randomized offers, overcomes this challenge by considering the dynamic treatment effects of a pay raise and retrieving the counterfactual outcome that the same teachers would have experienced without the pay raise. Similarly, Leaver et al. (2021) employ a cross-randomization design to disentangle teacher sorting effects from compensation effects in the hiring of public officials. Finally, the literature on teacher compensation has primarily focused on the short-term effects on teacher outcomes (Crawfurd and Pugatch, 2020). In contrast, our study delves into the effects over an extended period, providing insights into the dynamic selection in future jobs and effort as teachers accumulate more seniority in the market and assume more managerial roles as principals.

2 Institutional Context

Primary education in state-funded schools

We study state-funded *primary schools* of Costa Rica. Primary education is mandatory, begins in February of a child's sixth birthday year, and lasts six years. The country has near universal attendance in primary education. The school year runs between the end of February and early December. There are about $4,000$ primary schools enrolling $500,000$ students. Private schools are an urban phenomenon, represent about 8% of primary institutions (compared to, for example, 11% in Mexico and 55% in Chile), and enroll less than 5% of the primary school age population. The number of state-funded schools remained relatively stable over the period considered in our analysis. Primary schools tend to be small.

The *Servicio Civil* acts as the coordinating agency to ensure common pay scales, job classifications and working conditions in the public sector. The overall teaching force in the public sector is large: about $80,000$ employees (29% of the public workforce) with an annual cost of 4% of national GDP. Civil-service teachers work in a highly regulated and unionized market and are hired under open-ended or temporary contracts. Open-ended contracts have little risk of termination and are regulated by collective bargaining agreements. Temporary contracts are used to fill vacancies at specific schools.

We consider offers for teaching positions in all schools, and for principal positions in schools with at most 90 students. This selection covers about 93% of vacant jobs in Costa Rican primary schools for the recruitment drives considered in this work. These positions are for full-time appointments that cannot be filled directly by schools. The recruitment process is conducted centrally by the *Servicio Civil* and is used to grant tenure (open-ended contracts) and decide about mobility of tenured staff.[3]

Centralized recruitment of teachers

Only applicants enrolled in a *national registry* are eligible for recruitment. The key requirement for enrolling in this registry is to hold a Bachelor's degree; principal positions also require some

[3] Our analysis excludes offers for principals in schools with more than 90 students. These positions are filled using a different recruitment procedure, which is not centralized and entails shortlisting applicants and interviews conducted by panels nominated at each school.

previous experience. Registration indicates only an expression of interest and is conducted prior to awareness of specific vacant positions for future academic years. Only registered applicants are considered for upcoming jobs until a new registry is formed by the *Servicio Civil*, which occurs irregularly, usually every two to four years (in November). The opening of a new registry is advertised nation-wide. There are no monetary or reputation costs associated with enrollment.

Tasks and responsibilities depend on the *job profile*, which is detailed in the national regulation (*Estatuto del Servicio Civil*). There are *three* such profiles in our analysis. The first profile (P0) is for schools with at most 30 students, where only one teacher is employed. This profile entails a mix of teaching and managerial responsibilities: in addition to teaching classes, this person is responsible for the day-to-day management of operations. Instead, all other schools must employ one principal and a number of teachers that depends on student enrollment. Principals at schools with between 31 and 90 students are the second profile (P1), which has the same managerial duties as P0. The main difference is that P1 staff must also advise and evaluate teachers under their supervision. Teachers at schools with 30 students or more are the third profile (T). They have no administrative responsibilities and must report to their principal. In general, there is one teacher in schools with up to 30 students, two or three teachers in schools with $31-90$ students, and four to six teachers in bigger schools.[4]

Applicants must indicate in the national registry which job profile is being sought (multiple choices are allowed, e.g., T and P0). Applicants are ranked based on credentials (degrees and certifications) and experience. Qualifications and certified years of experience are automatically scored by the system.[5] Applicants are ordered using this score, proximity to the school district, experience (in days), and a *random* number to break ties. Separate *rankings* for P0, P1 and T profiles are formed, and applicants seeking employment in multiple job profiles appear in different rankings. In addition, applicants must rank the school district where they seek employment. There is no limitation to the number of choices, and applicants can indicate their willingness to work anywhere in the country.

[4]These figures do not include teachers for specialized subjects such as arts, music and sports.

[5]The score is calculated considering educational attainment (90 points for Bachelor's degree; 106 points for Licentiate's degree), experience in job profile (up to 8 points), other experience (up to 2 points), other academic degree (up to 2 points), if the degree program is accredited by the National Accreditation System (2 points), and professional courses and training (up to 3 points).

Offers for tenured positions

Vacant positions are published before the new academic year (in December), and after the deadline for enrollment in the national registry. The *Servicio Civil* initially seeks to fill these vacancies by offering tenured (open-ended) jobs, with offers determined through a two-step process. The first step uses a Deferred Acceptance (DA) algorithm to select applicants who will receive an offer in a specific job profile and school district. Applicants are selected one at a time, following the rankings, in the most preferred district with available positions in the job profile of choice. For example, this step selects applicants clearing the bar for one of the P0 positions in San Jose. In the second step, vacant P0 positions in San Jose are matched to applicants in the order of their alphanumerical code, which was randomly generated in the national registry. The second step results in *randomized offers* to applicants selected in the first step.

After offers for tenured jobs are out, applicants have three days to accept. Offers can be rejected at no cost and, in this case, applicants are *not* canceled from the registry. Jobs turned down remain vacant, ruling out any distortions from waiting lists (De Chaisemartin and Behaghel, 2020). During this three-day period, the Department of Education (DoE) populates the listing of positions as they remain vacant and starts a separate procedure to fill these positions with temporary (short-term) appointments, usually with a duration of one year. The registry of applicants, along with the assigned scores based on their credentials, forms the foundation for filling vacant positions nationwide. All applicants in the registry who have not yet accepted an offer for a tenured position are eligible for temporary appointments.

Offers for temporary positions

Applicant-school matches for temporary appointments are formed in a decentralized manner. The DoE must first approve the budget for each position. Vacant positions are then handled by offices at the DoE that are organized by region and consider applicants with a preference for districts of that region. There is no coordination between these offices, meaning that an applicant may receive uncoordinated phone calls from different offices with unpredictable timing and depending on when the DoE has budgeted a position. Offices must offer positions following rankings in the registry, so that applicants ranked high and still available will be the first to know about a new vacancy. When contacted, applicants must accept the offer with a tight deadline (usually a few hours) before the position is offered to the next in line.

In practice, the unpredictability of phone calls and positions budgeted by the DoE leaves no room for strategic behavior. The process is inefficient, and it is often concluded after the start of the academic year. Also, given how matches are formed, it is unlikely to remain at the same school when the temporary contract terminates (even if the teacher does not wish to move).[6]

3 Teacher Salaries and Turnover

Pay schedules

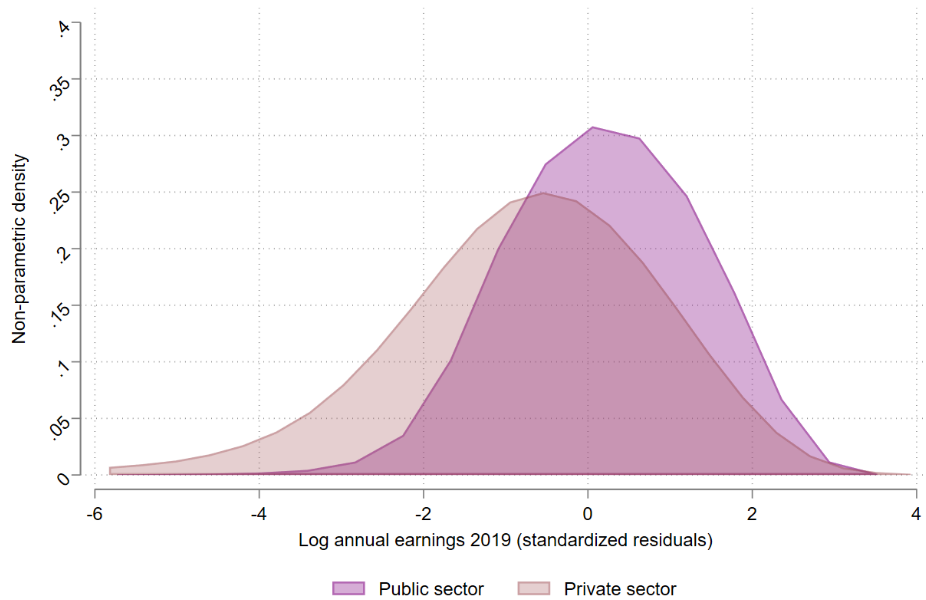
Teaching jobs are well paid. Costa Rica features low earnings differentials between teachers and other professionals compared to other Latin American countries (Mizala and Nopo, 2016). The ratio of teacher monthly salary to GDP per-capita is 1.9 and wages are 80% higher than the minimum wage for college graduates. Panel A of Figure 1 shows the distributions of annual salaries, obtained from the administrative sources described in Section 4, for teachers with comparable demographics working in primary schools of the public and the private sector. Panel B of the same figure shows that differences in earnings between sectors persist at different ages and that the public-sector premium varies between 30% and 50%.[7]

Salaries are set centrally by the *Servicio Civil* and follow from a lockstep compensation scheme subject to fixed schedules that reward seniority and are independent of performance. The base salary depends on academic credentials (mostly experience) and educational attainment (Bachelor's degree or Licentiate's degree). Other than this, salary supplements depend on two components: the job profile (P0, P1 and T) and eligibility for an annual bonus payment. The former component depends on the specific tasks and responsibilities involved in the job: the compensation for P0 positions is higher than for T positions, and lower than for P1 positions. The bonus payment is for positions in hard-to-staff schools located in disadvantaged areas, as we explain next. There's no apparent disadvantage in accepting a temporary position: base salary, pension benefits and salary top-ups are the same for open-ended and temporary contracts.

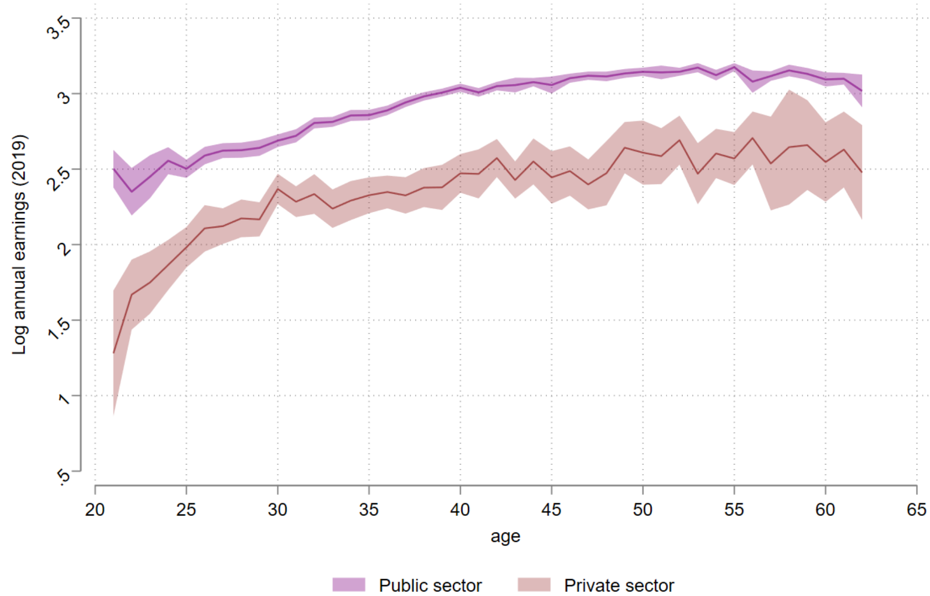
[6]Zeitlin (2020) discusses the implications of high teacher turnover on student learning.

[7]The likelihood of holding a second job is relatively low for primary school teachers. Second jobs are more common among secondary school or college education teachers, who are remunerated by the hour and not employed full time like in primary education.

Figure 1. Annual salary: public sector vs private sector teachers.



Panel A. Earnings Distribution



Panel B. Earnings Age Profile

Notes. Panel A shows non-parametric densities of residuals from a regression of log annual earnings for 2019 on a quadratic polynomial in age and dummy for male individuals. This regression is estimated using teachers working in primary schools of the public sector or private sector. Residuals from this regression are standardized to have zero mean and unit variance in the full sample. Panel B shows age profiles obtained by computing age-specific averages of log annual earnings for 2019 by sector of employment.

Annual bonus

In 1996, the DoE and the teacher unions agreed to establish a financial incentive (bonus) to attract and retain a skilled and motivated workforce in hard-to-staff schools of the country. The bonus pay depends on school location, is not conditional on subsequent effort or value-added, and is not portable across schools if a teacher moves. The bonus is, therefore, an *unconditional pay increase* for everyone at the school.

The 488 administrative regions of Costa Rica are classified into four mutually exclusive groups that depend on an index of social development computed by the National Department of Planning: high, medium, low, and very low. The index combines a number of socio-demographic indicators.[8] Only schools in administrative regions with low and very low social development pay the bonus. These regions serve a disproportionately higher number of low-income students, as we show below in Figure 4. As we shall explain in Section 4, the geography of administrative regions does *not* coincide with that of school districts considered to form DA matches.

The bonus is paid once a year and is calculated as a fixed share of the monthly salary. This share varies with the social development index as well as the educational attainment of the teacher (see Appendix Table B.1). In our data the bonus varies between 6% and 7.5% of annual salaries and this range is explained almost entirely by appointments in low or very low development areas (94.71% of primary school teachers hold at least a Licentiate's degree).[9] Importantly, by working in hard-to-staff schools, teachers do not accrue additional qualifications. This rules out the concern that teachers earning the bonus may achieve higher qualification scores in subsequent recruitment drives, improving their prospects for accessing better and higher-paid jobs.

[8] The index is updated every 5 years and its value is unlikely affected if a school strategically keeps graduation rates or pass rates low to remain eligible. Social development is measured by the combination of five indicators: health, economic development, safety, civic participation, and education. Specifically, the health dimension combines statistics, such as access to clean drinking water and mortality rates of infants, to evaluate nutrition and quality of local health services. Internet and electricity consumption are employed as proxies for economic development. Safety is measured using information about homicides and traffic accidents. Civil participation uses data on vote turnover. Finally, the educational dimension measures the availability and access to education (e.g., school infrastructure and coverage of secondary education).

[9] To put this number in context, the change in annual salaries implied by this bonus is smaller than in many studies on unconditional pay raises for teachers (see the Introduction) and similar is size the to the pay change considered in Krueger and Friebel (2022).

Teacher turnover

There is substantial mobility of tenured teachers in Costa Rica. A tenured (open-ended) contract of employment is *not* tied to a specific school; rather, it is a contract with the DoE and serves as an entry point to the public sector. The tenure status is portable in the event of transfer to a different school. For these reasons, a *tenured teacher* in what follows is someone who has enrolled in the national registry, received an offer for a tenured position from the centralized system, and accepted it.

There are two types of transfer for tenured teachers: both are voluntary and a right recognized and protected by the national labor laws. The first transfer is a *permanent* move to another school. Teachers are allowed to apply for a permanent transfer to another school only after two years at the school where they originally received tenure. Tenured teachers wishing to do so must apply through the centralized system again and receive an offer. The second reason to move is a *temporary* transfer (or *leave*). Specifically, tenured teachers may take leave from one school and hold a temporary job at another school. These transfers follow from accepting an offer from a regional office to fill a vacant position which need not be in the same job profile (for example, staff tenured as T can fill temporarily a P1 position).

The school cannot prevent tenured teachers from taking leaves, and transfers to fill temporary positions may occur with short notice. Furthermore, teachers on leave retain the option to return to their original school at any time. These temporary leaves contribute to a significant turnover after tenure: approximately 30% of tenured teachers in our dataset are on leave at another school.

4 Data

We use a number of administrative data sources over a 13-year period, which are linked through unique identifiers of individuals, contracts, and schools to all placement records. We have a panel of $4,420$ teachers who received offers for a tenured job from the centralized system during this period, and a total of $4,420 \times 13 = 57,460$ teacher/year observations. These teachers have worked, for at least one year, in $3,369$ public primary schools (out of the $3,716$ in the country). The average number of teachers employed at these schools is about 5.

Teacher employment and social security records

We use administrative records from the *Servicio Civil* with applications considered in *four* national recruitment drives (from registries formed in November of 2013, 2015, 2016 and 2017). We will refer to *recruitment drives* using the academic year following the publication of a registry. For example, the 2014 recruitment drive is for offers made using the registry formed in November 2013.[10] We have a total of 5,670 tenured positions offered in these recruitment drives (488 P0 or P1 positions, and 5,182 T positions). Each recruitment drive considered about 10,000 applicants, for whom we observe educational qualification, experience, and tie-breaking score assigned by the centralized system. We also have information on all tenured positions offered and the offer status (i.e., who received the offer and if it was accepted). Information on the province and district of residence of applicants was obtained through the Supreme Electoral Tribunal.

The information on teachers and employment histories is from DoE administrative payroll records. This information spans a 13-year period between 2008 and 2020. Specifically, this archive contains teacher demographics, job profiles and type of contract (open-ended or temporary, and duration), and information on the school of employment. We linked these records with employer-employee data from the Social Security Fund archive, which tracks characteristics of the job match such as occupations, month-to-month labor earnings and sick-leave status. Importantly, this linkage tracks information on the careers and earnings of individuals from their first entry into the labor market if employed with the DoE and, also, outside the public sector.

The wage offers presented in Section 9 pertain to temporary positions that became available for the 2018 school year. As explained in Section 2, these temporary positions arise from jobs that the *Servicio Civil* could not fill with tenured contracts through the centralized system during the 2018 recruitment drive.

School census data

We use DoE school census data from 2008 to 2020. This administrative archive contains year-to-year information on grade enrollment, student demographics, location, and the presence of

[10] The next registry after the 2018 drive was formed in November 2021. No offers were made in the 2019 academic year because of a national legal action. A recent fiscal reform mandated a certification process for applicants prior to enrolling in the registry. Because of this reform and the COVID pandemic, no offers were made in the 2020 and 2021 academic years.

specific facilities at the school (such as libraries, computer labs, recreation, and athletic facilities). We also have data on indicators of student behavior like the number of student-teacher conflicts.

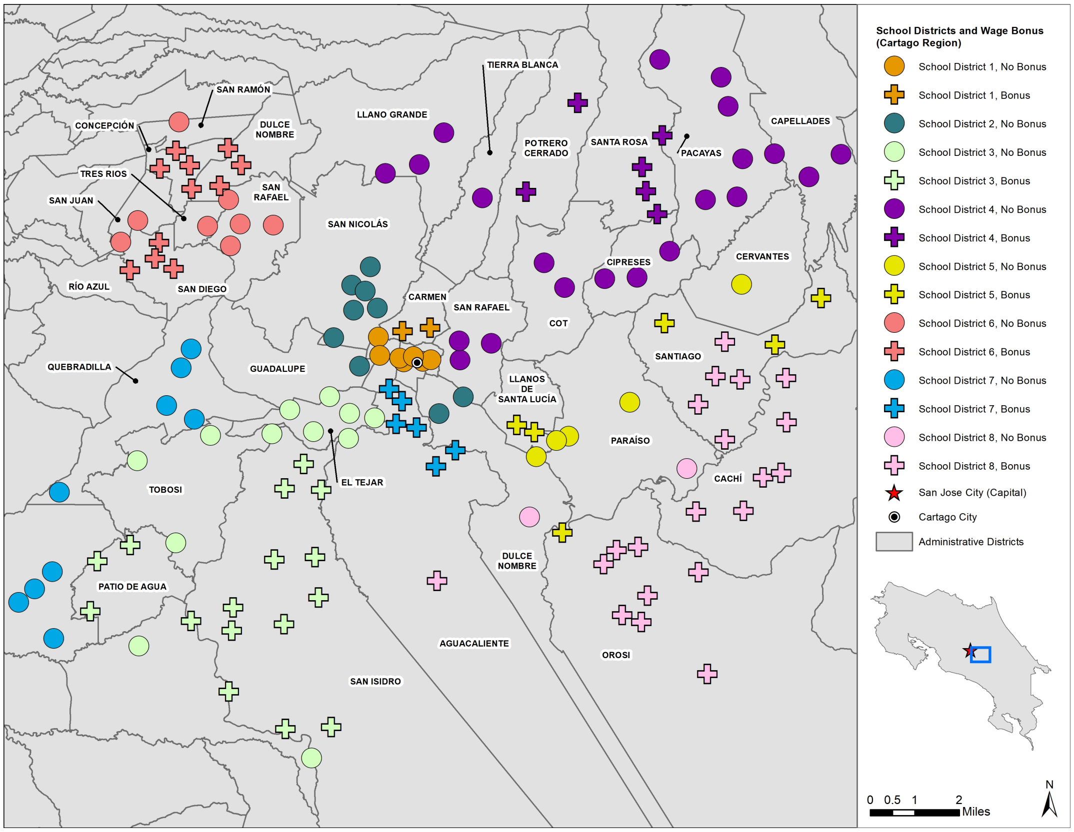
Census data provide indicators like retention and drop-out rates by school, grade, and academic year. Standardized assessment of primary school students in Costa Rica was piloted for the first time in 2020. Because of this, we can *not* use standardized scores to assess student learning outcomes in our analysis. Progression across grades depends on teacher assessments, and all schools must organize teaching activities and assess students following the National Educational Plan. Moreover, we do not have student-level academic outcomes and we cannot match teachers to grades or classes within schools. However, many children in Costa Rica study in small schools with a single classroom per grade, and, in some rural locations, children are taught in multi-grade classrooms.

School districts and administrative geography

Primary schools in Costa Rica are grouped in 201 school districts and 27 regions. These districts include between 5 and 30 schools and span over 90 square miles, on average. Their boundaries are different from those of administrative regions, which are defined by the political geography of the country. Specifically, school districts are governed by the regional offices of the DoE and have a socio-demographic composition resulting from boundaries disconnected from the administrative geography. On the other hand, administrative regions represent the smallest organizational unit shaping the structure of municipal governments and regional development plans. Importantly, the eligibility for bonus payments depends on the social development index which varies only by administrative region. Public investment and the targeting of the areas most in need are implemented by following the same administrative geography.

Because of the difference between administrative and school-district geographies, about 90% of school districts consist of schools located in different administrative regions. These differences in boundaries also imply that applicants selected by the DA algorithm will receive random offers to fill vacancies at schools with and without the bonus. Figure 2 visualizes examples for the Cartago region, stretching southeast from the capital city of San Jose and encompassing both rural and urban regions. Schools of the same district are grouped by color, and administrative regional boundaries are drawn in the background. Crosses are for schools eligible for the bonus

Figure 2. School districts and administrative geography.



Notes. This figure shows examples of differences between *school district* and *administrative district*. Only the Cartago region is considered. Same-color symbols are for schools of the same school district. Administrative district boundaries are drawn in the background. Crosses are for schools eligible for the bonus pay, and dots are for schools without the bonus. District-level data in this map and below, including the social development index, were obtained through the National Department of Planning.

pay, and dots are for schools without the bonus. For instance, school district 3 (in light green) consists of 28 schools in 5 administrative regions. Random offers from the centralized system are for applicants seeking a position in this district. Only 16 schools, in San Isidro and Patio De Agua, pay the bonus.

5 Descriptives on Randomized Offers

Balancing tests for the randomization of offers

We start by considering regressions demonstrating the randomization of offers. Our working sample is restricted to teachers selected by the DA algorithm described in Section 2. We consider teacher-offer observations, meaning that teachers with offers in multiple recruitment drives (about 20% of the sample) are repeated in the data. We group observations into strata defined by the combination of recruitment drive, job profile and school district. As explained above, the national algorithm makes offers for tenured jobs at random within these strata. The characteristic x_i is for teacher i in stratum r_i, z_i is an indicator for offers from a school with bonus (instead of a school without this bonus), and $\alpha_0(r_i)$ is shorthand for a set of strata effects:

$$x_i = \alpha_0\left(r_i\right) + \alpha_1 z_i + \omega_i. \tag{1}$$

The coefficient α_1 is obtained by using the cross-sectional variation of z_i within randomization strata. Standard errors are clustered on strata, and p-values in Panel A and B of Table 1 are adjusted to control the family-wise error rate for performing multiple hypothesis tests. We additionally present results obtained by restricting the data to first-time offers, where each teacher appears only once in the sample.

Teachers with offers with a bonus pay ($z_i = 1$) and without a bonus pay ($z_i = 0$) were similar prior to the offer. This can be seen from Panels A and B of Table 1, where – in the first two columns – we show estimates of α_1 for each variable at the left (we discuss later in this section how value-added was computed). P-values for the significance of this coefficient are reported within brackets in column (2). The size of the effects is small compared to the variable's standard deviation, which is shown within square brackets in column (1). The same conclusions hold if one considers the sample of first-time offers, in the last two columns of Table 1. Panel C demonstrates that the take-up of offers from school with and without bonus is statistically the same. In this panel, we report estimates of α_1 using, on the left-hand side of (1), an indicator for whether the offer is accepted.

Compliers with offers from schools with bonus pay

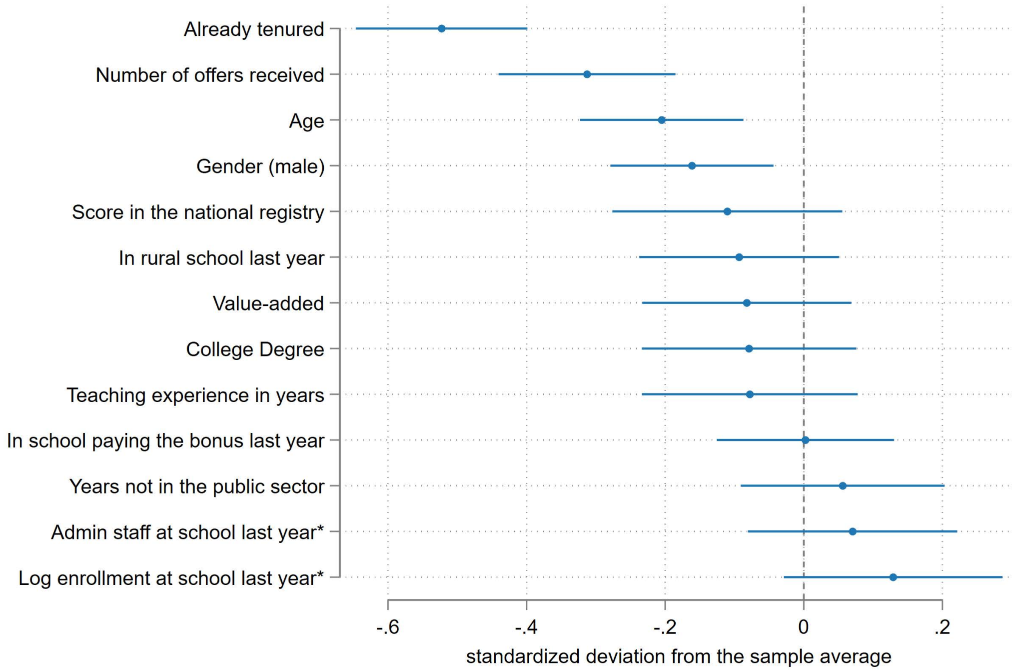
Teachers who comply with offers with a bonus pay (*compliers* for short) are those working in a school that pays the bonus the academic year after receiving the offer. The demographics of compliers can be characterized by exploiting the randomization of offers under the monotonicity of teacher behavior with potential offers. Specifically, monotonicity requires that receiving an offer with a bonus pay cannot decrease the chance of working in a school that pays the bonus

Table 1. Balancing tests for the randomization of offers.

	All Offers		First-Time Offers	
	Mean	Difference	Mean	Difference
	(1)	(2)	(3)	(4)
	’anel A. Teacher demographics when offer is mad			
Age	40.720	-1.185	40.580	-1.249
	[7.684]	()	[7.859]	()
Gender (male)	0.164	0.003	0.141	-0.006
	[0.370]	()	[0.348]	()
College Degree	0.977	-0.006	0.974	-0.007
	[0.149]	()	[0.159]	()
Score in the national registry	102.300	-0.245	102.000	-0.297
	[5.083]	()	[5.284]	(0.457)
Already tenured	0.321	-0.035	0.149	-0.032
	[0.467]	()	[0.356]	()
Value-added				
	[]	()	[]	()
Number of offers received	1.550	0.054	1.246	0.012
	[0.831]	()	[0.586]	()
	Panel B. Past employment when offer is made			
Teaching experience in years	10.060	0.238	9.592	0.205
	[3.446]	()	[3.370]	()
Years not in the public sector	0.862	-0.104	0.984	-0.077
	[1.805]	()	[1.913]	()
In rural school last year	0.406	0.038	0.366	0.035
	[0.491]	()	[0.482]	()
In school paying the bonus last year	0.421	0.062	0.398	0.055
	[0.494]	()	[0.490]	()
Admin staff at school last year*	1.758	-0.063	1.825	-0.064
	[0.941]	()	[0.933]	()
Log enrollment at school last year*	5.216	-0.035	5.333	-0.079
	[1.389]	()	[1.354]	()
	Panel C. Causal effects of offer			
Offer take-up	0.664	0.005	0.804	0.009
	[0.473]	()	[0.397]	()
Observations	1,583		1,203	

Notes. Placebo regressions for teacher demographics (Panel A) and characteristics of past employment (Panel B) at the time of offer. Panel C considers offer take-up. Columns (1) and (2) show means and standard deviations (in square brackets) for variables listed at the left. Coefficients in columns (2) and (4) show estimates of α_1 from equation (1). In Panels A an B, p-values for the significance of α_1, shown in brackets in columns (2) and (4), are adjusted to control the family-wise error rate for performing multiple hypothesis tests. Clustering on randomization strata is used throughout. The first two columns of the table use all teacher-offer observations, meaning that teachers with offers in multiple recruitment drives are repeated in this sample. The last two columns of the table use one observation per teacher using the first offer received. Observations for variables with $*$ are missing if employment in the year before the offer was not with the Department of Education.

Figure 3. Characterization of compliers with offers with a bonus pay.



Notes. 2SLS estimates of γ_1 from equation (2) considering teacher demographics (Panel A) and characteristics of past employment (Panel B) at the time of offer. The coefficient γ_1 estimates the average of each variable at the left for compliers. This coefficient is parameterized to be zero if, in expectation, there is no difference between a complier and a teacher randomly chosen from the sample. This parameterization is attained by standardizing the x_i variable at the left of equation (2) to have zero mean and unit variance in the sample. A positive (negative) value of coefficients in this figure implies that the average for compliers is γ_1 points of a standard deviation above (below) the average in the sample. Coefficients are sorted in the figure using their absolute value. Horizontal lines denote confidence intervals with 95% coverage. Observations for variables with $*$ are missing if employment in the year before the offer was not with the Department of Education.

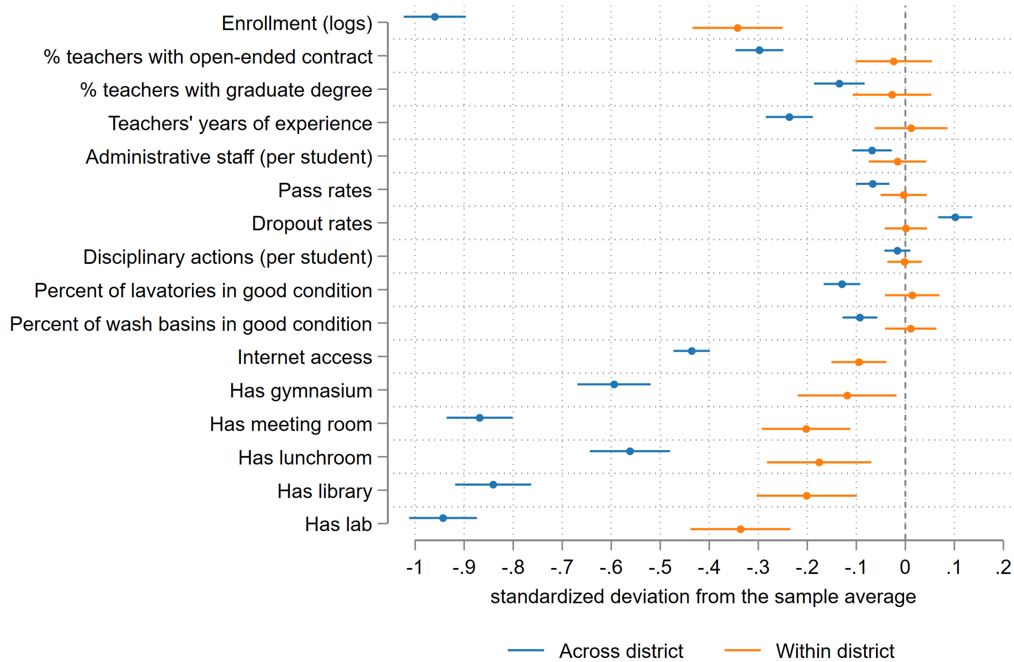
the academic year following the offer. We maintain this assumption, and estimate the following cross-sectional equation:

$$b_i x_i = \gamma_0 (r_i) + \gamma_1 b_i + \zeta_i, \tag{2}$$

where $\gamma_0(r_i)$ is shorthand for a set of strata effects, b_i is an indicator for working in a school that pays the bonus in the academic year after the offer, and x_i are the same demographics considered above. Estimation is carried out using teacher-offer observations, which is the same sample used in columns (1) and (2) of Table 1. We obtain the value of the coefficient γ_1 in equation (2) via 2SLS, instrumenting b_i with the offer indicator z_i. This value is an estimate of the average of x_i for compliers.

Figure 3 shows that, relatively to the average teacher in the sample, compliers are more likely

Figure 4. Characterization of schools paying the bonus.



Notes. Estimates of ϱ_1 from equation (3) for characteristics of teaching staff and for facilities a schools. This coefficient is parameterized to show standardized deviations from the sample average. This parameterization is attained by standardizing the f_{sdt} variable at the left of equation (3) to have zero mean and unit variance in the sample. *Within district* estimates are obtained from the specification in (3), which controls for district and year fixed effects. *Across district* estimates are obtained without controlling for district fixed effects. Coefficients are sorted in the figure using their absolute value in the *within district* specification. Horizontal lines denote confidence intervals with 95% coverage.

to be women (0.18σ) and less likely to be tenured at the time the offer arrived (-0.45σ). This means that jobs at schools with the bonus are more likely taken by teachers without permanent employment in the education sector. Consistent with this finding, we also find that compliers are younger (-0.21σ) and received fewer offers in the recruitment drives used in this work.

Characteristics of schools with the bonus pay

What working environment should teachers expect at schools that pay the bonus? Figure 4 shows how these schools compare in terms of facilities, teaching staff, student composition and learning environment to other schools in the same school district. We report estimates from regressions computed using administrative data for all primary schools in the country from the 2014 school year. Specifically, the characteristics f_{sdt} are for school s located in district d in academic year $t = 2014, \ldots, 2019$, b_{sd} is an indicator for schools entitled to pay the bonus, and $\varrho_0(d,t)$ is shorthand for a set of district and year effects. We consider the following specification clustering standard errors on schools:

$$f_{sdt} = \varrho_0(d,t) + \varrho_1 b_{sd} + e_{sdt}, \tag{3}$$

where outcomes are standardized to have zero mean and unit variance in the sample. Figure 4 shows estimates of ϱ_1 using the outcome variables listed at the left. Two specifications are considered. The across district specification compares schools with and without the bonus controlling only for year effects instead of $\varrho_0(d,t)$. The within district specification is as in equation (3), and estimates ϱ_1 by contrasting schools within the same district. The within district variability in b_{sd} stems from the differences between administrative and school-district geographies discussed in Figure 2.

Schools with the bonus are smaller and lack essential facilities like libraries, labs, and space dedicated to teachers compared to other schools in the same district. Figure 4 shows that, although it is true in general that schools with the bonus are significantly different from schools without the bonus, these differences are contained if one compares schools of the same district. For example, we find no differences in pass rates, dropout rates and learning climate (measured by disciplinary actions) within districts. This result follows most likely from the homogeneity of the student population in the district, in a setting where enrollment is predominantly determined by distance. The teaching force employed at schools is also homogeneous within districts, as can be seen by considering qualifications, contracts and years of experience of teachers.

Teacher value-added

We calculate measures of teacher value-added by analyzing the pass rate (the proportion of enrolled students promoted to the next grade) and the dropout rate (the proportion of enrolled students leaving school) at the schools where teachers are employed before and after receiving offers. We use these performance indicators due to the lack of standardized testing. Since teachers are only linked to schools and not to specific grades within schools, we leverage *teacher mobility across schools* over time for identification. Teacher turnover is substantial before offers for permanent positions due to the short-term nature of temporary contracts, as discussed in

Section 3. Additionally, as mentioned there, turnover among tenured teachers is high because of temporary leaves at other schools.[11]

We let the outcome at school s in academic year t, $rate_{st}$, depend on school and time effects, $\nu(s,t)$, and a set of teacher-specific intercepts before (ν_i^{pre}) and after (ν_i^{post}) the offer, or the *first* offer in case there is more than one:

$$rate_{st} = \nu(s,t) + \sum_i \nu_i^{pre} k_{ist}^{pre} + \sum_i \nu_i^{post} k_{ist}^{post} + \varepsilon_{st}. \tag{4}$$

The index i varies across teachers, s across schools that ever employed those teachers, and $t = 2008, \ldots, 2020$. The variables:

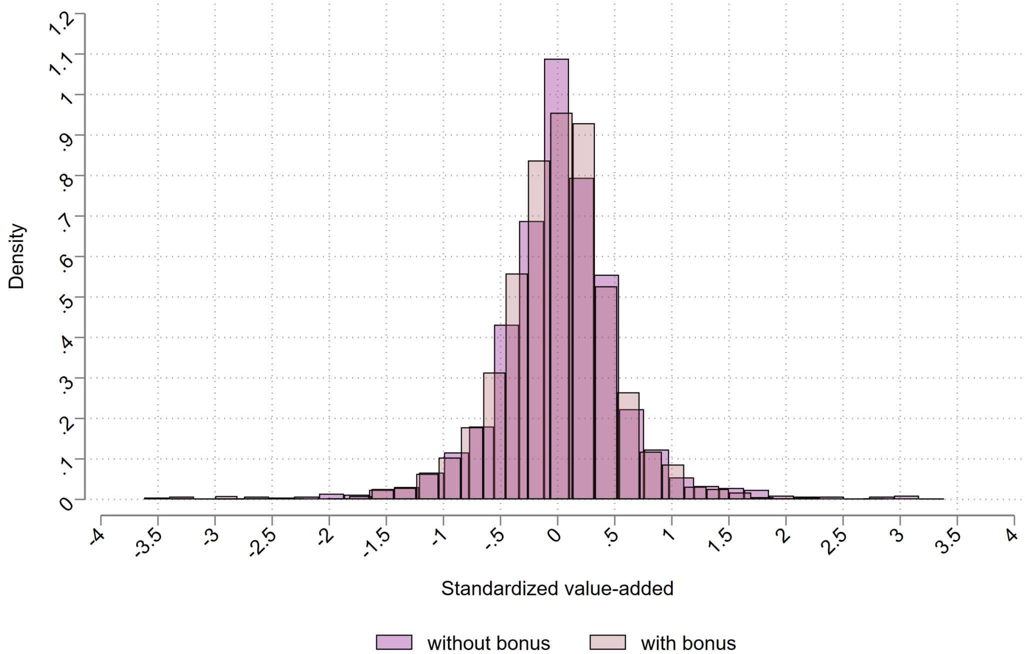
$$k_{ist}^{pre} \equiv 1(s(i,t) = s) 1(t < r_i), \qquad k_{ist}^{post} \equiv 1(s(i,t) = s) 1(t \geq r_i),$$

depend on the indicator $1(s(i,t) = s)$, which takes value one if the school where i worked in academic year t, denoted by $s(i,t)$, is s. Here, with a slight abuse of notation compared to equation (1), r_i represents the recruitment drive when the offer was received by teacher i. The parameters ν_i^{pre} and ν_i^{post} measure the contribution to the outcomes at schools where teacher i worked before ($t < r_i$) and after ($t \geq r_i$) the offer, respectively. For example, positive values of ν_i^{pre} are associated with pre-offer contributions above the usual school outcomes, which we model with school fixed effects. Equation (4) also controls for interactions of school district intercepts with a *quadratic* trend in t to allow for non-differential trends in school outcomes across districts between 2008 and 2020, as well as the number of teachers and student enrollment. Standard errors are clustered on schools.

Teachers receiving offers with bonus and without bonus shared the same value-added, on average, prior to the offer. This finding can be seen from Figure 5, which is derived as follows. First, we obtain two estimates of ν_i^{pre} for teacher i using pass rates and dropout rates on the right-hand side of equation (4). Then, as explained in Appendix A, we assume that the correlation between these estimates arises through one common factor denoting teacher i's value-added. Finally, we obtain an empirical Bayes estimate of this factor as in Angrist et al. (2017), and plot its distribution across teachers. In addition, Panel A of Table 1 shows the value of α_1 from equation (1) using teacher i's value-added on the left-hand side.

[11] Equation (4) below yields intercepts for about 95% of teachers in our sample. To put this number in context, Biasi (2021) uses mobility across grades and schools to retrieve value-added for 70% of teachers in her sample.

Figure 5. Value-added at the time of first offer.



Notes. Densities of value-added for teachers with offers from a school that pays the bonus and from a school that does not pay the bonus. Value-added is obtained using estimates from equation (4) adjusted using the empirical Bayes procedure described in Appendix A. Value-added in this figure is computed using appointments at schools before the first offer is received.

6 Effects of Offers on Earning Profiles

Empirical specifications

To address the challenge posed by unobserved teacher-level attributes, we rely on within-teacher variation from periods before the offer to periods after the offer. We estimate causal effects on some variable $outcome_{it}$ in a panel of teachers i in academic years $t = 2008, \dots, 2020$. For each teacher we consider the recruitment drive $r \in \{2014, 2016, 2017, 2018\}$ when the offer was received, using the timing of the *first* offer in case of repeated offers. We group teachers by recruitment drive and decile of the qualification score, which summarizes experience and qualifications when the offer was received. Indexing these groups to g, we distinguish between teachers with offers for a tenured job in schools with the bonus ($z_i = 1$) and without the bonus ($z_i = 0$).

We estimate difference-in-differences regressions *separately* for each group g. Specifically, we consider dynamic specifications which include teacher and year (two-way) fixed effects, denoted by $\widetilde{\beta}_{0g}(i,t)$, along with lead and lag indicators around the recruitment drive r when group g received the offer:

$$outcome_{it} = \widetilde{\beta}_{0g}(i,t) + \sum_{j\in[-6,\tau_r]} \beta_{jg} 1(t-r=j) z_i + u_{it}. \tag{5}$$

The variable $1(t-r=j)$ takes value one if time t falls j years from the offer, and the window considered is between -6 and τ_r (the coefficient in the year before the offer, β_{-1g}, is normalized to zero). The upper limit of the window, τ_r, is constrained by the length of the panel and depends on the recruitment drive (e.g., $\tau_r = 6$ and $\tau_r = 2$ for offers in the 2014 and 2018 drives, respectively).

Identification relies on pre-offer common trends with and without the bonus, in the same recruitment drive, for teachers in the same qualification score decile. The event-study graphs below plot weighted averages of the β_{jg}'s across groups g:

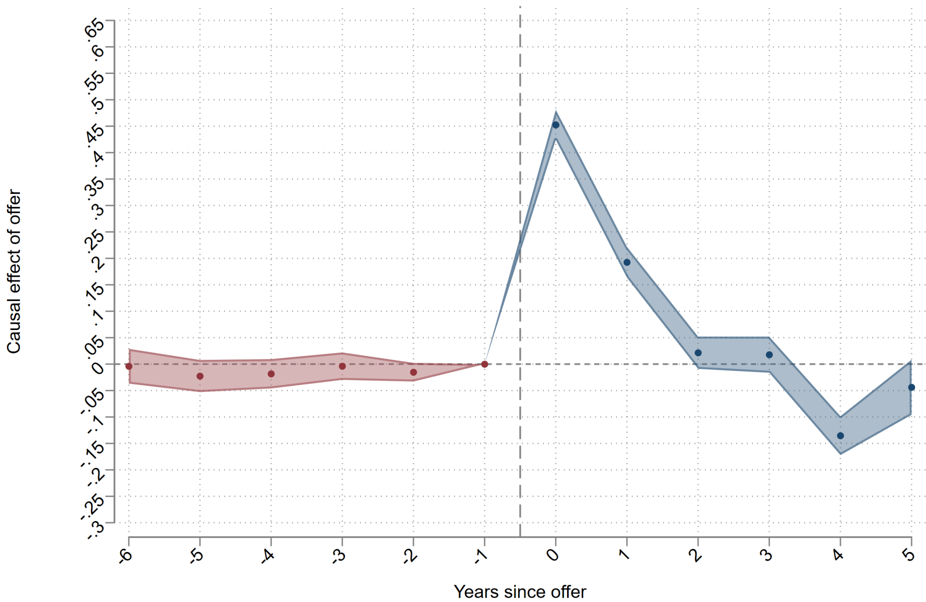
$$\beta_j \equiv \sum_g \beta_{jg}\omega_g, \tag{6}$$

with the ω_g's representing the relative number of offers from a school with bonus in each group. The last expression is an average of causal effects in event time, and our empirical approach overcomes the identification problems arising from effect heterogeneity and staggered timing of offers (see Sun and Abraham, 2021, and de Chaisemartin and D'Haultfoeuille, 2022, among others). The coefficients of interest are the $\{\beta_j\}_{j\geq 0}$, which represent the outcome difference between teachers with offers with and without the bonus j years after the offer. The placebo coefficients $\{\beta_j\}_{j<0}$ are used to visualize the lack of pre-offer differences between these two groups of teachers. We present results considering a six-year window before and after the offer, $j \in \{-6, \ldots, 5\}$.

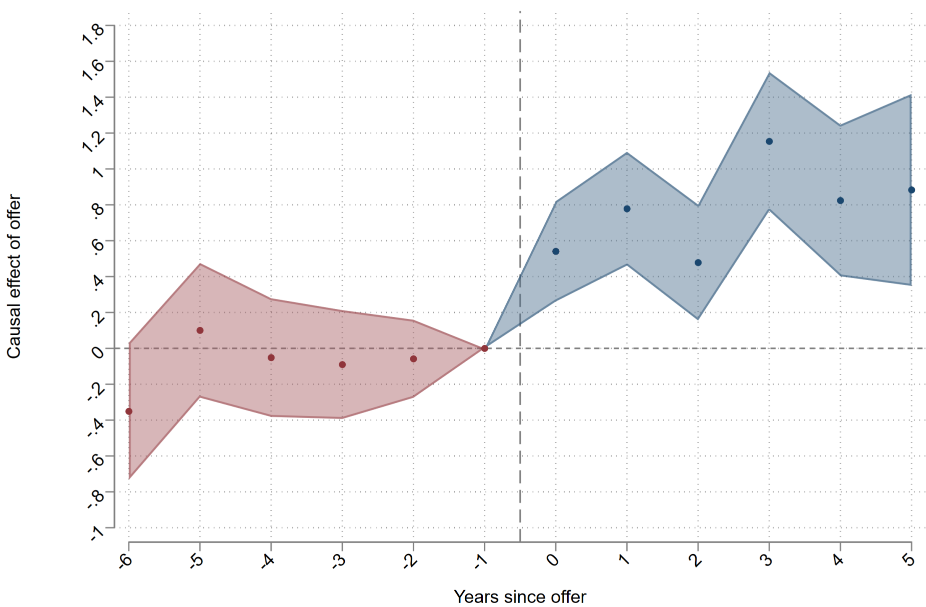
Causal effects of offers on future earnings

We begin by showing the causal effects of the offer z_i. Panel A of Figure 6 shows that an offer from a school with bonus increases by about 45 points the probability of receiving the bonus the academic year after the offer. This number is the value corresponding to zero on the horizontal axis, and is obtained as the $j = 0$ coefficient in (6) when the variable $outcome_{it}$ used in equation (5) is an indicator for working in a school with bonus. Because of mobility and the

Figure 6. Compliance with the bonus offer and effects of offer on earnings.



Panel A. School with Bonus



Panel B. Annual Earnings

Notes. This figure shows the event-study coefficients in (6) which are obtained from estimates of equation (5). The treatment variable z_i denotes receiving an offer from a school that pays a bonus, as opposed to receiving an offer from a school not paying the bonus. A value j on the horizontal axis denotes years before (negative values) and after (positive values) the recruitment drive when the offer was received. The dots show the outcome evolution for $z_i = 1$ teachers from period 0 to j, compared to $z_i = 0$ teachers. Shaded areas are confidence bands obtained from 200 bootstrap replications. Areas in navy denote the causal effects of z_i after j years. Areas in maroon are for placebo effects j years prior to the offer. Standard errors are clustered on teachers. Panel A is derived by considering for $outcome_{it}$ in equation (5) an indicator for working in a school with bonus. In Panel B, the variable $outcome_{it}$ is annual earnings in thousands of USD.

nature of contracts, which we discussed in Section 2, teachers could be employed at a school with bonus before the recruitment drive. Thus, the value of 45 points should be interpreted as the causal effect of z_i on "switching" status (e.g., from no bonus to bonus) between period -1 and 0.[12] Consistently with the randomization of z_i, the employment histories at schools that pay the bonus are statistically the same across teachers before receiving the offer. The effects of z_i between -6 and -2 in Panel A of Figure 6 are small and not statistically different from zero. The coefficients for event times 1 to 5 signal the *dynamic selection* of teachers in different jobs in the five academic years following the offer, as we discuss further below.

Panel B of Figure 6 shows the causal effect of offers on annual earnings (in thousands of USD). In the first academic year after receiving the offer with a bonus pay, the effect on earnings is estimated at about \$600 (see the value corresponding to zero on the horizontal axis). Thus, compared to the average in the sample (\$19,000), the causal effect of z_i on earnings is $600/19,000 \simeq 3.2\%$ in the academic year following the offer. As we shall see, changes in the effect on earnings after the first academic year reflect the dynamic selection of teachers into new jobs. Specifically, we see that the effects of offers over event times 3 to 5 in Panel B of Figure 6 average at about \$1,000 per year, or $1,000/19,000 \simeq 5.3\%$.

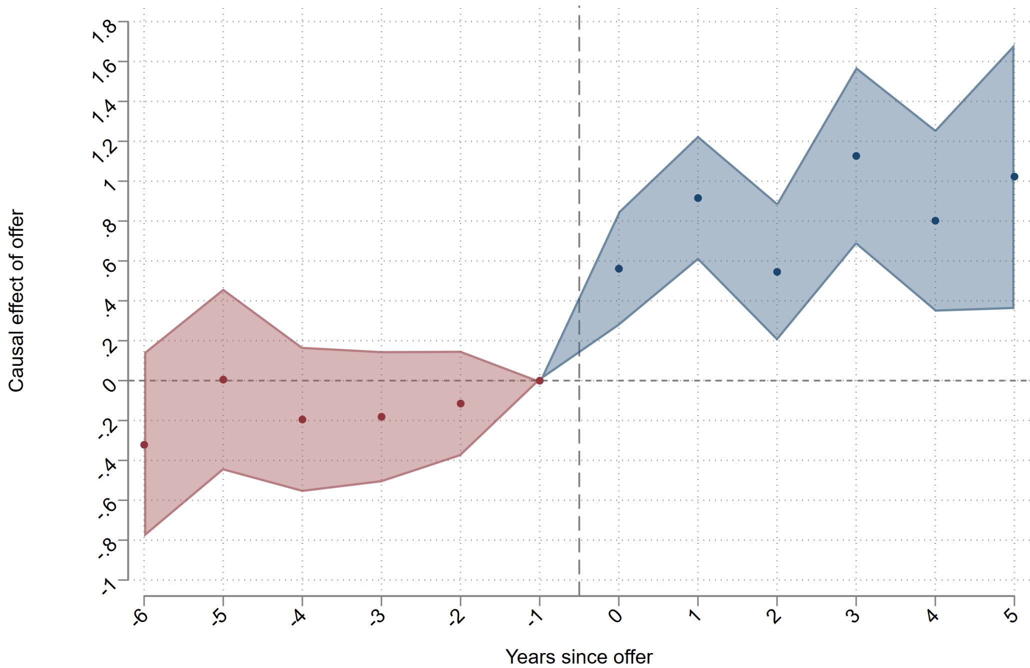
We conclude that teachers receiving offers from schools with the bonus experienced salary trajectories 3% to 5% higher, on average, than what the same teachers would have experienced otherwise.

Causal effects of the bonus pay on future earnings

The instrumental variable logic would use random offers as instruments for being employed in a school with bonus the academic year after the offer. Within this framework, reduced-form effects are visualized in Panel B of Figure 6 and the first-stage effect is the jump at period zero in Panel A of the same figure. The Wald-DID ratio from these two panels, however, does not identify the LATE for teachers moving to a school with bonus at period zero. Bounds on this LATE parameter could be obtained under conditions discussed in de Chaisemartin and D'Haultfoeuille (2017). We identify the causal effects of the bonus paying using a different approach.

[12] Teachers may also switch from bonus to no bonus between period -1 and 0, and the share of these units may vary between the $z_i = 1$ and $z_i = 0$ groups. This possibility has implications for how we interpret parameters in what follows, as we discuss below in the section (see also de Chaisemartin and D'Haultfoeuille, 2017).

Figure 7. Effects of receiving the bonus pay on future earnings.



Notes. This figure shows the event-study coefficients in (6) which are obtained from estimates of equation (5) after restricting the sample to offer-takers. Compared to Panel B of Figure 6, here the treatment variable z_i denotes working in a school that pays the bonus in period zero, as opposed to working in a school not paying the bonus. The variable $outcome_{it}$ used in this figure is annual earnings in thousands of USD. See footnote to Figure 6 for an explanation of how to interpret the vertical axis and horizontal axis.

Figure 7 shows the causal effects on future earnings (in thousands of USD) of receiving a bonus the year after the offer. This figure was obtained by restricting the sample used in (5) to teachers who accept the offer z_i (*offer-takers* for short). Because of this selection, the comparison in the figure is between teachers in schools with bonus in period zero and teachers in a school without bonus in period zero. This comparison introduces sample selection: although we documented in Table 1 that offers with and without bonus are accepted at the same rate, Figure 3 implies that the composition of offer-takers in these two groups may not be the same. However, the placebo coefficients in Figure 7 demonstrate that our difference-in-differences approach adjusts for sample selection successfully. By considering how effects change over time, this evidence confirms a long-term 5% premium on earnings caused by higher compensation in period zero.

Building on this evidence, all graphs in what follows will present estimates of causal effects of the bonus obtained from the sample of offer-takers.

7 Effects of Offers on Career Progression

Effects on employment profiles

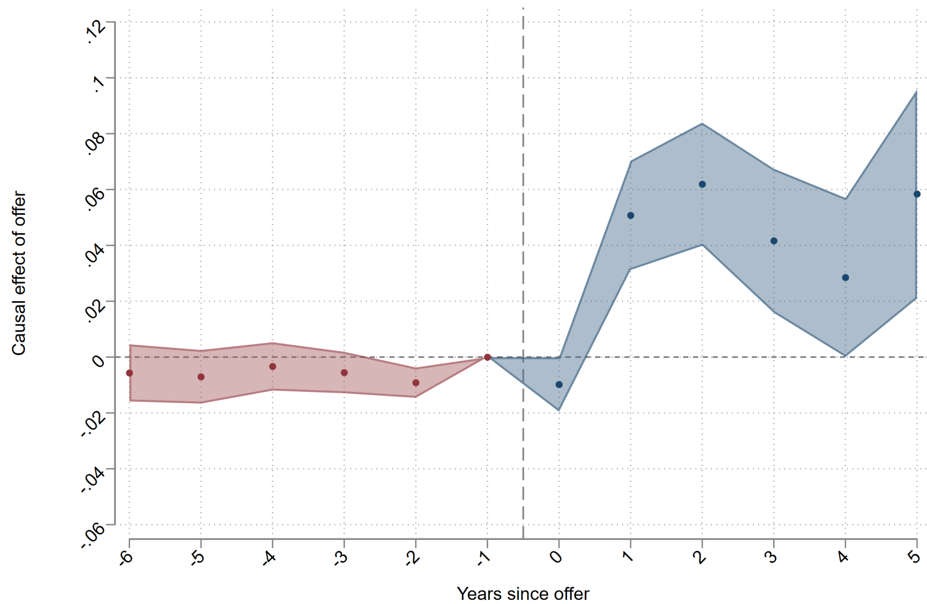
Panel A of Figure 6 shows that, starting from two years after the offer, the positive effect on the probability of employment in a school with bonus shrinks quickly towards zero. For example, the effect halves after two years (see period 1), and becomes statistically insignificant after four years (by period 3). By the end of the six-year window, teachers with an offer from a bonus school in period 0 are less likely to earn a bonus than their peers.[13] We conclude that the bonus pay does not serve the purpose of leveling the playing field by retaining teachers at hard-to-staff schools. On the other hand, Panel B of the same figure shows that the gap in earnings caused by the offer widens over time. What is the explanation for the effects on earning trajectories?

Panel A of Figure 8 shows that teachers with offers with the bonus are more likely to hold a temporary job at another school, in the years after the offer, compared to teachers with offers without the bonus. This graph is obtained by estimating equation (5) using, on the left-hand side, an indicator for being on leave. The effects on leaves become positive two years after the offer (period 1 on the horizontal axis), and do not drop after this time. This finding is most likely explained by the national regulations. After accepting offers, teachers must spend a mandatory probation period at the school where they are appointed to secure tenure. In practice, for most positions this probation period ends during the first year of appointment, after which a formal request for leave can be submitted. Six years after the offer, teachers with $z_i = 1$ are about 6 points more likely to be on leave compared to teachers with $z_i = 0$. Compared to the average share of tenured teachers on leave in the sample (about 10%), the causal effect of z_i six years down the line is $6/10 \simeq 60\%$. As we documented in Figure 4, schools with the bonus are more likely to appoint teachers on temporary contracts. The results is this section suggest that such contracts may be used to fill vacant positions from tenured staff on leave from these schools.

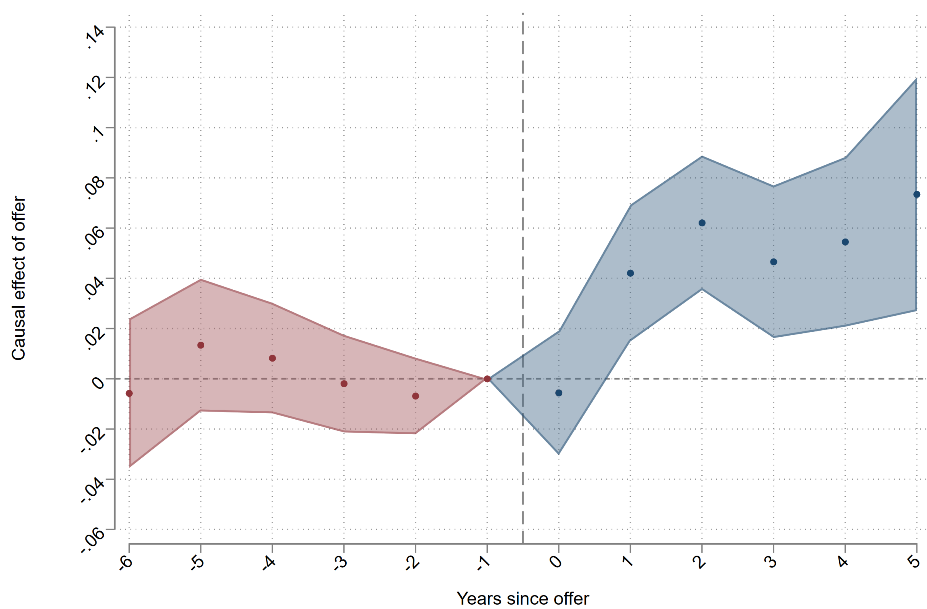
Teachers leave schools with the bonus to start employment in more managerial roles and in schools of less disadvantaged areas. Panel B of the Figure 8 shows that six years after the offer teachers with $z_i = 1$ are about 8 points more likely to be appointed as principals compared to teachers with $z_i = 0$. We obtain this result by using an indicator for employment in the role of school principal on the left hand side of equation (5). The pattern in Panel A of Figure 6 suggests

[13] Appendix Figure B.1 replicates Panel A of Figure 6 using the sample of offer-takers.

Figure 8. Effects of the bonus on leaves and school principal appointments.



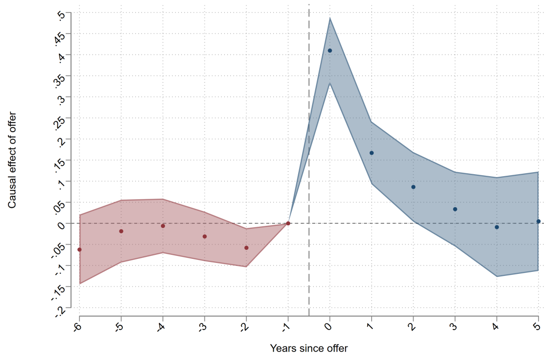
Panel A. Temporary Contract (Leave)



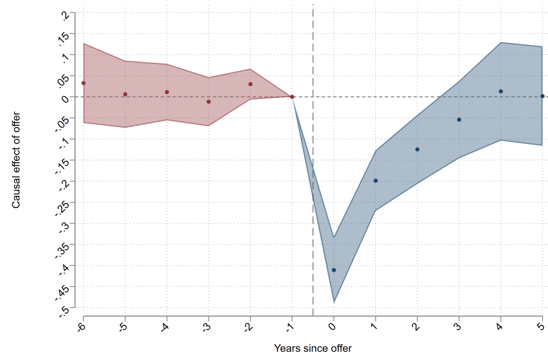
Panel B. School Principal Appointment

Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. Panel A is derived by considering for $outcome_{it}$ in equation (5) an indicator for being on leave from the school where tenure was originally granted. In Panel B, the variable $outcome_{it}$ is an indicator for employment in the role of school principal. Estimation is carried out using the sample of offer-takers.

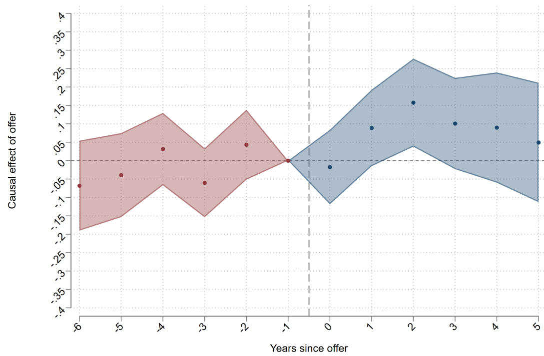
Figure 9. Effects of the bonus on characteristics of future appointments.



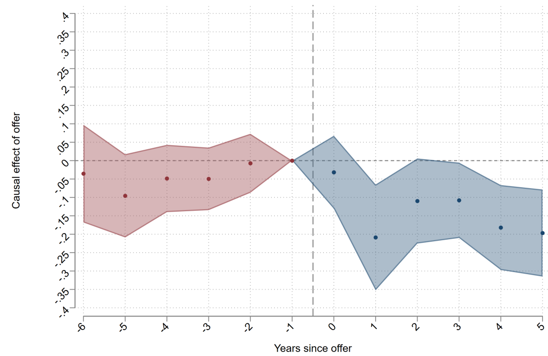
Panel A. Rural Area



Panel B. Student Enrollment



Panel C. Pass Rate



Panel D. Dropout Rate

Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. Panels are derived by considering for $outcome_{it}$ in equation (5) an indicator for working in a rural area (Panel A), school enrollment (Panel B), pass rates (Panel C) and dropout rates (Panel D). All outcome variables in this figure are standardized to have zero mean and unit variance in the sample. Estimation is carried out using the sample of offer-takers.

that teachers with $z_i = 1$ move gradually to areas with better socioeconomic development where the bonus is not paid.[14] This expectation is borne out by Figure 9, which shows that movers gravitate toward schools of more urban areas, with lower dropout rates, and higher pass rates. The panels in this figure are obtained by using on the left-hand side of equation (5) the variable $outcome_{s(i,t)}$, where $s(i,t)$ denotes the school where i is employed in year t.

Robustness to possible confounding factors

The effects on earnings of offers with the bonus are not confounded by possible changes in the tenure status caused by the offer. Specifically, the change in earnings trajectories in Panel B of

[14] See Boyd et al. (2013). Johnston (2020) documents teachers' strong willingness to pay for not working in low-achieving school and high-poverty areas.

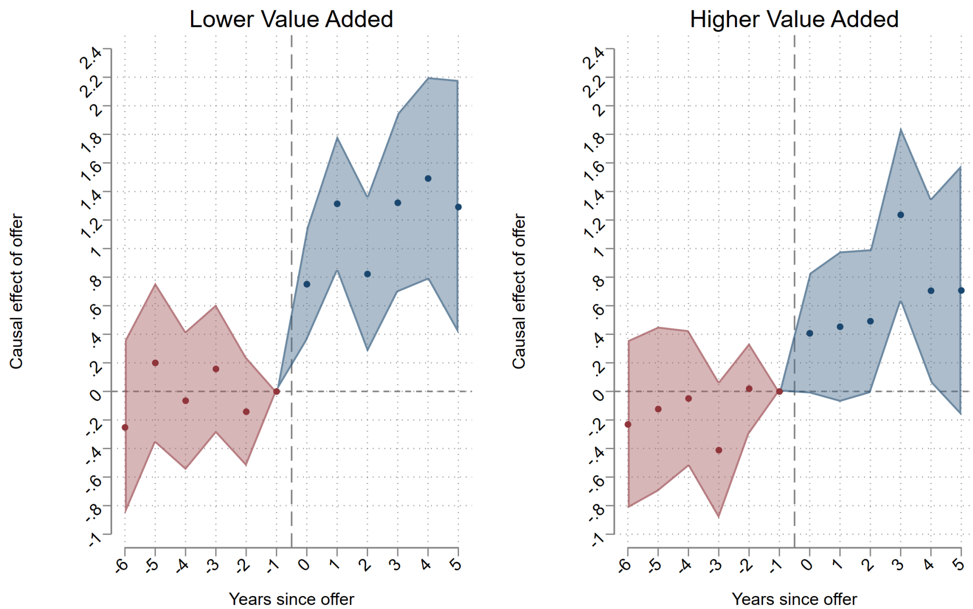
Figure 6 cannot separate the effects of increased job security because of tenure (i.e., an open-ended contract starting if the offer is accepted) from the effects of higher compensations because of the bonus pay. We can separate these two channels because tenured teachers wishing to transfer permanently to a new school can do so only if they receive an offer, as we explained in Section 3. Panel A of Appendix Figure B.2 shows the effects on earnings when the sample used in equation (5) is stratified by tenure status at the time of the offer. The positive effects on earnings remain for teachers who are already tenured, suggesting that future changes are most likely driven by offers with higher compensation. The statistical precision of this conclusion is somewhat affected by the limited number of tenured teachers in the sample at the time of the offer – see Panel A of Table 1, column (3). However, we showed that the take-up of offers is not affected by the bonus – see Panel C of Table 1, column (3). Thus, we conclude that the effects in Panel A of Figure B.2 for teachers without tenure are unlikely explained by compositional changes in the tenure status of the $z_i = 1$ and $z_i = 0$ groups caused by the offer.[15]

The mobility of teachers caused by offers with higher compensations is unlikely explained by the characteristics of schools paying the bonus. Figure 4 shows that schools with bonus are very different from the average primary school in the sample. It is therefore possible that the effects of z_i on mobility compound the effects of higher compensations and of a relatively worse working environment at schools. We separate these two channels by comparing offers with and without the bonus made by schools which are similar with respect to the characteristics considered in Figure 4. We do so following these steps. First, we use the same data in equation (3) to estimate the propensity score for being a school with the bonus as a function of school characteristics at the time of the offer.[16] Second, we replace the definition of group g used above, in equation (5), to include offers in the same recruitment drive and from schools in the same propensity score decile. The statistical properties of the propensity score ensure that teachers in group g received offers at the same time and from similar schools (on average) in terms of their characteristics in Figure 4. Finally, we obtain the event-study coefficients (6) using, as outcome, an indicator for being on leave. Figure B.4 shows that the effects on leaves are, if anything, stronger than in

[15]Panel B of Figure B.2 provides additional evidence on this channel, and is obtained by stratifying the sample using the qualification score at the offer. Almost all teachers with lower scores are not tenured, and the share of tenured teachers among those with higher scores is about 30% in our data. Steeper earnings trajectories caused by $z_i = 1$ are found in both strata.

[16]The propensity score is estimated from probit regressions, separately by recruitment drive $r \in \{2014, 2016, 2017, 2018\}$, and its distribution is shown in Appendix Figure B.3.

Figure 10. Effects of offer on earnings by teacher value-added at baseline.



Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. The figure is derived by considering for $outcome_{it}$ in equation (5) annual earnings in thousands of USD. The sample is stratified by considering the bottom two quartiles (Lower Value Added) and the top two quartiles (Higher Value Added) of the value-added distribution in Figure 5.

Figure 8, suggesting that teacher turnover is triggered by offers with higher compensations.

Heterogeneous effects by teacher value-added and experience

Who are the teachers benefiting the most from offers with higher compensations? Figure 10 looks at treatment effects heterogeneity by teacher quality. We use the measure of value-added in Figure 5 to distinguish between teachers in the bottom half (Lower Value Added) and top half (Higher Value Added) of the distribution at the time of offers.

The largest long-term returns on future earnings are for relatively worst teachers. An offer which provides a bonus payment made to lower value-added teachers increases their earnings by about $\$1,250$ (or $1,250/19,000 \simeq 6.6\%$) with respect to what these teachers would have experienced by receiving an offer with standard salary conditions. This effect size can be seen in the left-hand side panel of Figure 10, six years since the offer was received (period 5). The same effect computed for higher value-added teachers, on the right-hand side panel, is about \$750 (or $750/19,000 \simeq 3.9\%$).

On the other hand, we do not find evidence of differential effects of offers by experience. Panel B of Appendix Figure B.2 is derived by stratifying the sample using the qualification score at the offer (bottom and top half of the score distribution). The returns on earnings of offering higher compensations average at about \$1,000 per year at the end of the window considered. The income effects of offering higher compensations may be the mediating factor for finding increased fertility in Appendix Figure B.5. This effect is concentrated among female teachers with relatively less experience in the job at the time of the offer (see the left-hand side panel), arguably because of this group is younger.

8 Effects of Offers on Effort and Value-Added

We estimate the causal effects of z_i on teacher value-added by using a difference-in-differences specification similar to equation (5). Specifically, we consider a panel of teachers i in two periods denoted by τ: pre-offer (τ=1) and post-offer (τ=2). As we did above, teachers are grouped by recruitment drive and decile of the qualification score when the offer was received. We consider the following regression separately for each group, which we denote by g:

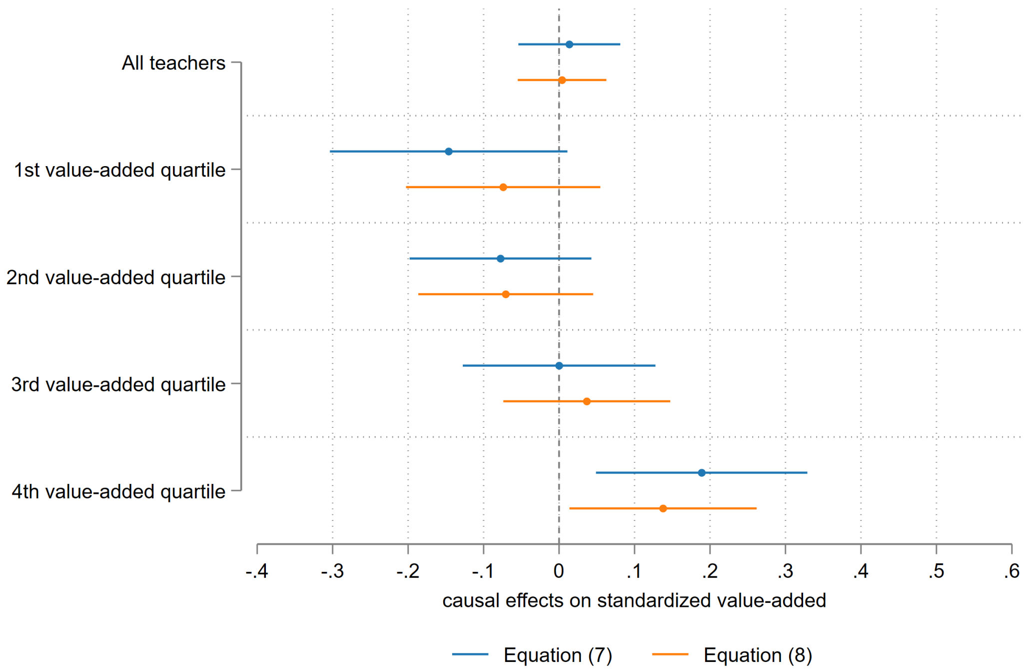
$$va_{i\tau} = \widetilde{\lambda}_{0g}(i,\tau) + \lambda_{1g}1(\tau = 2)z_i + e_{it}, \tag{7}$$

where $\widetilde{\lambda}_{0g}(i,\tau)$ is shorthand for sets of teacher and period effects, and $1(\tau = 2)$ is an indicator for observations after the offer is received. The coefficient λ_{1g} estimates the causal effect of the offer with bonus on value-added, compared to receiving an offer without the bonus payment. Estimating this equation by group has advantages. For example, given the recruitment drive, value-added estimates for teachers in the group are computed over the same calendar time before and after the offer. Moreover, we explicitly adjust for experience in the comparison by holding fixed the qualification score decile. We then aggregate group-specific estimates of causal effects by considering:

$$\lambda_1 \equiv \sum_g \lambda_{1g}\omega_g,$$

using the same weights ω_g defined in Section 6. Points estimates of treatment effects obtained from this approach are essentially non-parametric. We additionally consider the following para-

Figure 11. Effects on value-added.



Notes. Estimates of λ_1 from equation (7) and ϕ_1 from equation (8). These coefficients are parameterized to be zero if, in expectation, there is no change in teacher value-added from before to after receiving an offer with the bonus, as opposed to receiving an offer without the bonus. A positive (negative) value in this figure implies that value-added is λ_1 or ϕ_1 points bigger (smaller) when an offer with bonus is received. Horizontal lines denote confidence intervals with 95% coverage. The top panel is obtained using the full sample. The four remaining panels are obtained from stratifications on the quartile of value-added at baseline (see Figure 5).

metric specification:

$$va_{i2} = \phi_0 + \phi_1 z_i + \phi_2 va_{i1} + \phi_3 w_i + e_{it}, \tag{8}$$

where the effect of the offer z_i on va_{i2} is estimated by controlling for value-added at baseline, va_{i1}, and variables w_i consisting of a set of fixed effects for the same groups g defined above, gender, education, and a quadratic polynomial in age at the offer.

The long-term effects on earnings and career progression do not have any mediating effect on our measure of teacher quality. This conclusion can be drawn from Figure 11, where the top panel ("All teachers") reports estimates of λ_1 from equation (7) and ϕ_1 from equation (8). The causal effect of z_i is small and not statistically different from zero at the conventional level. The remaining panels of the figure show estimates obtained following the same steps after stratifying the sample by quartiles of value-added at baseline (i.e., the distribution in Figure 5). We find evidence of non-linear effects on teacher value-added of offering higher compensations.

Specifically, the figure shows negative values of λ_1 for teachers in the bottom quartile at baseline (about -0.15σ), and positive but not statistically significant values for the same parameter at the other side of the spectrum. The values for ϕ_1 convey a similar conclusion, with somewhat more precise estimates in the top quartile (about 0.13σ).

We conclude that relatively worse teachers before the offer becomes even less effective after the offer. Appendix Figure B.6 sheds additional light on the possible effects on teacher effort. The literature has looked at the effects on absenteeism. We don't have this information. However, as we explained in Section 2, this does not seem to be a prominent problem in Costa Rica. We therefore use information on sickness absences. Bearing in mind the lack of precision, point estimates suggest higher rates for relatively worst teachers.

The worsening performance of teachers with lower value-added at baseline may have negative long-term effects on the learning environment at schools. Appendix Figure B.7 shows that these teachers are likely to take up more managerial roles. The results in Johnston (2020) demonstrate that the quality of principals is among the most valued attribute and reduces teacher aversion to disadvantaged settings.

9 Job Search and Upward Mobility

Administrative data on offers for temporary positions in 2018

We now consider data for temporary positions offered during the 2018 academic year. These positions arose when the *Servicio Civil* couldn't fill vacancies through the tenured contract offers made during the 2018 national recruitment drive. As explained in Section 2, vacancies left unfilled prompt consideration for temporary contracts to teachers seeking jobs in the district where the position becomes available. The DoE's regional recruitment offices make these offers via uncoordinated phone calls to teachers ranked according to their scores in the national registry. The process begins by making an offer to the teacher with the highest score in the national registry, and subsequent phone calls are made following the ranking. Calls continue until the temporary position is filled or until there are no more teachers remaining on the list. Upon receiving a phone call, the teacher has only a few hours to decide before the process continues to the next teacher.

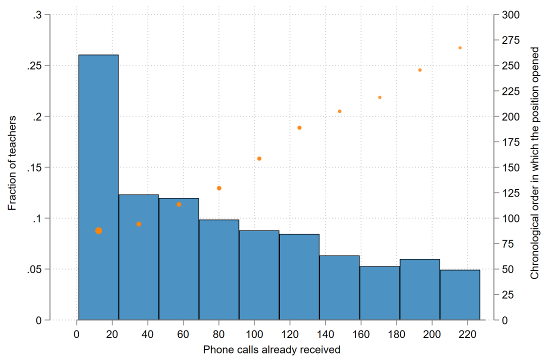
We use information sourced from the November 2017 registry, including scores and preferences of teachers, the names receiving offers, and the date when the position was filled. We replicate, with reasonable accuracy, the timing of phone calls made by regional offices. The resulting dataset consists of all $6,847$ teachers enrolled in the November 2017 registry. We distinguish between teachers with offers for a tenured position in any of the recruitment drives $r \in \{2014, 2016, 2017, 2018\}$ (i.e., $z_i = 1$ and $z_i = 0$ teachers) and teachers without previous offers for a tenured position. We consider all 284 temporary positions that became available, forming a panel of $6,847 \times 284$ teacher-job observations. We know if the offer was accepted, the order of the phone call among those received by each teacher, and those made by the regional offices to fill the position. Additionally, we have information on the wage offered (baseline figure and the bonus payment) and the current wage (including outside the public sector).

One important difference is between *phone calls received* and *offers considered*. The former serve as an overall measure of effort in the regional offices' pursuit of filling the positions, a factor external to the teacher. However, some of these incoming calls may involve offers that the recipient cannot consider due to prior acceptance of another offer. Therefore, the tally of offers considered represents the count of phone calls wherein a teacher must decide whether to accept or decline the offer presented. This count depends on the teacher's ex-ante risk of being considered for any of the 284 temporary positions.

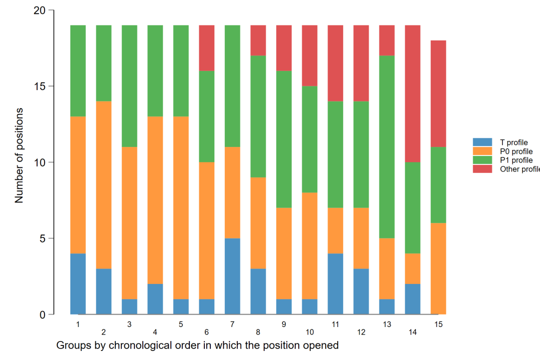
Timing and quality of job offers are unpredictable

We show that the lack of coordination between the DoE's offices results in offers with timing and quality that are, ex-ante, unpredictable for teachers. Since receiving an offer for a position is contingent on all prior attempts to fill that position being unsuccessful, Panel A of Figure 12 focuses on the timing of the initial offer, i.e., the first phone call made after a position opens. The recipients of these initial offers may have previously received phone calls for different positions. The bars show the distribution of the number of calls previously received. For instance, approximately 12% of the times (as indicated on the left vertical axis), when a new position becomes available, it is offered to a teacher who has already received around 60 calls for other positions. The dots in the figure also show that the number of calls previously received depends on the timing of when a new position becomes available. Each dot is constructed as follows. First,

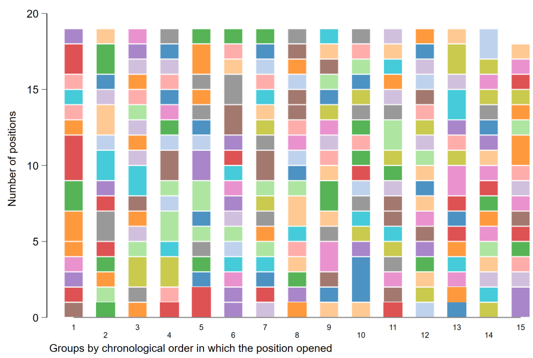
Figure 12. Unpredictability of offers for temporary positions.



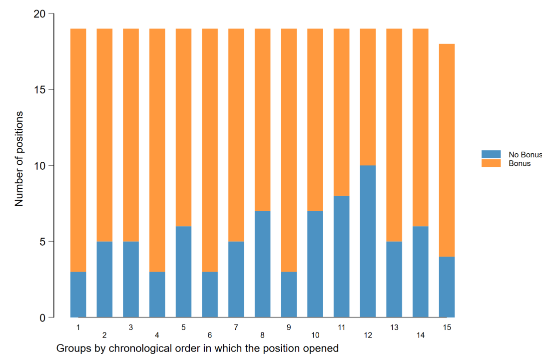
Panel A. Timing



Panel B. Job Profile



Panel C. School District



Panel D. Bunus Pay

Notes. Panel A considers the applicants who are the first to be contacted when a new position opens, displaying the number of phone calls they received for other positions by that time (see the text for details). Panel B categorizes the 284 positions into 15 groups based on the chronological order in which the positions became vacant, and shows the within-group distribution of positions by job profile. Panels C and D are constructed similarly to Panel B, and show the within-group distribution by school district and eligibility for bonus pay, respectively.

we order the 284 positions based on the chronological order in which they became available, assigning a value of one to indicate that the position was the first to open, two for the second, and so forth. Next, we calculate the average of these values for teachers falling within each bin of the histogram. Positions opening later in time, as indicated by higher ranks on the right vertical axis, are associated with an increased number of phone calls previously received, as shown on the horizontal axis.

The timing of positions becoming available is independent of the associated job profiles. Specifically, the horizontal axis in Panel B of Figure 12 categorizes the 284 positions into 15 groups, with all but the last one comprising 19 positions. These groups are defined from the chronological order in which the positions became vacant, with the initial 19 positions forming the first group, followed by subsequent groups in sequence. The vertical axis shows the distribution of these positions by job profile: T, P0, P1, and a collective category (other) encompassing P2, P3, P4, and P5 positions.[17] Positions became available with a relatively unpredictable pattern.

The last statement is further supported by the evidence in Panel C, which is constructed as the previous panel. The vertical axis here represents the distribution of positions by school district, with each district appearing in a distinct color. There is no obvious pattern regarding the distribution of new positions across districts. Finally, Panel D shows that vacancies are disproportionately located in the least developed areas, where the bonus is paid.

Teachers' revealed preferences for outside offers

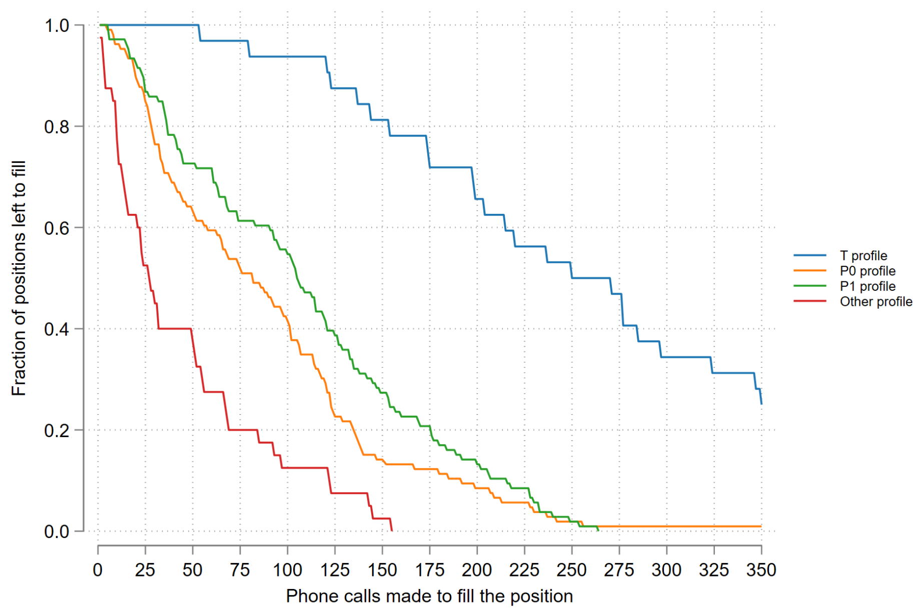
Teachers with $z_i = 1$ aim for positions with higher salary offers in their subsequent job searches. We see this by considering the stated preferences for job profiles detailed at enrollment in the national registry. The top panel of Figure 13 shows, among those with $z_i = 0$ (without bonus), $z_i = 1$ (with bonus) and the remaining applicants (tenure never offered), the proportion seeking positions by job profile. Teachers with $z_i = 1$ exhibit a lower propensity to apply for teaching positions (T profile) compared to their $z_i = 0$ counterparts. Conversely, they show a greater inclination to pursue managerial positions (P0 to P5 profiles). This shift most likely depends on the fact that, owing to their higher initial salary due to the bonus, managerial roles offer compensations that can match current earnings. Teachers who have never received offers for tenured positions up to and including the 2018 drive prefer teaching (T profile) positions.

Upon receiving offers, teachers reveal ordered preferences over job profiles. This can be seen from Panel B of Figure 13, where job positions are the primary unit of observation and are grouped based on their respective job profiles (T, P0, P1, and the collective category other). Within each group, we calculate the survival rate, which measures how the fraction of remaining unfilled positions evolves as the number of phone calls made increases. We find that among the various job positions, T positions consistently present the greatest challenge to fill. In contrast, both P0 and P1 positions tend to be easier to fill compared to T positions. Positions categorized

[17] P2 positions and above denote principals in schools with over 90 students. The sequence of calls for temporary positions at these schools is determined using a separate registry, following the same process as for T, P0, and P1 positions. Principals in P2 positions and above serve as the administrative heads of the school, responsible for managing day-to-day operations and evaluating the teaching staff under their supervision. Unlike T and P0 positions, they do not have teaching responsibilities.

Figure 13. Teachers' preferences for outside offers.

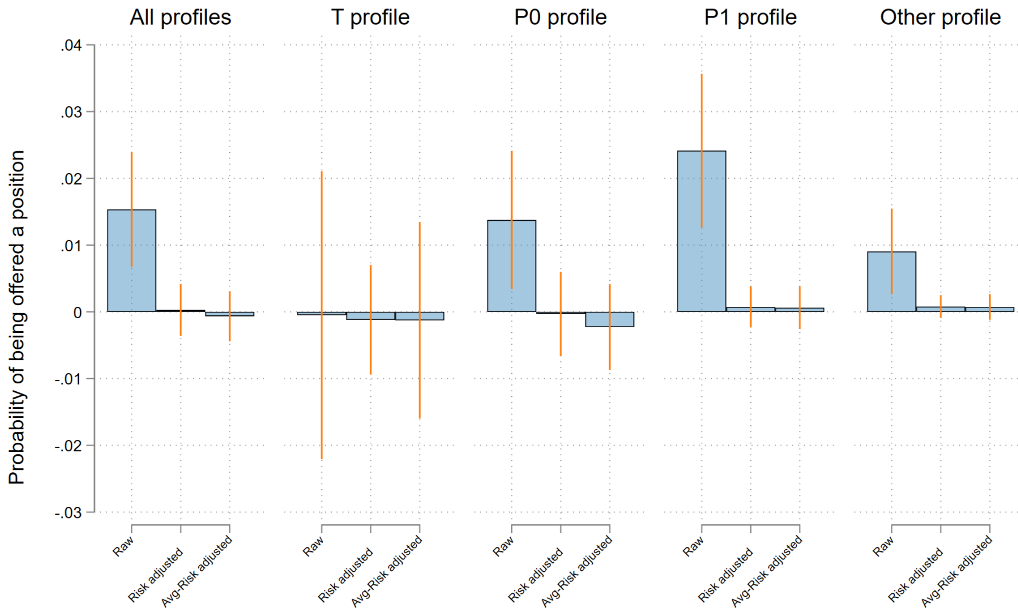
Panel A. Stated preferences in applications



Panel B. Revealed preferences from offer acceptance

Notes. Panel A displays the stated preferences for job profiles in the November 2017 registry, which was used for the 2018 recruitment drive. It groups applicants into $z_i = 0$ (without bonus), $z_i = 1$ (with bonus), and those who have not received any offers up to and including the 2018 recruitment drive (no tenure). Panel B uses the 284 job positions as the primary unit of observation, grouped by their respective job profiles. It shows how the fraction of remaining unfilled positions within each group evolves as the number of phone calls made increases.

Figure 14. Risk-adjusted comparisons for teachers with bonus ($z_i = 1$) and without bonus ($z_i = 0$).



Notes. This figure presents the estimated coefficient η_1 from equation (9) using all positions in the first panel, and by job profile in the remaining panels. The first bar in each panel (raw) is from a specification controlling for job, teacher, and recruitment drive effects. The second and third bars further adjust for the teacher-position risk of receiving an offer. The second bar (risk adjusted) is from a specification that additionally controls for p_{ij}, while the third bar (avg-risk adjusted) controls for the vector $\mathbf{p}_i$ instead (see the text for the definition of risk variables).

as P2 to P5 (the other category) are comparatively the easiest to fill.

The estimated coefficients from the following regression:

$$offer_{ij} = \eta_0(i, j, r_i) + \eta_1 z_i + u_{ij}, \tag{9}$$

show differences between $z_i = 1$ and $z_i = 0$ teachers in the propensity to receive offers. The equation is estimated using teacher-job observations, excluding teachers who have never received offers for tenured positions. Here, the variable $offer_{ij}$ indicates whether teacher i has received an offer for job j, and $\eta_0(i, j, r_i)$ is a set of job and teacher fixed effects, along with the recruitment drive $r_i \in \{2014, 2016, 2017, 2018\}$. The first bar (denoted with raw) in panels of Figure 14 shows the estimated coefficient η_1 from equation (9), using all positions and stratifying by job profile (standard errors use two-way clustering on i and j). We find that the probability of receiving an offer is higher for $z_i = 1$ teachers compared to $z_i = 0$ teachers, and this likelihood is driven by offers for more managerial positions. This finding is mechanically driven by differences in the preferences reported in the national registry, as shown in Panel A of Figure 13.

Risk-adjusted comparisons

We can summarize the results so far by stating that the likelihood of receiving offers for school principal positions is higher for $z_i = 1$ teachers than for $z_i = 0$ teachers, and that the timing and quality of these offers appears to be as good as random. We now demonstrate how the decentralized process used by DoE's regional offices can be employed to compare $z_i = 1$ and $z_i = 0$ teachers with, ex-ante, the same expected rate of offers.

We compute the ex-ante risk of receiving offers as in papers on centralized assignment, like Abdulkadroglu et al. (2017). The key insight is that the sequence of phone calls reflects an ordering determined only by two factors: the teacher's indication of interest in a position in the district and a job-profile specific score. Thus, the probability of receiving a phone call is zero for positions in districts that were not flagged in the national registry. Conditional on interest in the district, the ex-ante probability of receiving a call depends on the demand for job profiles and the score attributed to the teacher. For instance, the teacher with the highest T score will always be the first to receive a phone call for all T positions in the desired districts. Thus, we compute a variable p_{ij} denoting the expected risk that teacher i will receive an offer for each of the $j = 1, \ldots, 284$ positions. We set this risk to zero if teacher i is not seeking job in the school district and job profile of position j. If the risk is positive, we calculate the rank of teacher i in the score distribution of all competitors for position j. Letting N_j be the number of competitors, the teacher with the highest rank will have risk equal to $p_{ij} = \frac{N_j}{N_j}$, the second-best teacher will have risk equal to $p_{ij} = \frac{N_j - 1}{N_j}$, and so on, until the last teacher with risk $p_{ij} = \frac{1}{N_j}$. The second bar (denoted with risk adjusted) in panels of Figure 14 shows the estimated coefficient η_1 when the variable p_{ij} is added to equation (9). We further compute for each teacher i the average of p_{ij} by job profile across the 284 positions, yielding a total of seven variables. We group these variables in the vector $\mathbf{p}_i = [p_i^T, \ldots, p_i^{P5}]$, whose elements are the expected rates of T to P5 offers. The third bar (denoted with avg-risk adjusted) in panels of Figure 14 shows that, when equation (9) includes the vector $\mathbf{p}_i$ instead of the variable p_{ij}.

We conclude that the probability of receiving an offer is the same for $z_i = 1$ and $z_i = 0$

teachers sharing the same risk.

The option value of waiting

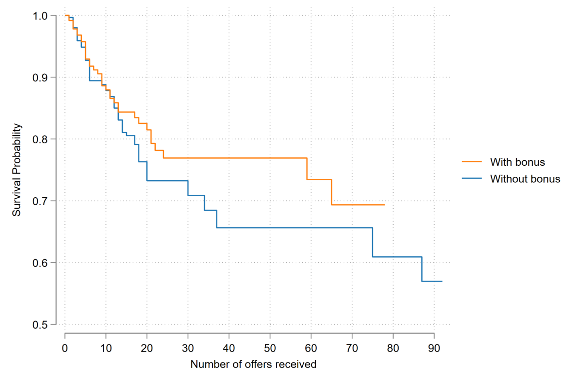
Figure 15 shows that the transition towards higher salaries among $z_i = 1$ teachers stems from a more patient approach to job searches (Panel A). In comparison to $z_i = 0$ teachers, $z_i = 1$ teachers experience lower forgone earnings when accepting offers for temporary positions (Panel B). In particular, Panel A presents Kaplan-Meier estimates for the time it takes for teachers to accept an offer, after restricting the sample to those with offers.

The interpretation faces two empirical challenges. The first challenge is ensuring that $z_i = 1$ and $z_i = 0$ teachers share the same distribution of the ex-ante risk variables $\mathbf{p}_i$. The second challenge arises from the values on the horizontal axis, which represent the number of offers received and will likely vary with $\mathbf{p}_i$. As a result, duration dependence in survival curves may be confounded by the fact that low-risk teachers receive fewer offers and may behave differently from high-risk teachers. To tackle the first challenge, we employ propensity score weighting. We estimate propensity scores from a logit regression of z_i on $\mathbf{p}_i$, and then construct weights such that the distribution of $\mathbf{p}_i$ among $z_i = 0$ teachers aligns with that among $z_i = 1$ teachers. To address the second challenge, we group teachers based on the expected number of phone calls received from the DoE's regional offices, which we predict from a regression of the actual number of calls received on $\mathbf{p}_i$. Appendix Figure B.8 shows, by tertile of the predicted number of calls received, the distribution across teachers of the number of offers considered (this is truncated when an offer is accepted). The number of offers varies by tertile group.[18]

The two curves in Panel A of Figure 15 are estimates for teachers in the top tertile of predicted call volume: the survival function of $z_i = 1$, and the propensity-score weighted survival function for $z_i = 0$. Thus, the panel compares teachers who (i) receive the highest number of phone calls from DoE's offices as predicted from $\mathbf{p}_i$, and (ii) share the same distribution of $\mathbf{p}_i$. The implicit assumption is that, on average, the number of offers received would have been identical for $z_i = 0$ and $z_i = 1$ teachers, with differences in this count arising from teachers' decision-making regarding acceptance. We see that $z_i = 1$ teachers generally exhibit a slower rate of acceptance compared to $z_i = 0$ teachers, who tend to accept more promptly, particularly after

[18] The medians are 1, 4, and 11; the 75th quantiles are 5, 12, and 24; and the 95th quantiles are 6, 16, and 87.

Figure 15. Impatience and forgone earnings from accepted offers.



Panel A. Time to offer take-up

Panel B. Wage differential

Panel C. Bonus pay differential

Notes. Panel A presents non-parametric estimates of the survival function for the $z_i = 1$ group and the propensity-score weighted survival function for the $z_i = 0$ group (see the text for explanations). The horizontal axis reports the number of offers considered, constrained to values below the 90th percentile of the distribution of this variable, separately for each group. Panel B shows the average difference between the wage offered and the current wage, contingent on the order of offers: before acceptance, upon acceptance, and after acceptance. Panel C mirrors the structure of Panel B, using differences in the salary top-up arising from offered and currently earned bonus payments. All panels use teachers in the top tertile of predicted call volume (see Appendix Figure B.9).

about 10 offers. Appendix Figure B.9 demonstrates much steeper survival functions for teachers in lower tertile of predicted call volume.

We conclude that teachers anticipating fewer phone calls are inclined to accept an offer more promptly, and the acceptance rate is similar for $z_i = 0$ and $z_i = 1$. However, when teachers expect a higher number of calls, there is more value of holding out for a potentially better opportunity rather than accepting the current offer. Teachers with $z_i = 1$ are relatively more patient in evaluating their options before making a decision.

Forgone earnings

Panel B of Figure 15 suggests that the faster acceptance rate observed among $z_i = 0$ teachers results in higher forgone earnings from potential future offers. This finding implies that $z_i = 0$ teachers, compared to $z_i = 1$ teachers, are less likely to accept offers as school principals, as the offered salaries increase only with job profile quality (given seniority) and the bonus pay.

Given that the DoE's offices operate independently, a teacher who has already accepted an offer may still receive subsequent phone calls offering positions that must be declined. We consider the difference between the wage offered and the current wage, computing the average of this quantity separately for $z_i = 0$ and $z_i = 1$, depending on the order of offers. Specifically, we calculate averages for offers turned down by the recipients (labeled as before acceptance), for offers accepted (upon acceptance), and for offers received afterward (after acceptance). The first bar in the panels indicates that offers rejected by $z_i = 0$ teachers have a wage lower than the current wage by approximately 9%. Conversely, the corresponding figure for $z_i = 1$ teachers is 54%, likely reflecting their higher earnings documented in Section 6. The second bar in the panels reveals that teachers accept offers for higher wages. On average, $z_i = 0$ and $z_i = 1$ teachers boost their current wage by 39% and 48%, respectively. However, these two groups differ in terms of their forgone earnings from future offers that could not be considered. Specifically, the forgone difference between the wage offered and the current wage is 49% for $z_i = 1$ teachers, approximately 1% higher than, and not statistically different from, the difference in the second bar.[19] Forgone earnings after acceptance, on average, are approximately 77% higher than the

[19] We test this significance using teacher-offer observations. We regress the difference between the wage offered and the current wage on a constant, an indicator for offers in the upon acceptance or after acceptance categories, and an indicator for offers in the after acceptance category.

current wage for $z_i = 0$ teachers, and 38% above the difference in the second bar. As shown in Panel B of Figure 13, a number of well-paid principal positions became available later in the process during the 2018 school year.

Finally, Panel C of Figure 15 is constructed similarly to the previous panel, this time considering differences in the salary top-up arising from offered and currently earned bonus payments (which are zero if not employed in one of the eligible schools). The bonus amount is calculated as a fixed share of the monthly salary and depends on the socioeconomic development of the school district. This implies that the bonus is highest for principal jobs in the most deprived areas of the country. Offers rejected by $z_i = 0$ teachers have a positive bonus pay differential, suggesting that positions in the most disadvantaged areas are the least preferred, given the strong preference for principal positions documented in Panel B of Figure 13. For $z_i = 1$ teachers, the bonus pay differential of rejected offers is negative. Upon accepting an offer, $z_i = 0$ teachers receive higher bonuses, corroborating the idea that the additional income from the bonus plays a role in the decision to accept. The forgone bonus pay differential for $z_i = 0$ teachers is attributed to principal positions in disadvantaged areas becoming available later in the process.

10 Conclusion

We leveraged random offers from hard-to-staff schools where teachers are entitled to a bonus pay to document that these offers have long lasting effects on future career progression, earnings, and effort. We showed that higher salaries paid in hard-to-staff schools attract teachers only temporarily. Teachers benefit from increased job security (tenure) by accepting offers from these schools and then transfer to schools in less disadvantaged locations.

Specifically, we showed that teachers in Costa Rica have the right to take leave from the school where they were granted tenured to fill temporary positions in other schools. We showed that higher wages in hard-to-staff schools are used to maintain the same wage after leaving the school. We explained that job security (tenure) and higher wages at hard-to-staff schools may give teachers more time for their search. The Costa Rican market for temporary positions at most primary schools is not run centrally, and teachers must decide about available vacant positions within a few hours from unexpected phone calls by from local offices of the Department of Education. The decentralized nature of the market for temporary positions can also lead to a fast-paced and unpredictable job search process. We argued that diminished job search pressure and higher wages allow teachers to target better job profiles more efficiently.

We documented that the positive effects on future earnings and career mobility do not spill over to value-added. We found no effects of offers with bonus on value-added across teachers in the sample. However, this average effect masks important dimensions of heterogeneity across teachers. Relatively worse teachers before the offer from schools with bonus tend to become even worse teachers in the long-term, after the offer is received. We find similar conclusions considering the effects on sick leaves, which we use to proxy for effort. These findings highlight the need for targeted interventions to support hard-to-staff schools.

Overall, this study provides insights into the teacher labor market in Costa Rica and highlights the need for further research to better understand the factors that influence teacher retention and career progression.

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Appendixes

For Online Publication.

Appendix A Empirical Bayes Shrinkage

This section explains how we obtained empirical Bayes estimates of teacher value-added *before* the offer. The same steps were followed to shrink value-added estimates *after* the offer. For each teacher i, we define a 2×1 vector of estimates from equation (4) containing $(\hat{\chi}_{1i}, \hat{\chi}_{2i})$, which are the estimates of ν_i^{pre} when the outcome $rate_{st}$ is pass rates (share of students admitted to the next grade) or retention rates (share of students who did not drop out of school), respectively. We impose the normalization that the first estimate $\hat{\chi}_{1i}$ is an unbiased but noisy measure of teacher i's value-added, denoted by ϑ_i:

$$\hat{\chi}_{1i} = \vartheta_i + \varepsilon_{1i}.$$

We also assume that the second estimate $\hat{\chi}_{2i}$ depends on ϑ_i through to the following equation:

$$\hat{\chi}_{2i} = (\vartheta_i + b_{2i}) + \varepsilon_{2i}.$$

Taken together, these two equations imply that the intercepts estimated from (4) using either pass rates or retention rates are correlated through their common dependence on ϑ_i. Thus, we have two estimates $(\hat{\chi}_{1i}, \hat{\chi}_{2i})$ of the same parameter ϑ_i, with one estimate possibly "biased". We use the following hierarchical model to obtain the empirical Bayes estimate of ϑ_i.

Assuming normality, we begin by considering the contribution to the likelihood function of teacher i:

$$\begin{bmatrix} \hat{\chi}_{1i} \\ \hat{\chi}_{2i} \end{bmatrix} | \vartheta_i, b_{2i}, S_i \sim N\left(\begin{bmatrix} \vartheta_i \\ \vartheta_i + b_{2i} \end{bmatrix}, S_i \right),$$

where we set the variance-covariance matrix S_i to the sampling variance of $(\hat{\chi}_{1i}, \hat{\chi}_{2i})$. Using the equations above and assuming normality, the following joint distribution of value added ϑ_i and bias b_{2i} is defined:

$$\begin{bmatrix} \vartheta_i \\ b_{2i} \end{bmatrix} | S_i \sim N\left(\begin{bmatrix} \mu_\vartheta \\ \mu_b \end{bmatrix}, \underbrace{\begin{bmatrix} \sigma_\vartheta^2, & \rho\sigma_\vartheta\sigma_b \\ \rho\sigma_\vartheta\sigma_b, & \sigma_b^2 \end{bmatrix}}_{\Sigma} \right),$$

where the hyperparameters $\left(\mu_\vartheta, \mu_b, \sigma_\vartheta^2, \sigma_b^2, \rho\right)$ shape the latent distribution of value-added across teachers. We estimate these hyperparameters by maximum likelihood. Specifically, assuming independence across n teachers, we start from the likelihood function of $(\hat{\chi}_{1i}, \hat{\chi}_{2i})$:

$$|S_i|^{-n/2} \exp\left(-\frac{1}{2}\sum_{i=1}^{n}\begin{bmatrix}\hat{\chi}_{1i}-\vartheta_i\\ \hat{\chi}_{2i}-\vartheta_i-b_{2i}\end{bmatrix}' S_i^{-1}\begin{bmatrix}\hat{\chi}_{1i}-\vartheta_i\\ \hat{\chi}_{2i}-\vartheta_i-b_{2i}\end{bmatrix}\right),$$

and then obtain the posterior distribution $p\left(\mu_\vartheta, \mu_b, \sigma_\vartheta^2, \sigma_b^2, \rho\right)$ from the density of (ϑ_i, b_{2i}):

$$|\Sigma|^{-1/2} \exp\left(-\frac{1}{2}\sum_{i=1}^{n}\left(\begin{bmatrix}\vartheta_i-\mu_\vartheta\\ b_{2i}-\mu_b\end{bmatrix}' \Sigma_i^{-1}\begin{bmatrix}\vartheta_i-\mu_\vartheta\\ b_{2i}-\mu_b\end{bmatrix}+\begin{bmatrix}\hat{\chi}_{1i}-\vartheta_i\\ \hat{\chi}_{2i}-\vartheta_i-b_{2i}\end{bmatrix}' S_i^{-1}\begin{bmatrix}\hat{\chi}_{1i}-\vartheta_i\\ \hat{\chi}_{2i}-\vartheta_i-b_{2i}\end{bmatrix}\right)\right). \tag{10}$$

Using the properties of the Normal distribution, one can get explicit expressions for the maximum likelihood estimates of μ_ϑ and μ_b:[1]

$$[expressions]$$

These expressions are functions of the hyperparameters σ_ϑ^2, σ_b^2 and ρ. We concentrate the likelihood function (10) by substituting the expressions for the hyperparameters μ_ϑ and μ_b, and maximize the profile likelihood with respect to σ_ϑ^2, σ_ϑ^2 and ρ. The profile likelihood is parameterized to estimate the logs of variances, $\log\left(\sigma_\vartheta^2\right)$ and $\log\left(\sigma_b^2\right)$, and the Fisher's transformation (inverse hyperbolic tangent) of the correlation coefficient:

$$0.5\log\left(\frac{\rho+1}{1-\rho}\right),$$

to avoid numerical problems. We assume independence across teachers to construct the likelihood function.

The hyperparameters are used to obtain the empirical Bayes posterior means for all teachers:

$$\vartheta_i^* \equiv E\left(\vartheta_i|\hat{\chi}_{1i}, \hat{\chi}_{2i}\right) =$$

which are the quantities employed in the main text. Figure X compares the distribution of $\hat{\chi}_{1i}$ to the distribution of empirical Bayes estimates ϑ_i^*.

[1] See Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., & Rubin, D.B. (2013). Bayesian Data Analysis (3rd ed.). Chapman and Hall/CRC. https://doi.org/10.1201/b16018.

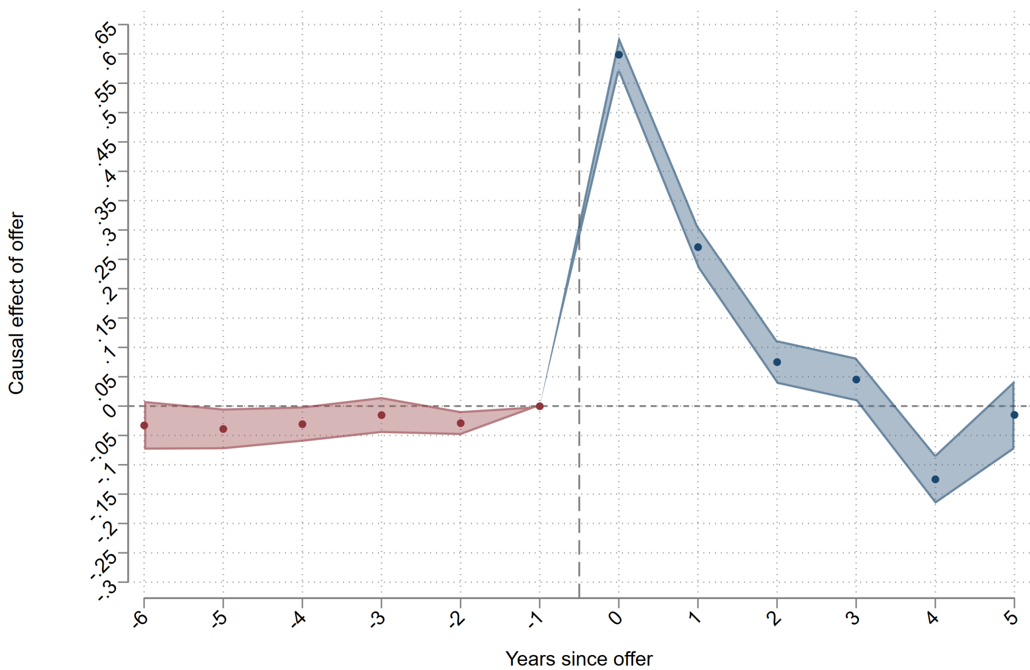
Appendix B Additional Figures and Tables

Table B.1. Eligibility for the bonus pay.

	Education of the Teacher			
	Higher National Diploma	Professional Teaching Certificate	Bachelor's Degree in Education	Licenciate's degree in Education or higher
Area Development				
High	0%	0%	0%	0%
Medium	0%	0%	0%	0%
Low	2,5% annual	3,33% annual	5,83% annual	6,66% annual
Very low	3,33% annual	4,16% annual	6,66% annual	7,50% annual

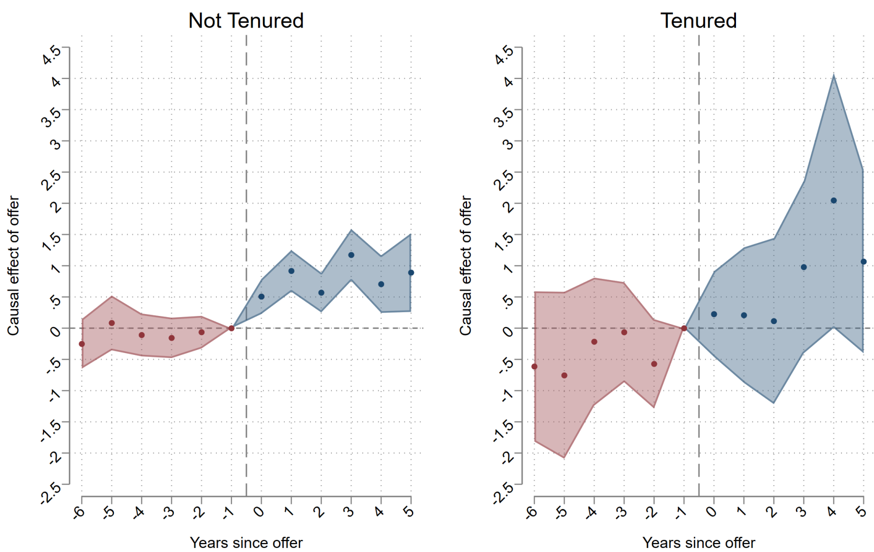
Notes. The eligibility for receiving the bonus pay depends on the index of social development computed by the National Department of Planning, at the right-hand side of the table. Only teachers in schools of administrative regions with low and very low social development can receive the bonus. The amount received by eligible teachers depends on their educational qualifications, which are shown across columns of the table (the Higher National Diploma was awarded by the *Instituto de Formación Profesional del Magisterio* and by Costa Rican vocational schools called *Escuelas Normales*; both institutions ceased to exist in the 1970s). Each cell in the table shows the amount of bonus pay as percentage of the annual salary. In our data, 94, 71% of teachers hold at least a Licentiate's degree in Education - the last column in the table.

Figure B.1. Effects on working in a school with the bonus.

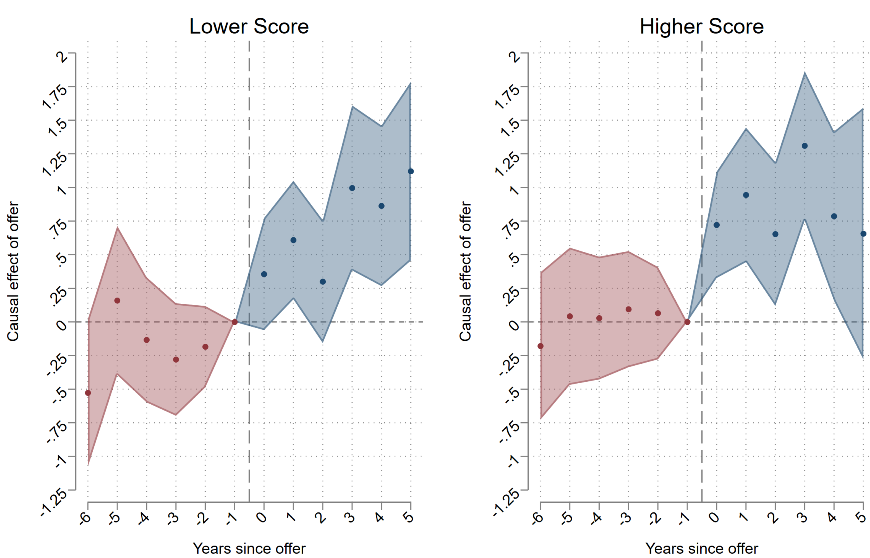


Notes. This figure shows the event-study coefficients in (6) which are obtained from estimates of equation (5) after restricting the sample to offer-takers. Compared to Panel B of Figure 6, here the treatment variable z_i denotes working in a school that pays the bonus in period zero, as opposed to working in a school not paying the bonus. The variable $outcome_{it}$ used in this figure is an indicator for working in a school with bonus. See footnote to Figure 6 for an explanation of how to interpret the vertical axis and horizontal axis.

Figure B.2. Effects of offer on future earnings by seniority.



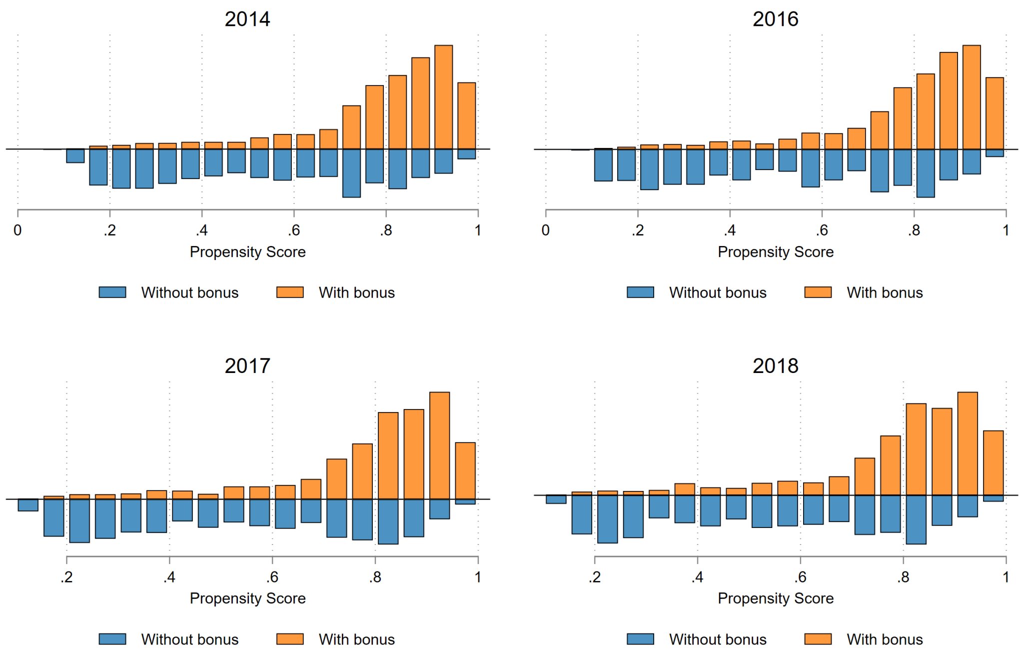
Panel A. Tenure Status at Offer



Panel B. Qualification Score at Offer

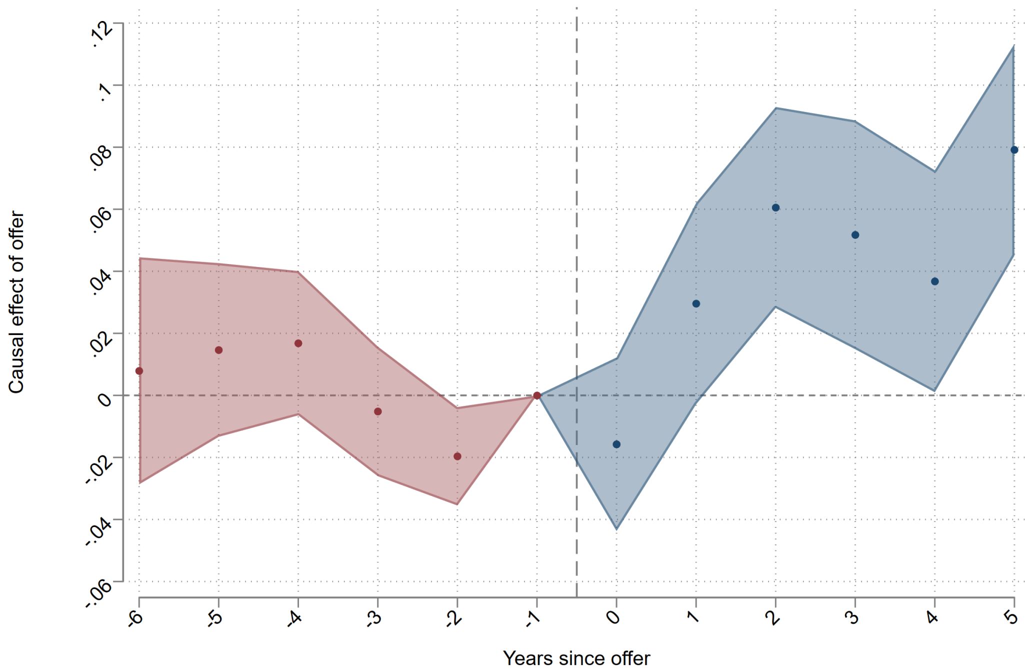
Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. Both panels are derived by considering for $outcome_{it}$ in equation (5) annual earnings in thousands of USD. In Panel A, the sample is stratified by consideringthe tenure status when the offer was received. In Panel B, the sample is stratified by considering the bottom two quartiles (Lower Score) and the top two quartiles (Higher score) of the qualification score when the offer was received.

Figure B.3. Propensity score.



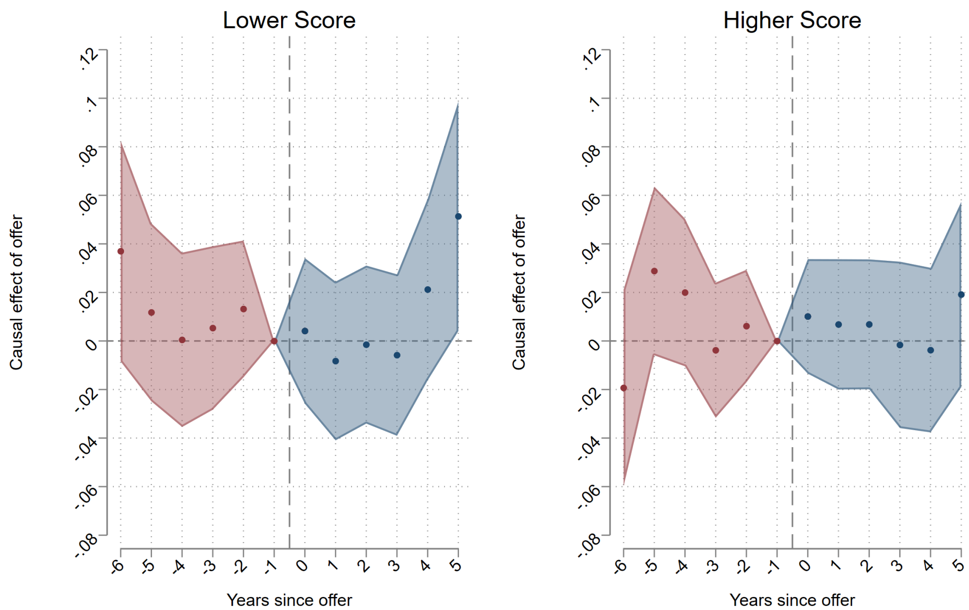
Notes. To be added.

Figure B.4. Effects on leaves of offers from schools with similar characteristics.



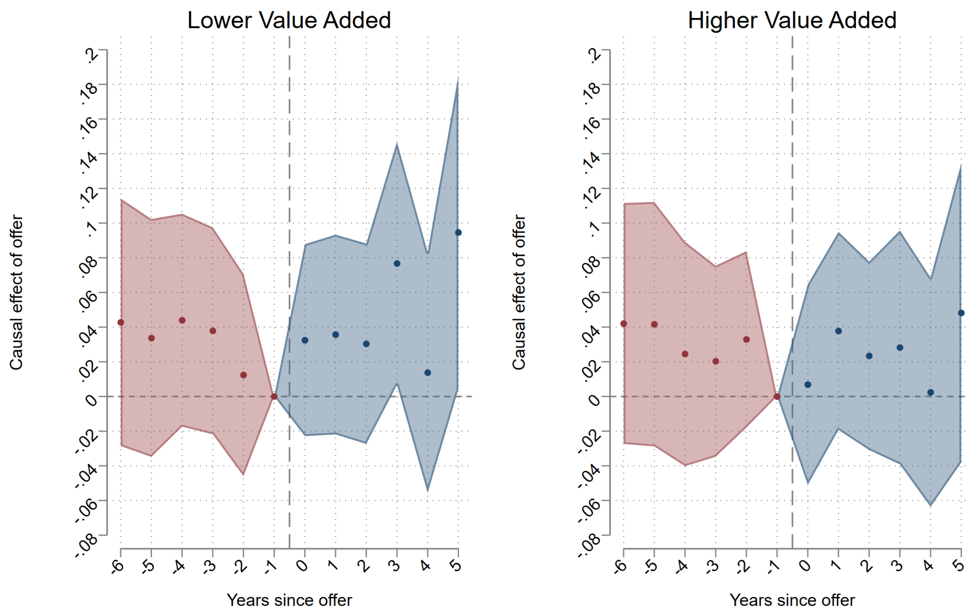
Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. The figure is derived by considering for $outcome_{it}$ in equation (5) an indicator for being on leave from the school where tenure was originally granted.

Figure B.5. Effects on maternity leaves.



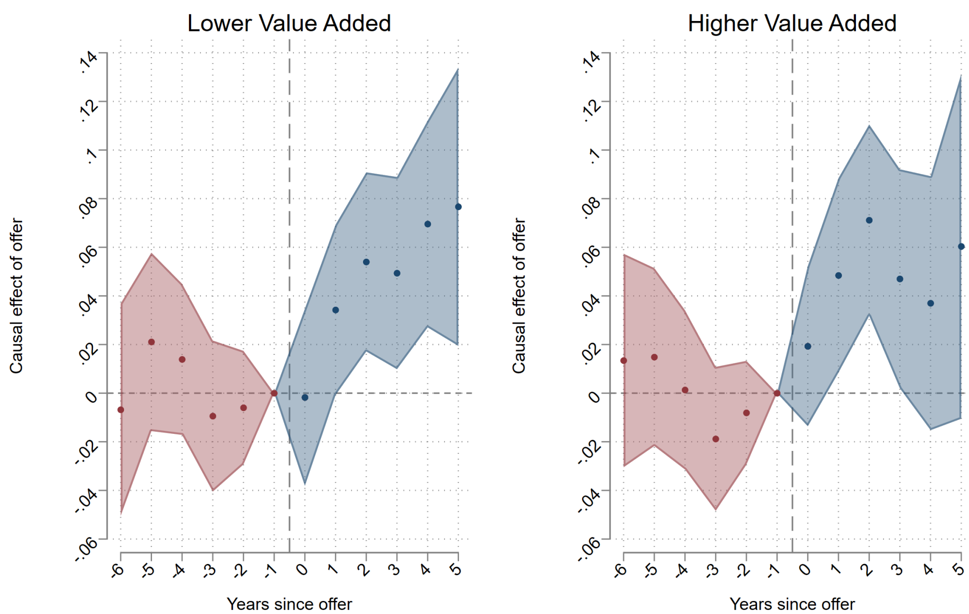
Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. The figure is derived by considering for $outcome_{it}$ in equation (5) an... The sample is stratified by considering the bottom two quartiles (Lower Score) and the top two quartiles (Higher score) of the qualification score when the offer was received.

Figure B.6. Effects on sickness absences.



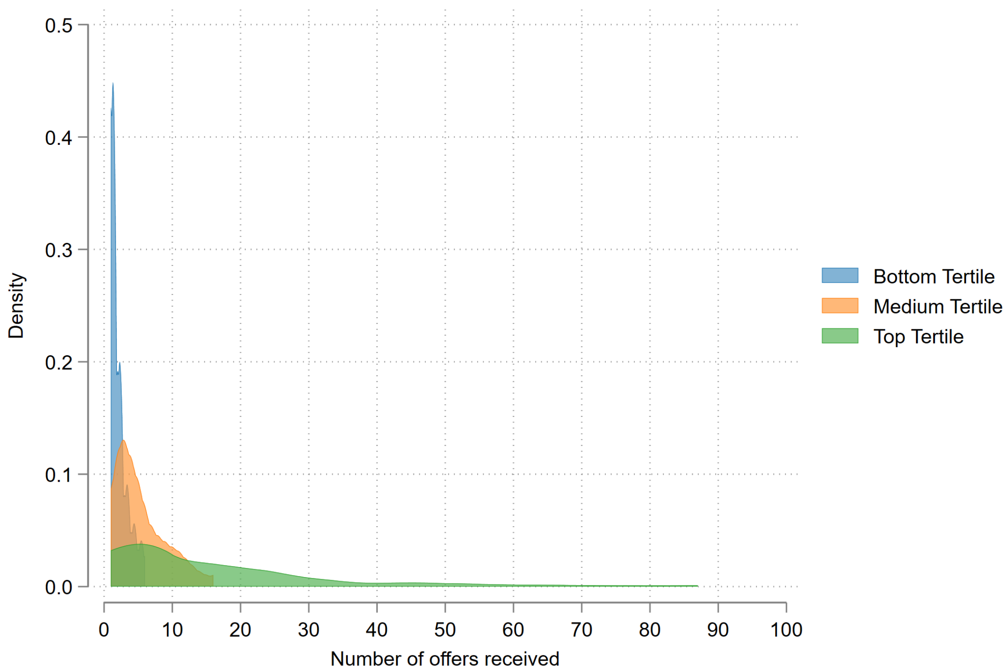
Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. The figure is derived by considering for $outcome_{it}$ in equation (5) an... The sample is stratified by considering the bottom two quartiles (Lower Value Added) and the top two quartiles (Higher Value Added) of the value-added distribution in Figure 5.

Figure B.7. Effects of offer on progression to principal by value-added at baseline.



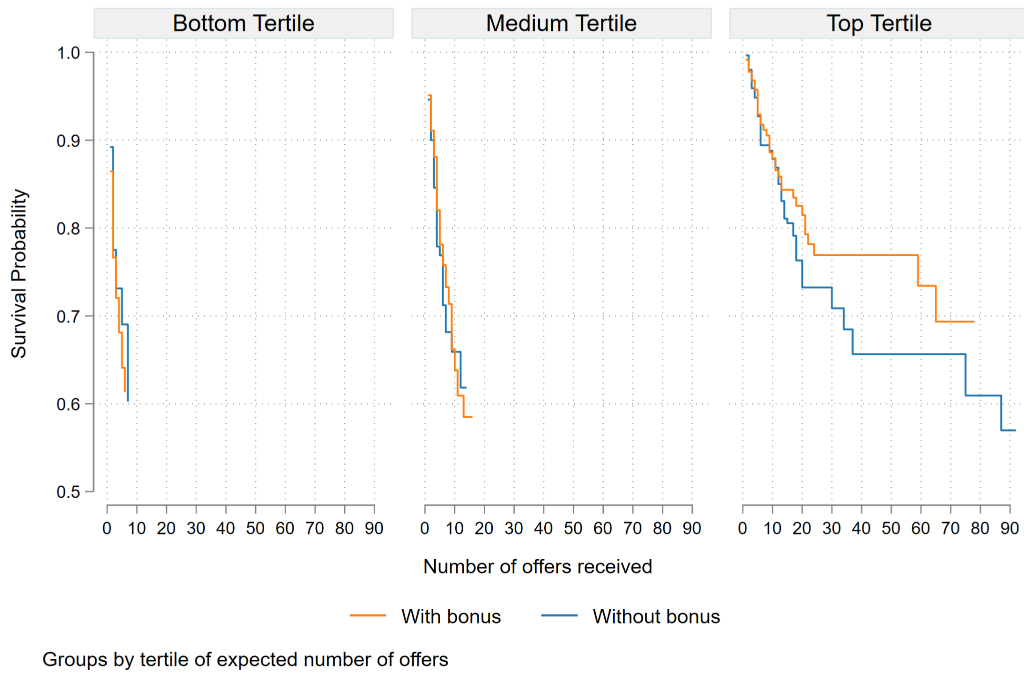
Notes. See footnote to Figure 6 for an explanation of what is reported on the vertical axis and horizontal axis. The figure is derived by considering for $outcome_{it}$ in equation (5) an... The sample is stratified by considering the bottom two quartiles (Lower Value Added) and the top two quartiles (Higher Value Added) of the value-added distribution in Figure 5.

Figure B.8. Number of offers considered by predicted call volume.



Notes. This figure presents the distribution of the number of offers considered by teachers, by tertiles of the predicted number of calls received. The variable is truncated if an offer is accepted, meaning that for each teacher, it represents the minimum between the total number of offers received for the 284 positions, assuming the teacher rejected all offers, and the number of offers received until acceptance, if the teacher accepted one offer.

Figure B.9. Impatience and forgone earnings from accepted offers.



Notes. This figure corresponds to Panel A of Figure 15 in the text. It presents non-parametric estimates of the survival function for the $z_i = 1$ group and the propensity-score weighted survival function for the $z_i = 0$ group. The horizontal axis indicates the number of offers considered, limited to values below the 90th percentile of the distribution of this variable, separately for each group. The three panels in this figure categorize teachers by tertile of the expected number of phone calls received from the DoE's regional offices, which we predict from a regression of the actual number of calls received on $\mathbf{p}_i$.