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ISSN: 2365-9793

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ABSTRACT

Altruism or Money? Reducing Teacher Sorting Using Behavioral Strategies in Peru*

Inequality in access to high-quality teachers is an important driver of student socioeconomic achievement gaps. We experimentally evaluate a novel nation-wide low-cost government program aimed at reducing teacher sorting. Specifically, we tested two behavioral strategies designed to motivate teachers to apply to job vacancies in disadvantaged schools. These strategies consisted of an "Altruistic Identity" treatment arm, which primed teachers' altruistic identity by making it more salient, and an "Extrinsic Incentives" arm, which simplified the information and increased the salience of an existing government monetary-incentive scheme rewarding teachers who work in underprivileged institutions. We show that both strategies are successful in triggering teacher candidates to apply to such vacancies, as well as make them more likely to be assigned to a final in-person evaluation in a disadvantaged school. The effect among high-performing teachers is larger, especially in the "Altruistic" arm. Our results imply that low-cost behavioral strategies can enhance the supply and quality of professionals willing to teach in high-need areas.

JEL Classification: I24, D91, I25

Keywords: identity, monetary incentives, priming, altruism, prosocial behavior, teacher sorting

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* AEARCTR-0004676. We thank Michela Carlana, Ruben Durante, Fernanda Estevan, Martin Fiszbein, Alejandro Ganimian, Guilherme Linchand, Maria Lombardi, Veronica Montalva, Anne Sofie Olsen, Vladimir Ponczek, Norbert Schady, participants of the APPAM Conference, LACEA-BRAIN, BIG, the IDB-Education BBL, the IDB Behavioral Group, and the IDB regional seminar on teacher assignment for their valuable comments. We thank the Ministry of Education of Peru for their willingness to collaborate, especially Anna Balbuena, Karim Boccio, Luz Jaramillo, Gelsys Meza, Cynthia Neira, and Carlos Venturini. Isabela Innocente Gomes provided outstanding research assistance. We thank Ingrid Olea for the graphic component of the intervention. We acknowledge the Inter-American Development Bank for funding the research presented in this paper. The opinions expressed in this publication are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent. The authors have no conflicts of interest or financial and material interests in the results. All errors are our own.

1 Introduction

Public education is fundamental to providing equality of opportunity for students of different socioeconomic backgrounds. Yet, in many countries, the widespread problem of teacher sorting (Jackson 2009, Lankford et al. 2002, Boyd et al. 2013, Pop-Eleches and Urquiola 2013) threatens this role: low-income students are more likely to attend schools with less qualified teachers and understaffed schools, thus exacerbating potential achievement gaps (Sass et al. 2012, Thiemann 2018). This problem is not only detrimental in terms of equity, but also in terms of efficiency: the sorting of candidates leads teacher assignment systems to be congested and, ultimately, does not optimize teachers' well-being as they risk their chances of securing a job vacancy. Although this problem of teacher sorting has been well-documented in the literature, policy responses have primarily focused on increasing compensation of hard-to-staff school positions, which is not only expensive but does not always have a significant effect on teachers' employment decisions (Glazerman et al. 2012, Rosa 2017, Elacqua et al. 2019).

In this paper, we present the results of an experimental evaluation of a low-cost nation-wide government program designed to reduce the sorting of candidates in the teacher selection process in Peru.[1] This novel program consisted of two behavioral strategies aimed at motivating teacher candidates to apply to job openings in disadvantaged schools, which are typically low-performing and understaffed. The strategies were designed based on insights from the behavioral economics and psychology literature, particularly with regards to psychological frictions and the determinants of altruistic behavior.

The decision to work in a disadvantaged school could be seen as a prosocial behavior, as the intent is to benefit others (i.e. students most in need). Prosociality is commonly fostered by a variety of motivations, which can be extrinsic (e.g., monetary incentives) and intrinsic (e.g., feelings of satisfaction derived from helping others in a purely altruistic way, Ariely et al. 2009).[2] Likewise, identity factors can also matter: teachers who perceive themselves as prosocial or altruistic (i.e., agents of social change) may apply to work in a disadvantaged school in an effort to align their behavior with the norms associated with their perceived identity (Akerlof and Kranton 2000, Kessler and Milkman 2016).

Relying on such insights, candidates in Peru's centralized 2019 teacher selection process (*Concurso*

[1] The experiment presented in this paper was conducted in every region of Peru, with the exception of the metropolitan area of Lima and the Constitutional Province of Callao. It covered 86% of the teachers applying to positions and 73% of teachers selecting vacancies in 2019. As it is explained in the pre-registration plan, we ran a different experiment in Lima and Callao. However, there was an implementation error in those two regions and therefore we were not able to analyze the treatment effects. We provide more details in Section 4.

[2] This is not an exhaustive list. Intrinsic motivations could include, for instance, a sentiment of fulfillment from working in a challenging environment. Image motivation might also be a factor.

de Nombramiento)– where participants apply for positions through an online platform after having passed a qualifying exam (*Prueba Única Nacional* - PUN)–were randomly assigned to one of two treatments implemented by the government to either make altruistic identity or external rewards more salient. Both strategies caused a shift in teachers' preferences (on average) and allocation patterns towards disadvantaged schools (among certain groups, such as high-performers), thus contributing to a reduction in teacher sorting.

In the "Altruistic Identity" (henceforth "Identity") treatment arm, the program sought to make teachers' prosocial/altruistic identity salient through a combination of three elements: (a) a five-minute "introspection exercise" that asked teachers to reflect and write about their motivations for choosing teaching as a career, (b) a set of text-messages priming their prosocial/altruistic identity (e.g., "Thank you for being an agent of social change"), and (c) pop-ups on the online application platform designed to prime this facet of their identity.[3] In the "Extrinsic Incentives" (henceforth "Extrinsic") treatment arm, the program made the monetary incentives for teachers working in disadvantaged schools simpler and easier to understand through a combination of three elements: (a) a five-minute exercise that asked teachers to reflect and write about the potential benefits associated with these monetary incentives (e.g., higher salaries or career path advantages from working in disadvantaged schools), (b) a set of text-messages reminding them about the rewards associated with these schools, and (c) pop-ups on the online application platform that showed simplified information related to the extrinsic rewards.[4] In simplifying the way the information was presented and highlighting the incentives, the strategy aimed to capture candidates' attention while also reducing the psychological frictions associated with the informational complexity of the process and the structure of the incentives.

Finally, the control/placebo arm replicated a similar structure as in the treatment arms: a neutral reflection exercise, complemented by a set of neutral text-messages (the same number of communications, but providing general information about the application process, without any components related to altruism, social change, or monetary rewards), and neutral pop-ups on the online application platform. Note that in all of the conditions, "disadvantaged" schools were labeled on the platform, making them easily identifiable by the candidates. To this end, we placed indicative icons next to each disadvantaged school that were identical in each of the three conditions (see Figure 1).

We find that both strategies were similarly effective in shaping teachers' preferences, on average: candidates in the treatment arms were significantly more likely to apply to vacancies in disadvantaged

[3] The phrasing of the text messages and pop-ups followed Bryan et al. 2011. That is, they were mostly framed as the enactment of a personal identity (e.g., "being an agent of social change") as opposed to a simple action (e.g., "someone who creates change").

[4] Emphasizing the monetary or career-related benefits of a job has recently been employed in other contexts, such as the public sector, as shown by Ashraf et al. 2018.

schools.[5] In particular, we find that the proportion of disadvantaged schools included in teachers' choice sets was respectively 1.9 and 2 pp higher in the "Identity" and "Extrinsic" arms (versus the control, from a baseline of 46%).

Interestingly, we find suggestive evidence of the effects being driven by male teachers. Indeed, the effect on the proportion of disadvantaged schools included in male teachers' choice set was 3.4 and 3 pp higher in the "Identity" and "Extrinsic" arms, respectively. This result is perhaps unsurprising considering that female teachers are usually less likely to select schools with longer commuting times (such as those targeted in the intervention) and are thus less likely to be affected by the treatment.[6]

When exploring outcomes related to assignment, we find that the "Identity" treatment arm was more effective than the "Extrinsic" one. The likelihood of being assigned to the final in-person evaluation in a disadvantaged school was 2.6 pp higher in the "Identity" treatment, and 6 pp higher among male teacher candidates. In the case of the "Extrinsic" treatment, we are only able to identify a significant effect on the likelihood of being assigned to the final in-person evaluation in a disadvantaged school among male teachers (3.7pp).

A hypothesis to explain this difference between the effectiveness of the treatment arms in terms of teachers' assignment is related to the *composition* of teachers affected by each type of intervention. While, on average, both treatments had a similar effect in terms of teachers' preferences, the "Extrinsic" arm was particularly effective among teachers with relatively lower performance in the qualifying exam (given that test scores are correlated with income, it is plausible that monetary incentives were more appealing for lower-score/income teachers), the opposite was true for the "Identity" arm. This difference is relevant because teachers with the highest scores are more likely to be assigned to their preferred choices.

Finally, we document a significant effect on the probability of being assigned to a disadvantaged school in the final stage of the process (after the in-person evaluation) among male teachers (3.4 pp) and, in particular, among high-performing male teachers (that is, a teacher who scored above the median on the qualifying exam; 5.2 pp), only in the "Identity" arm.

These are important results, as they suggest that such strategies — in particular, the "Identity arm" — might help to successfully mitigate the widespread problem of teacher sorting in education, and, as a result, the socioeconomic achievement gap (Thiemann 2018).[7]

5 We provide a detailed description of the teacher selection process in Section 2.

6 See for instance Bertoni et al. 2019.

7 Because the targeted schools (i.e., "disadvantaged schools") are typically less prone to being selected by candidates, the Peruvian government provides additional incentives for teachers who decide to work in these institutions: monetary rewards and the possibility of more rapid professional advancement. Since this external rewards incentive scheme is in place in all three conditions, the results of this experiment should be interpreted as the effect of the two interventions on teachers' preferences and allocation patterns.

Our paper relates to several strands of the literature in behavioral economics and education. First, it builds on research on teacher sorting and inequality. A vast literature shows that low-income and low-performing students are more likely to attend schools with less qualified teachers (Boyd et al. 2006, Dieterle et al. 2015, Feng and Sass 2018, Lankford et al. 2002, Jackson 2009, Sass et al. 2012) and that limited access to better teachers has a negative impact on their educational outcomes (Aaronson et al. 2007, Sass et al. 2012, Thiemann 2018). However, relatively little work has been conducted on the strategies that might mitigate teacher sorting. Moreover, most of these studies focus on monetary incentives, which have been found to have a small or non-significant impact on teachers' preferences for disadvantaged schools (Clotfelter et al. 2008a, Falch 2011, Glazerman et al. 2012, Springer et al. 2016, Rosa 2017, Bueno and Sass 2018, Feng and Sass 2018, Elacqua et al. 2019). We add to this literature by showing how a novel low-cost behavioral intervention can complement and improve the effectiveness of extrinsic rewards.

Second, our paper intersects with a growing literature on the economics of identity. Numerous studies in economics and psychology show that identity is malleable and that the facets of one's sense of self (gender, profession, ethnicity, religion) can be salient at different moments (Nolan et al. 2008). Since deviating from the prescriptions associated with one's identity is costly (Akerlof and Kranton 2000), people endeavor to adjust their behavior to align with their own identity. Interventions that prime specific facets of individuals' identity and thus make them salient have accordingly proven to be effective in influencing behavior in a number of contexts.

For instance, Kessler and Milkman 2016 show that priming the facet of individuals' identity associated with a generosity norm significantly increased donations. Similarly, Benjamin et al. 2010 demonstrate that making ethnic identity salient affects individuals' risk aversion in a way that is consistent with stereotypes. Meanwhile, Benjamin et al. 2016 provide evidence that priming religious identity affects key economic decisions, such as the contribution to public goods. We complement these papers in several ways. First, unlike most of the experimental literature on this topic (Kessler and Milkman 2016 being a remarkable exception), our setting is a large-scale field experiment, as opposed to a lab experiment. Second, we show how identity priming affects real-life decision making in a high-stakes context. In particular, our study provides experimental evidence that identity affects a relevant yet little explored economic domain: individuals' employment decisions.

Our paper is also related to the literature on the ways external rewards affect prosocial or altruistic behavior (Deci 1975, Bénabou and Tirole 2006). The empirical evidence thus far is mixed. In some contexts, scholars document a crowding-out effect (Gneezy and Rustichini 2000, Frey and Oberholzer-Gee 1997 and Mellström and Johannesson 2008), while others show a positive effect of economic incentives on prosocial behavior (Lacetera et al. 2012, Goette and Stutzer 2020, Lacetera et al. 2014). We complement such studies by showing that, even without varying the real economic incentives, making them more salient has a significant positive effect on prosocial behavior. This means that, if there was crowding-out, it was offset by the effect of the external rewards.

Finally, our paper builds on the literature that shows how subtle reductions in psychological frictions can improve take-up rates in diverse settings, from student applications for financial aid (Bettinger et al. 2012), to social benefits claims (Bhargava and Manoli 2015). With specific regard to incentives for teachers, empirical evidence suggests that the eligibility criteria and differential compensation schemes often appear complex to teachers (Clotfelter et al. 2008b). Our study contributes to this literature by showing how a subtle intervention that makes information on monetary rewards both more salient and easier to understand can significantly increase the effectiveness of financial incentives programs.

Furthermore, the potential policy implications of these insights are substantial. The strategies we evaluate here were designed to address a fundamental problem in education and, more generally, in development: teacher sorting and teacher shortage in vulnerable areas. From the perspective of the teachers, diversifying their options could be very beneficial, as they can increase their chances of getting a job. When most teachers apply to few job vacancies, the system becomes very congested and many candidates end up without a position (in 2018, for instance, out of the 22,000 teaching candidates that applied to vacancies after passing the qualifying exam, only 46% were assigned to a full-time permanent position).

Moreover, reducing teacher sorting is very relevant for equity purposes. Indeed, teachers are a crucial input in the education production function as they have a significant effect on students' test scores (Rivkin et al. 2005, Kane and Staiger 2008), non-cognitive outcomes such as absenteeism and school suspension (Ladd and Sorensen 2017, Jackson 2018), as well as long-term outcomes, including college attendance, earnings, and teenage pregnancy (Chetty et al. 2014). Importantly, teachers' impact has been found to be larger among low-performing and low-income students (Aaronson et al. 2007, Araujo et al. 2016, Marotta 2019, Elacqua and Marotta 2020). Yet, disadvantaged schools experience more severe shortages of teachers and often fail to attract higher quality professionals (Sutcher et al. 2016, Dee and Goldhaber 2017, Bertoni et al. 2020).[8] The concentration of teacher shortages and lack of high-quality instructors in more vulnerable schools has serious implications for social inequalities in education.

[8] According to the literature, teachers have stronger preferences for specific school characteristics. In general, they prefer to work close to where they live or to where they grew up, as well as prefer to teach in urban schools (Boyd et al. 2005, Reininger 2012, Rosa 2017, Bertoni et al. 2019). Moreover, teachers tend to avoid schools with higher concentrations of low-income and low-performing students (Carroll et al. 2000, Engel et al. 2014, Bertoni et al. 2019).

Our paper shows that low-cost, easy to scale, behavioral strategies can help to improve the equity and efficiency of the system, by mitigating teacher shortages in disadvantaged schools and increasing the flow of qualified teachers to low-performing institutions.

We proceed as follows. Section 2 provides background information on the teacher selection process in the Peruvian public school system. Section 3 describes the characteristics of the disadvantaged schools and the external rewards scheme. Section 4 presents the experiment while Section 5 introduces the data and the empirical strategy. Section 6 provides the main results and interpretation. Finally, Section 7 concludes.

2 Institutional Context

2.1 Government efforts to reduce teacher sorting in Peru

In Peru, teacher sorting has always been a concern for the central government, for its harmful implication for students in disadvantaged schools and for its inefficiency (that is, in a "congested" market like Peru's teacher allocation system, many teachers end up without a position, while many vacancies remain unfilled). Many of the government policies are, thus, oriented towards alleviating this problem. Among those, probably the most important one is a policy that rewards teachers who work in disadvantaged and understaffed schools with a salary enhancement and faster career progression.

Other government policies to improve Peru's teacher allocation system includes adjustments in the algorithm that assigns teachers to school vacancies, improvements in the usability of the application platform, and increasing information about school vacancies so that teacher candidates can make more informed choices. In this context, and given budget constraints in the last few years, Peru's Ministry of Education has been working on several low-cost strategies to improve educational policies[9].

The government policies evaluated in this paper aimed at improving the quality and transparency of information provided throughout the teacher application process with an objective to motivate teachers to apply to understaffed schools, while not restricting their choices. To achieve this goal, the messages used in the treatment were tested in focus groups organized by the government with local teachers in order to ensure that the information was clear and not misleading. Moreover, the platform clearly stated that none of the exercises involved in the treatment were mandatory and that they would not have any consequences to the application results.

[9] For instance, in 2016, Peru launched the "MineduLAB", an innovation laboratory that promotes innovation and learning through the design, implementation, and evaluation of cost-effective educational policy interventions. See http://www.minedu.gob.pe/minedulab/.

2.2 Teacher selection process in the Peruvian public school system

The government program under analysis was implemented during the 2019 teacher selection process, which followed the standard procedures that have governed the system since 2015.[10] To be eligible to apply for a teaching position in the public system, candidates must hold a bachelor's degree in education as well as pass two consecutive evaluation stages: a national-level assessment and then a final in-person evaluation.

The first stage is carried out by the Ministry of Education (MINEDU) and includes a standardized written test (the *Prueba Única Nacional* - PUN) comprising three sub-tests: logical reasoning (25%), reading comprehension (25%), and pedagogical knowledge of the specialization (50%). Applicants, are evaluated within a specific area of specialization in terms of school level (pre-primary/primary/secondary) and subject area (e.g. secondary sciences), and must answer at least 60% of the questions correctly on each sub-test in order to pass and continue on to the next stage. The PUN passing rate has been consistently low in each teacher selection process: 13% in 2015, 11% in 2017, 12% in 2018 and 7% in 2019.

Only those candidates who score above the required threshold are eligible to apply to school vacancies within their area of specialization and within one of the 26 regions of Peru (our sample covers 24 out of the 26 regions).[11] In this stage, candidates select and rank their preferred vacancies, choosing as many available posts as they like. The MINEDU uses a a matching algorithm that takes into account the PUN score and candidates' ranked preferences, ultimately assigning them up to two vacancies. Candidates who missed the first round of vacancy selection or who were assigned to only one or no vacancy can participate in a second round of vacancy selection. Each vacancy can have up to 6 candidates.[12]

Once candidates have been assigned to up to 2 of their preferred school vacancies, they are assessed through a final in-person evaluation, which is carried out by the school or by the local education administrative unit (*Unidad de Gestión Educativa Local* - UGEL) in the case of a single-teacher institution. This final stage of the selection process includes an examination of the teacher's resume (25%), a personal interview (25%), and a mock lesson (50%). To pass this final evaluation, candidates need a score of 30 points (out of 50) on the mock lesson component.

Finally, the MINEDU uses the weighted sum of the scores obtained at the national stage and for the

[10] The most relevant change being that from 2017 onward in which teachers could select and rank an unlimited number of vacancies of their choice, while in 2015 they could select and rank a maximum of 5.

[11] Peru counts 24 regions and 2 provinces with special regime, namely, the Lima Metropolitan Region and the Constitutional Province of Callao.

[12] One school can have more than one vacancy in the same subject area, in which case, each vacancy can have up to 10 candidates.

final in-person evaluation (the former has a weight of 67% on the final score) to allocate teachers to a vacancy based on both merit and the candidate's preferences.[13] Our paper mainly focuses on the effect of identify priming and extrinsic rewards priming on teachers' preferences for vacancies in disadvantaged schools during the first, national stage. However, we also report the impact of both treatments on the probability of participating in the final in-person evaluation at a disadvantaged school and on the probability of being finally assigned to a disadvantaged school at the end of the process. Figure 2 summarizes the 2019 teacher hiring process in Peru.

3 Disadvantaged schools and the external rewards scheme

In order to address teacher sorting, the program targeted disadvantaged schools. Indeed, such institutions tend to be avoided by teachers and are therefore more likely to suffer instructor shortages as well as have a higher proportion of temporary and low-performing teachers. Not surprisingly, these schools are often concentrated in the most vulnerable areas.

In this regard, Table 1 shows that out of the 12,300 public schools that had vacancies in the 24 regions of Peru in 2019, 6,424 (52%) were not selected by any candidate at the national stage. The difference in terms of observable characteristics between these two groups of schools is striking and illustrates teacher preferences for more advantaged institutions: those not selected are notably more rural, farther from the province capital, with less access to basic services, and with a greater proportion of low-performing students (these preferences are consistent with the findings in other papers; see, for instance, Bertoni et al. 2019).

In light of such patterns and preferences, in 2013, the Peruvian government implemented a reward scheme to attract teachers to disadvantaged schools. Regardless of the type of contract, teachers' monthly salaries are composed of a basic wage (*Remuneración Integral Mensual* - RIM), incentives, benefits, and bonuses. The RIM is determined according to the teacher salary scale and working hours. The salary scale is composed of 8 levels, where the (8th) highest level corresponds to 210% of the lowest salary level. All new teachers in the public system receive the first (lowest) salary level of S/2200 (approx. $650).[14] Permanent teachers can increase their salary through public contests after completing the time requirements in each level, while temporary teachers only receive the salary amount corresponding to the lowest level.

13 In case of a tie in the final score for the same vacancy, the Ministry of Education applies the following criteria in order of priority to identify a single winner for each vacancy: (1) higher score on the classroom observation; (2) higher score on the pedagogical knowledge of the specialization sub-test; (3) higher score on the resume in terms of educational and professional training; (4) higher score on the resume in terms of professional experience; (5) higher score on the resume in terms of merits. If the same applicant wins for more than one vacancy, the MINEDU automatically assigns the vacancy with the highest priority level, according to the preferences of the applicant.

14 This amount increased to S/2300 in 2020.

The monetary incentives are offered to teachers who work in schools in certain locations and with specific characteristics (see Table 2). Locations include: (1) rural areas, spanning from 3% to 23% of the basic salary according to the "gradient of rurality," defined at the central level based on population size and accessibility to the nearest provincial capital (i.e., Rural 1, Rural 2, and Rural 3, where Rural 1 defines the most remote schools); (2) frontier areas, corresponding to 5% of the basic salary; and (3) the Valle de los Ríos Apurímac, Ene y Mantaro (VRAEM), a remote area with high levels of poverty, corresponding to 14% of the basic salary. School characteristics include: (1) single-teacher institution, corresponding to 9% of the basic salary; (2) multi-grade school, corresponding to 6% of the basic salary; and (3) bilingual school, corresponding to 7% of the basic salary. Teachers can receive up to 5 incentives if they are not mutually exclusive, and permanent and temporary teachers receive the same amounts. Alva et al. 2017 analyze Peru's teacher compensation scheme and find that offering higher wages for teachers in Rural 1 schools increases the probability that vacancies are filled by 10 percentage points.

In addition to monetary rewards, there are also non-monetary incentives for permanent teachers who work in disadvantaged schools. For example, working in a rural or frontier area increases permanent teachers' reallocation opportunities and shortens the time of service required before being eligible to apply for a higher salary scale. In other words, teachers in these schools can advance their careers at a faster pace.

The schools targeted by the government–referred to as "disadvantaged schools"–are those institutions that fall under this incentive scheme (rural of any type, in the VRAEM area, in frontier regions, bilingual, single-teacher and/or multi-grade). Two premises guided the implementation of the behavioral intervention. First, that the choice of school by the government is based on an objective criterion (i.e., real needs of the government/education system). Second, that we would test the two strategies targeting exactly the same schools. Since one of the strategies endeavors to prime existing extrinsic rewards, the other strategy could target only those schools that were eligible for both the monetary and non-monetary scheme.

There is consequently an important caveat to the interpretation of our findings. Since the evaluation targeted schools that were eligible for the governments' reward scheme, we consequently interpret the results of the "Identity" treatment as the effects of making altruistic identity salient on teachers' preferences only when an extrinsic reward is already in place.

Figure 3 presents the distribution of disadvantaged schools across the 24 regions of Peru, while Figure 4 shows that the targeted ("disadvantaged") schools are notably poorer, farther away from the province capitals, and more likely to be under-staffed and have temporary and low-performing teachers. Thus, by definition, if the treatments are effective, they can reduce the sorting of teachers across schools.

4 Experimental design

4.1 Final sample and adjustments to the pre-analysis plan

The experiment was implemented in the 2019 Peruvian national teacher selection process. The evaluation involved 11,568 teacher candidates who successfully passed the national assessment stage of the selection process in all regions of Peru with the exception of those in the Lima Metropolitan Region and the Constitutional Province of Callao (our sample represents approximately 86% of the total pool of applicants in Peru). These two provinces were excluded from the main experiment because none of their schools provide monetary incentives to attract teacher candidates.

As we explained in our pre-registered analysis plan, we ran a similar experiment in these two provinces that included only one treatment (the "Altruistic Identity" arm). Moreover, in that experiment, the definition of "disadvantaged schools" was created *ad hoc*: schools that were in the bottom quintile of the math performance distribution in each region according to Peru's 2018 national standardized test. Unfortunately, in the case of Lima and Callao, there was an implementation problem. To conduct the *ad hoc* classification, schools were ranked according to their performance in math, but the system did not separate primary and secondary schools. By construction of the scales, secondary schools have higher performance than primary schools, and, thus, the sample of disadvantaged schools was mostly composed of primary schools, losing most of the variation–that is, on the platform, primary school teacher candidates only could see schools labeled as "disadvantaged," while second school teacher candidates mostly saw schools without that label. We thus discarded the experiment in Lima and Callao and kept only the one correctly implemented for the rest of the country.

The candidates in our experiment are at the top of the performance distribution given that the national assessment stage is highly selective: in 2019, out of the 183,569 participating teacher candidates, only 11,568 (6%) passed the PUN and could participate in the final evaluation stage. We randomly assigned these 11,568 teacher candidates to three groups, stratified by region: 3,861 (33%) were assigned to a control group (henceforth, Control - C) and received the "Neutral"/placebo intervention, 3,852 (33%) were assigned to the "Identity" treatment group, and 3,855 (33%) were assigned to the "Extrinsic" treatment group.

Out of these 11,568 candidates, 9,690 (84%) ranked their preferences while the remaining 16% dropped out of the process. Although we do not know why these candidates left the process, we can test if dropout correlates with the allocation to different treatment arms, which could undermine the validity of our results. In Table 3 (Columns 1 and 2 of Panel A) we show that the probability of a teacher dropping out (not selecting vacancies) is not statistically different between treatment and control groups. In the same table (Panel B) we also show that the sub-sample of teacher candidates who dropped out do not differ in their observable characteristics between each arm.

Finally, we excluded from the sample the candidates located in districts where there was no variation in vacancies in terms of disadvantaged schools–that is, either districts where all of the available vacancies were located in disadvantaged schools or districts where there were no vacancies in disadvantaged schools (this restriction excludes 2,085 individuals). Although it is theoretically possible, applying to a position that requires moving is extremely unlikely in this context (as an example, 50% of the candidates select vacancies between 1 and 2 districts and less than 15 km away from the province capital). We also excluded teacher candidates who were applying to special and alternative education programs (167 individuals), which by definition are restricted in the set of options they have (applying to these schools is a decision made by teachers at the moment of taking the PUN and therefore is, by definition, unaffected by the treatments). In Table 3 (Panel A, columns 3 and 4) we show that the probability of being excluded from the final sample for any of these reasons (no variation or teaching in alternative education programs) does not differ across treatment arms. Moreover, in section 5 we show that these exclusions did not trigger any unbalance in the final sample in terms of observable characteristics. In our pre-registered analysis plan, we did not anticipate the fact that some districts lacked variation in the type of schools and, therefore, our plan did not include this restriction. Thus, for transparency purposes, we also show in the Appendix our results including the full sample of teacher candidates.

Our final sample comprises of 7,217 individuals. The experiment was conducted between August and September 2019 and combined three components – text messages, an online exercise, and pop-ups – described in detail below. Every effort was made to ensure that the structure of the intervention was as similar as possible across these three groups.

4.2 Design of the treatment arms

The "Identity" treatment arm takes inspiration from studies in behavioral economics, cognitive psychology, and the economics of identity. While teachers' identities have multiple facets, a vast literature shows that norms or prescriptions related to altruism and prosocial behavior are notably present in instructors' motivation and sense of self. Such norms include the importance of helping children to thrive, making a contribution to society or, more generally, assisting others (Brookhart and Freeman 1992, Saban 2003, OECD 2005, Richardson and Watt 2006, Thomson et al. 2012). This treatment arm was designed to make these prescriptions more salient right before teacher candidates chose specific school vacancies.

The "Extrinsic" treatment arm was guided by two strands of the behavioral economics literature. First, a number of papers emphasize the power of salience in capturing individuals' attention (Taylor and Thompson 1982, Kahneman 2003). Even when the necessary information is readily available, making a particular feature of the latter more or less apparent has been shown to drastically affect choices in different settings, particularly in the presence of limited attention or cognitive overload (see for instance Chetty et al. 2009, DellaVigna and Pollet 2009, Ajzenman and Durante 2020). Although the external rewards scheme was present in every condition, this arm aimed to make it prominent at a targeted moment. Second, this "Extrinsic" strategy draws on the behavioral economics literature on psychological frictions (Bhargava and Manoli 2015, Mani et al. 2013). Such studies demonstrate that psychological frictions associated with informational complexity can affect individuals' economic decisions (Bettinger et al. 2012, Hoxby et al. 2013, Bhargava and Manoli 2015). By simplifying the way information was presented, this treatment aimed to reduce informational complexity and confusion.

Finally, the control/placebo arm replicated the structure of the treatment arms, providing more general information that did not prime either individual's intrinsic or extrinsic motivations. Each of the three arms was designed to have exactly the same structure, comprised of three components: Component I (text messages), Component II (an online exercise) and Component III (on-platform pop-ups). The only difference between arms is thus the content of the messages, exercises, and pop-ups included in the intervention.

4.3 Component I (8/2/2019 - 9/7/2019): Text messages

A total of 10 text messages, summarized in Table 4 (reported in original language in Table A1), were delivered to the candidates in each group during the application process. [15] Although the number and frequency of the messages were identical in each condition, their content varied in order to emphasize either the altruistic identity facet, extrinsic rewards, or neither in the case of the control.

Component I - "Identity" treatment arm

The "Identity" text messages were based on the idea, as shown in several papers, that prosocial behavior can be fostered in different settings using priming techniques that make altruistic identity more salient. For instance, Kessler and Milkman 2016 demonstrate that priming altruistic identity with simple reminders in donation request letters (such as "date of last donation" or "community belonging") significantly increased the likelihood of previous donors contributing again. In our setting, general

[15] We were able to verify that 97% of the candidates in both treatment arms received the text messages, whereas text messages were successfully delivered to 100% of the candidates in the control group.

reminders (e.g., "In a few days, you will be able to select your preferred vacancies") were sent along with messages aimed specifically at priming teachers' altruistic identity, such has, "Thank you for improving lives" (message #1), "Thank you for being an agent of social change" (message #2) or "Thank you for choosing to improve lives" (message #6). Another text emphasized their "teacher vocation" (#3), similar to the approach used in Kessler and Milman's (2016) letters. Lastly, in light of prior research (Aaronson et al. 2007, Araujo et al. 2016), the text messages sent in this treatment arm also underscored that, in certain schools, teachers could have a greater impact on student learning. The idea being to remind teachers that they belong to a group of people characterized by norms/prescriptions involving a commitment to social change. The 10 text messages can be summarized as follows:

1. **Identity:** 6 messages containing tailored information for the treatment group, which emphasized teachers' altruistic identity.
2. **General information:** 4 general reminder messages, identical for all teachers (treatments and control). These texts provided basic information relevant for all of the candidates: information about the application rounds, extension dates, and reminders to make a selection (if they hadn't already done so).

Component I - "Extrinsic" treatment arm

Messages in this condition were designed to make the incentive benefits (salary enhancement and faster career progression) provided to teachers who work in disadvantaged schools more salient and easier to understand. For instance, message 1 reminded candidates that working in disadvantaged schools could increase their salary by up to S/1150 (nearly $350) and message 3 pointed out that they could advance faster in their careers if they worked in a disadvantaged school. The 10 texts consisted of:

1. **External rewards:** 6 messages containing tailored information for the treatment group, which emphasized monetary incentives and the possibility of a more rapid career advancement when working in a disadvantaged school.
2. **General information:** 4 general reminder messages, identical for all teachers (treatments and control). These texts provided basic information relevant for all of the candidates: information about the application rounds, extension dates, and reminders to make a selection (if they hadn't already done so).

Component I - "Control/Placebo" arm

All 10 messages in this condition were general and neutral, and made no reference to either the altruistic facet of teachers' identity or to the external rewards scheme. They provided basic information relevant for all of the candidates: information about the application rounds, extension dates, and reminders to make a selection (if they hadn't already done so).

4.4 Component II (8/7/2019 - 9/7/2019): Online exercise

The second component was implemented on the online platform, just before candidates made their choice of vacancies. At this crucial moment, they were asked (in both the treatment arms and the control) to complete a voluntary written exercise. While the structure of the exercise was the same for all groups, the question asked varied in each condition. The complete set of questions is presented in Table 5, and in its original language in Table A2.

Component II - "Identity" treatment arm

Individuals in this group were asked to complete an "introspection exercise," designed to prime teachers' altruistic identity. Specifically, the platform asked them to take five minutes to share the main reasons why they had chosen to become teachers.

This component draws on other papers that have used similar techniques to prime facets of individuals' identity. A prototypical example is Cohn et al. 2014, in which the authors prime bank employees' professional identities by asking questions about their professional background (e.g., "At which bank are you presently employed?", "What is your function at this bank?"). Using a similar procedure, Benjamin et al. 2010 make ethnic identity salient by asking questions such as "What languages do you know?", "Do your parents or grandparents speak any language other than English?", "What language do you speak at home?", while LeBoeuf et al. 2010 asking questions such as "Where were you born?" or "What is your favorite Chinese holiday?" To maximize the effectiveness of this type of intervention, the exercise implemented here varied in two ways. First, a single question required teachers to provide a comparatively more elaborated answer (as opposed to responses to multiple, simple questions). Second, teacher candidates had five minutes to complete this exercise, thus allowing for time to reflect before answering.[16]

Component II - "Extrinsic" treatment arm

The online platform asked this group to complete an identically structured introspective exercise as

[16] A simple text analysis of their answers shows that, as expected, the treatment was effective in directing their thoughts towards altruistic identity norms. Of those who completed the exercise (around 80% of our sample), 50% used words associated with an altruistic identity: "society," "social," "change," "help," "need," "change lives," "future," "serve," "transform."

that implemented in the "Identity" arm, but in response to a different question: "In what way do you think monetary incentives promote teachers' welfare?" The goal being to make the extrinsic rewards (particularly the monetary incentives) more salient precisely when teachers had to select vacancies. Specifically, the question aimed to encourage teachers to think more concretely about how they could benefit from earning a higher salary. [17]

Component II - "Control/placebo" arm

The platform asked this group to complete an identical introspective exercise as that used in the "Identity" and "Extrinsic" arms, but asked a different, more neutral, question: "What is your opinion about the registration process for the 2019 teacher selection competition?" The goal being to motivate candidates to reflect on aspects completely unrelated to extrinsic rewards or altruism.

Figure 5 presents the results of a basic text analysis of the different groups' responses. We observe that in the "Identity" treatment arm, the answers often included words more closely related to social change, such as "vocation," "change," "society," and "values." In the "Extrinsic" treatment arm, several candidates mentioned "improving quality of life." Finally, candidates in the control group used words related specifically to the teacher selection process itself, such as "information," "vacancies," and "easy."

4.5 Component III (8/7/2019 - 9/7/2019): Pop-ups

Like the introspective exercise, the final component was also implemented through the online application platform. When using the platform (across the conditions), teacher candidates viewed a list of schools within their region and specific field (e.g., secondary-sciences) and needed to select and rank their preferred vacancies. Furthermore, across the groups, the applicants had access to a basic set of information about each school: its local education administrative unit (*Unidad de Gestión Educativa Local* - UGEL), school ID, name, type, and management (public with public management or public with private management). They also saw all of the characteristics related to the monetary incentives (i.e., whether the school is rural of any type, in the VRAEM area, a frontier region, bilingual, single-teacher and/or multi-grade).

In order to facilitate the easy identification on the platform of the disadvantaged institutions targeted by the government, the schools were labeled with icons highlighting their associated incentive scheme. Specifically, these consisted of a money bag in reference to the monetary incentives, a ladder

[17] A simple text analysis of the teachers' answers shows that, as expected, the treatment was effective in making them think in these terms. Of those who completed the exercise (around 65% of our sample), almost 60% used words associated with money, professional career, or monetary expenditures: "quality of life," "solvent," "family," "masters," "professional," "economic."

icon highlighting the opportunity for faster career progression, and a school within a heart indicating places where teachers could have a greater social impact. These icons were shown to all teachers, regardless of the treatment condition (see Figure 1). All disadvantaged schools were labeled with the three icons–that is, both the extrinsic and identity rewards were accentuated.

Importantly, in all three arms, when teachers hovered their mouse cursor over the icon, a small pop-up was displayed with a description of the icon. Although all groups saw the same general information (monetary incentives, faster career progression, and high social impact), there were subtle differences in the phrasing of these pop-ups across the arms so as to make either altruism or external rewards more salient. Teachers in the control group viewed only objective information.

Component III - "Identity" treatment arm

For this group (Figure 6), the pop-up linked to the "heart" icon included subtle cues aimed at priming the altruistic facet of teacher candidates' identity. Specifically, the pop-up text read that such schools with greater needs require "teachers like you" (thus suggesting that the teacher candidate belongs to a particular group of people that want to help more vulnerable students). In addition, the pop-up included a message in bold ("do not miss the opportunity to be an impactful teacher"), reinforcing the idea that teachers who care more about social impact tend to select these schools. Finally, the pop-up also contained an image evoking the norm of generosity/prosociality that we endeavored to trigger.

Note that both the text messages and pop-ups were intentionally phrased in such a way as to make "altruistic identity" even more salient. Following Bryan et al. 2011, we framed most of the messages for this group as the enactment of a personal identity (e.g., "being an agent of change") as opposed to a simple action (e.g., "generate a change"). Indeed, use of a self-relevant noun instead of a verb is important, as nouns have been proven to encourage people to see attributes as more representative of their own characteristics (i.e., identity) across different settings (Gelman and Heyman 1999, Walton and Banaji 2004).[18]

Component III - "Extrinsic" treatment arm

For this group (Figure 7), the two pop-ups linked to the external rewards icons were designed to be particularly salient. First, the pop-up linked to the "money bag" icon contained specific information about the amount of the monetary reward–e.g., "In this school you could receive up to X monthly additional soles" (where X varied depending on the type of school)–and a note in bold adding, "Don't miss the opportunity to increase your monthly salary!" The idea being not only to emphasize the existence of the monetary incentives but also to simplify the provided information by displaying a specific

[18] A few exceptions were made in the text messages where using a noun rather than a verb sounded unnatural (such as message # 10 in Table 4).

amount of money. Although the information about the monetary incentives is publicly available, the pop-up providing candidates with the exact monetary reward associated with each school was a means of saving them the cognitive cost of doing the calculations themselves. This strategy was guided by the premise that small cognitive costs can represent substantial psychological friction (Bhargava and Manoli 2015, Mani et al. 2013).

Second, the pop-up linked to the "ladder" icon showed an image of a person walking up stairs along with a heading indicating that "In this school you could advance faster in your teaching career" and a note in bold reading "Do not miss the opportunity to boost your professional career!"

Component III - "Control/Placebo" arm

In the control arm (Figure 8), the pop-ups were informative but written in a comparatively neutral tone. In the case of the "money bag" icon, the pop-up text simply read "School with monetary incentives"; that related to the "ladder" icon indicated "School that provides faster career progression"; and the pop-up linked to the "heart" icon said "School where you can generate greater change in student learning."

It should be noted that the teacher candidates were exposed to all three intervention components, according to their treatment condition. Thus, while all of the components have the same objective (e.g., making teachers' identity salient), we are not able to isolate each component.[19]

5 Empirical strategy, data, and balance tests

This paper uses administrative data from the 2019 public school teacher selection process in Peru. The data include candidates' application by school level (pre-primary/primary/secondary) and subject, demographic characteristics (gender and age), teacher scores at every stage of the competition, ranked school preferences within a region, assigned final in-person evaluations, and, finally, the school where they were appointed a position. Moreover, for each school that opened a vacancy, the data include school characteristics such as location (region, province, district, UGEL), area (urban/any type of rural), type (multi-teacher, multi-grade or single teacher), and an indicator of whether the school is bilingual, in the VRAEM area, or in a frontier region.

[19] The texts used in all the three components were validated in two focus groups (organized by the Promotion of Welfare and Teacher Recognition Division in the Ministry of Education) with teachers in the regions of Ayacucho and Loreto. The components were tested to verify that teachers understood the text messages and the written exercise and that language was not perceived as hostile or threatening (so to avoid triggering stress, a sense of stigma, guilt, or loss of autonomy among teaching candidates). User experience on the platform was also tested in the Lima Metropolitan Region. Documentation of the focus groups is available upon request.

Table 6 presents a summary of the candidate-level variables used in the model estimation. The group of teacher candidates considered in our analysis is 64% female, 36 years old on average, and scored 144/200 on average on the PUN (where the passing score is 120/200). Less than 1% of the candidates are disabled, while 51% scored below the PUN median (henceforth, "low-performing"). Of the candidates that participated in the national assessment stage, 79% were assigned a final in-person evaluation. The average choice set is composed of 47% vacancies labeled with an icon on the online platform ("disadvantaged" vacancies); 81% of candidates included at least one disadvantaged vacancy in his/her preference set, and 53% of these individuals were assigned to a disadvantaged school in the final in-person evaluation.

Table 7 presents balance tests for the candidates in our sample that selected vacancies in the regions of the experiment. As expected, given the random assignment, candidates in each treatment arm and in the control group are very similar in every observable characteristic.

5.1 Empirical strategy

To measure the overall impact of the information provision on different teachers' selection outcomes, we run regressions of the following form:

$$y_i = \alpha T_i + X_i\beta + \varepsilon_i \tag{1}$$

where y_i is a "preference" or "assignment" outcome for teacher candidate i. The choice set for each candidate is the set of available vacancies within one of the regions (24 in our sample) and a specific area of specialization (educational level and subject, e.g., Secondary-Sciences). T_i is a dummy that indicates whether candidate i received either one of two treatments, and X_i is a vector including a constant and candidate control variables, namely age, gender, disability, and score on the PUN. We also control for region dummies (there are 26 in our sample), the variable that we used to stratify our sample.

The analysis follows closely the pre-analysis plan. We include three set of outcomes. (A) Two outcomes related to the inclusion of disadvantaged schools in teachers' choice set: the proportion of disadvantaged schools selected by teacher candidate i and a dummy indicating whether she applied to at least one vacancy in a disadvantaged school; (B) a set of outcomes related to the ranking of the disadvantaged schools in the teachers' choice set (that is, higher or lower priority); (C) a set of outcomes related to the teachers' assignment to schools. For this category we include four outcomes: if the teacher candidate i was assigned to a disadvantaged school for the final in-person evaluation; if she was assigned to *any* school for the final in-person evaluation; if she was assigned to a disadvantaged school in the (second) final stage; and if she was assigned to *any* school in the (second) final stage.

6 Results and interpretation

Tables 8 through 13 show the estimations for the main outcomes. For each outcome we present five set of results: the main model for the full analytical sample and the same model estimated for four sub-samples that provide interesting suggestive insights. The sub-samples are the following: female candidates, male candidates, low performing candidates, and high performing candidates. Each model includes all the relevant controls described in Section 5. For the assignment outcomes, we also present the results for a sub-sample of "male-high performing" candidates. A candidate is classified as "Low performing" if her score on the PUN was below the median. It is important to emphasize that, given how strict the qualifying exam is, our sample is composed of the very best teacher candidates in the country and, thus, "low performing" should be interpreted in relative terms.

These two pre-registered heterogeneous effects (by gender and by performance) are particularly relevant for several reasons. First, teachers' preferences tend to be systematically different between men and women, the latter being significantly less likely to teach in poorer and remote regions. This may be due to different levels of labor flexibility for these groups. Such patterns, which have already been documented in the literature (see Bertoni et al. 2019), are confirmed in our sample.[20] Given how remote the disadvantaged schools are (approximately four times farther away from the province capital than the rest of the schools), it is plausible that the treatments were not effective among individuals with lower mobility (e.g., those for whom commuting longer distances is more costly), who are more often women.

The second heterogeneity analysis (high- and low-performing teachers) is also relevant, especially from a policy perspective. Attracting *any* of these teachers to disadvantaged schools–even if they are at the bottom of the sample distribution–would be a positive outcome, since our sample is comprised of top candidates that successfully passed a qualifying exam (PUN). However, the higher the quality of applicants and winners of vacancies in disadvantaged schools, the more effective the treatment would be in alleviating teacher sorting.

[20] For instance, when assessing teachers' preferences in the control group, we observe that female teachers are much less likely to apply to vacancies in disadvantaged schools. The share of disadvantaged schools included in an average male choice set is around 50% while, for females, the share is around 42%.

6.1 Main estimates

Disadvantaged schools in teachers' choice set[21]

As Table 8 shows, we find, on average, an increase of 1.9 ("Identity") and 2 pp ("Extrinsic") in the proportion of disadvantaged schools included in the teachers' choice set (with a mean of 46% in the control group, Columns "1"). In both cases, we find suggestive evidence that the effect seems to be driven by the male teachers, where the point estimate becomes 3.5 ("Identity") and 3 pp ("Extrinsic").

When analyzing the effects by performance on the qualifying exam, we find a particularly large effect for high-performing teacher candidates in the "Identity" treatment: 2.5 pp (versus 1.1 pp for low-performers). In the case of the "Extrinsic" treatment, we find a considerably greater effect for low-performing teachers: 2.5 pp (versus 1.5 pp for high-performers). Although these heterogeneous results are only suggestive (by design, the sample size is not big enough to identify significant effects on interactions), it is not surprising that the "Extrinsic" treatment seems to be larger for low-performers, as they usually come from relatively lower-income regions and, as a result, could be more responsive to monetary incentives.

As Column "2" of the same table shows, we also find significant and positive effects of the treatments on the probability of applying to at least one disadvantaged school. Specifically, we observe an increase of 1.8 pp and 2 pp in the probability of candidates including at least one disadvantaged school in their choice set - significant at the 10% level - in the "Intrinsic" and "Extrinsic" treatment arms, respectively. Similar to the previous results, the data suggest that the effects are being driven by males, for whom the magnitude becomes respectively 3.5 ("Intrinsic") and 3.3 pp ("Extrinsic") - significant at 10%. As in the previous estimation, the effect seems to be driven by high-performers in the "Identity" treatment (2.5 pp, although not precisely enough to be significant, versus an also insignificant effect of 0.7 pp among low-performers), while the opposite is true in the "Extrinsic" arm: 2.5 pp, significant at the 10% level, among low-performers versus 1.5 pp, insignificant, among high-performers.

Priority of disadvantaged schools in teachers' choice set

For candidates to be finally assigned to a disadvantaged school for the in-person evaluation, what matters is not only the proportion of disadvantaged schools they include in their choice sets, but also how high they rank these schools. In our data, the probability that a candidate participates in the final in-person evaluation in a school ranked below the 4th position in her choice set is only 38%.

[21] In this section we present the results using the sample described in Section 4.1. For transparency purposes, we also present the main results using the unadjusted sample in the Appendix (Tables A3 to A5).

To explore this, we analyze five different dummies: "Up to N" takes a one if at least one disadvantaged school was included in the first N positions of teachers' choice set, and "N" ranges from 1 to 5.[22]

Table 9 shows the results. Panel A (full analytical sample) shows a significant effect from N = 3 to 5 in the case of the "Extrinsic" arm, and only for N = 4 in the case of the "Identity" arm. As expected, the results become considerably larger in magnitude in the sub-sample of male teachers (Panel B), for both treatment arms. Also consistent with the previous results, Panel D shows that the effects for high-performers become insignificant for the "Extrinsic" arm while, in contrast, they become much larger in the case of the "Identity" arm. More importantly, in the "Identity" arm the effects are significant for N = 2, 3 and 4, meaning that, within the sub-sample of high-performers, the "Identity" treatment was effective enough to motivate candidates to include disadvantaged schools even as their second preferred choice.

In our sample, the probability that a school ranked below the 3rd position of a teacher's choice set is assigned to her in the decentralized stage is only 17%. In addition, naturally, high performers have a larger probability of being assigned to their top choices. Therefore, these results predict that, on average, the "Identity" arm should be relatively more effective in increasing the chance of being assigned to a disadvantaged school.

Assignment

We divide the assignment outcomes in two categories: first, the result of the decentralized stage, in which candidates are assigned according to an algorithm to up to two schools where they completed the final in-person evaluation (what we referred to as "1st stage" on tables 10 and 11); and, second, the final assignment of candidates to a school vacancy (referred to as "2nd stage"). As we explained above, this final assignment is based on candidates' performance–specifically, the weighted sum of their scores on the qualifying exam "PUN" (67%) and on the in-person evaluation (weights 33%)–and their preferences.

In Table 10 we show the results for the full analytical sample, male candidates, female candidates, high performers, low performers, and for high-performing males. For each sub-sample, column (1) refers to the probability of being assigned to at least a disadvantaged school in the "1st stage," and column (2) to the probability of being assigned to a disadvantaged school in the 2nd (and final) stage of the process.

We first document a positive and significant at 5% effect of the "Identity" treatment arm on the likeli-

22 Using the actual ranking of disadvantaged schools in teachers' preference set could provide an easier interpretation but it would be affected by a selection problem, as the probability of including at least one disadvantaged school in the set is directly affected by the treatment.

hood that a teacher was assigned to a disadvantaged school in the first stage (2.7 pp, being the mean in control of 51%). The effect was, again, probably driven my male teachers, where the magnitude reached 6 pp, significant at 1%. Interestingly, the magnitude among high-performers reaches 4.7 pp - significant at 5% - in the "Identity" treatment.

In the case of the "Extrinsic" treatment arm, we do not identify a significant effect for the full sample, but we do identify a positive and significant effect for males (3.6 pp) and for high-performers (both significant at 10%).

The fact that the "Identity" treatment arm was relatively more successful in assigning candidates to disadvantaged schools in the 1st stage is likely due to the fact that, in this arm, the effects on preferences were mostly driven by high performers, while the opposite was true in the case of the "Extrinsic" arm. This is important because low performers are unconditionally less likely to be allocated to their most preferred schools than high performers.

We do not find a significant effect of the treatments on the final allocation ("2nd stage", Columns "2") for the full analytical sample, but we do identify significant effects for certain groups. In particular, males (3.4 pp) and, especially high-performing males (5.2 pp), in both cases the effect is significant at 10%. Although all of the effects at this stage go in the right direction, they are certainly smaller than those of the first stage. In the next sub-section we explore different hypotheses to explain this.

In Table 11 we analyze if the treatments were successful in increasing the probability of being assigned to *any* school (disadvantaged or not). Given that disadvantaged schools are typically under-demanded, our intervention could have helped to reduce the system's congestion and thus increase its efficiency in terms of clearing the market and helping teachers secure a job. As in the previous case, column (1) of each sample refers to allocation in the first stage, while column (2) refers to allocation in the second stage (final).

We find a pattern consistent with the previous results. In the case of final assignment (Columns 2, final stage), the results go in the right direction. We identify significant effects among male teachers (3.4 pp) and, particularly, among male-high PUN teachers (5.2 pp) In sum, the "Identity" treatment arm was effective in reducing congestion and, thus, helping male candidates to secure a job.

6.2 From assignment in the first stage to final assignment

Our results show a strong and significant effect of the treatments on teachers' preferences. Moreover, we document significant effects on the probability of being assigned to a disadvantaged school in the decentralized stage (and thus, to be invited to an in-person final evaluation), especially for the

"Identity" arm. However, although the results related to the final assignment go in the right direction, some of the point estimates (when considering the full sample, instead of sub-samples) are not precise enough to detect a significant effect. Moreover, even in the sub-samples where we identify a significant effect on the final assignment, the point estimates are smaller than those of the first stage assignment.

A reduction of the point estimates are somewhat expected after analyzing the results related to the ranking of preferences in Table 9. After the first stage, candidates are assigned to, at most, two schools of their preference to complete the in-person evaluation. In the second stage, the candidate is likely to be offered a vacancy in her top ranked school (within the subset of schools where she completed the in-person evaluation). Indeed, conditional to having received an offer in the second stage, the probability that the offer comes from the candidate's most preferred school in the first stage is 67%. Given that none of the treatments was effective enough to motivate teachers to include a disadvantaged school as the first option of their choice set (at most, within the first two, in the sub-sample of high-performers), it is expected that we find a smaller effect of the treatment on the final allocation. In turn, in only 40% of the teachers that received a final offer, a disadvantaged school was the top choice within the two schools assigned in the first stage. Nevertheless, in this section we explore alternative hypotheses that could also help explain these results.

A first potential explanation could be related to the second part of the final in-person evaluation. Disadvantaged schools are, on average, farther away. Teachers assigned in the first stage to a disadvantaged school may have decided not to take the in-person evaluation if they realized they were farther away than expected. If they do not show up in the final interview, they cannot be assigned a position in that school.

Another hypothesis is that, once they went to the disadvantaged school to complete the in-person evaluation, they were less motivated about the vacancy (for instance, they realized the school was not a good match or harder to reach than they had initially anticipated), and, as a result, they under performed and reduced their chances of receiving an offer from those schools.

To explore these hypotheses, we estimate the effect of the treatments on three outcomes: "Showing up," which takes a one if a teacher candidate shows up to the in-person evaluation and zero otherwise; "Interview Score," which represents the candidate's performance on the interview in the final stage; and "Class Score," which is the candidate's performance on the mock lesson in the final stage. With respect to the last two outcomes, the final in-person evaluation was completed in each school where they were assigned in the first stage (if they actually showed up). For each of these outcomes, we estimate a model at the teacher-school level, including teacher fixed effects. More specifically, we estimate the following model:

$$y_{is} = \alpha T_i + X_i\beta + Teacher_i + \varepsilon_{is} \quad (2)$$

Where y_{is} is the outcome for each teacher candidate i taking the in-person evaluation at school s. $Teacher_i$ is a teacher fixed effect. We include all the controls described in Section 5. We only consider teacher-school combinations for which an invitation to the in-person evaluation was delivered (and therefore, the teacher could show up). For the "Score" outcomes, the sample is naturally restricted to teacher-school combinations for which the final in-person evaluation was completed. Thus, each result should be interpreted as suggestive and not causal, because the composition of the sample (e.g., being assigned to a certain school in the first stage) was directly affected by the treatment and, therefore, there is selection to the sample by definition.

These results are shown in Table 12. Columns (1) shows the results for "any" school (disadvantaged or not), while Columns (2) show the results including an interaction of each treatment and a "disadvantaged school" dummy. The probability of showing up to the interview at a disadvantaged school is not different between any of the treatment arms and control groups (Column (2)).

In the case of the in-person evaluation scores – the interview ("Interview Score") and the mock class ("Class Score") – the results present a similar pattern. For any of the treatment groups, teachers did not seem to have under performed on the final evaluation in both disadvantaged and non disadvantaged schools.

The fact that teachers in different arms were equally likely to show up for the in-person evaluation and performed equally well on this stage in a disadvantaged school suggests that the reduction in point estimates between the 1st and 2nd stages cannot be explained by a decrease in motivation when candidates are assigned to complete the in-person evaluation at a disadvantaged school.

6.3 Medium-term effects: did the intervention increase turnover?

A potential concern about the treatments is that some teachers who were motivated to apply to disadvantaged schools by the intervention would not accept the job offer or would quit soon after realizing that the school assigned to them was not a good fit. Although the intervention was relatively recent and we are not able to test the long-run effects, we explore this hypothesis by estimating the treatment effects on the probability of being actively teaching a year after the selection process. By definition, we restrict the sample to teachers who received an offer and, thus, the results should be interpreted as suggestive. We estimate Equation 1, including the same controls as in the main results. We present the estimates for the full analytical sample and for the following sub-samples: only male, only female, high-performers and low-performers. The outcome variable is "Teaching in 2020" and takes a one if, in 2020, the teacher was teaching in the school to which they were assigned in the 2019 selection process (it takes zero, otherwise).

Columns (1) show the results for "any school" (disadvantaged or not), while Columns (2) are restricted to teachers that are teaching in a disadvantaged school. We do not identify any negative effect in any of the treatment arms. This means that, once the teacher was assigned to a school, the probability of quitting after a year is not significantly different among teachers of the treatment and control arms.

6.4 Interpretation

The results present some interesting patterns. First, overall the interventions triggered a change in teachers' school preferences for more disadvantaged schools. The fact that both the extrinsic and altruistic conditions were equally effective could suggest a plausible interpretation related to information updating. If teachers had no information about disadvantaged schools, both arms could have had an effect of capturing teachers' attention and providing new information about these schools. Although we are not able to test this hypothesis, it seems unlikely considering the context of the experiment. In the focus groups organized by the government with local teachers, the issue related to information about the monetary and career-related benefits was discussed. The problem was not that teachers did not know about the existence of these benefits, but many of them did not really seem to fully understand the design of the incentives (for instance, which schools would qualify). Consequently, the government increased its efforts to make communication on this topic more transparent and, as a part of that effort, the Ministry redesigned the platform to make information clearer.

In Figures 9 and 10 we show an example of the application platform in 2018 (the year before the intervention) and 2019 (the year of the intervention). As it is evident from the comparison, in 2019 the information related to monetary/career-related benefits was much clearer. For instance, in 2018 there were many pieces of information that can be used to assess if a school is eligible for benefits or not (for example, if a school is located in a frontier area), but there was no clear indication if that was *actually* the case. In the 2019, the intervention was designed to make knowledgeable for every arm (including control) which schools would provide extra benefits for teachers.

A second interesting point arises from the analysis of the heterogeneous effects. In terms of teachers' preferences, the effect seems to have been driven by male candidates in both arms, a result that could plausibly be explained by the fact that women tend to have lower mobility (i.e., commuting longer distances is more costly) and disadvantaged schools are, on average, farther away.

However, when analyzing the effects separately for candidates based on their performance in the qualifying exam, we observe suggestive evidence that the effect was driven by high-performers in the case of the "Identity" arm, while the opposite is true for the case of the "Extrinsic" arm. Given that income tends to be a strong predictor of test scores, a plausible hypothesis (although non-testable in this context) is that extrinsic motivations worked better for those who were relatively more in need of money. This result has substantial policy implications: while monetary incentives may not be the best options for every teacher, they can have an important effect on teachers' preferences among certain groups.

Related to this, not only higher-performers tend to be more affected by the "Identity" treatment in terms of their willingness to include a larger proportion of disadvantaged schools in their choice set, but also in terms of how high they rank these schools. Again, the opposite is true for the "Extrinsic" arm. This is important to understand the results on school assignment, but it is also relevant for policy implications. In the context of Peru, in which the qualifying exam is so selective, and where there are so many understaffed schools, attracting *any* teacher to a disadvantaged school is desirable. However, in other contexts, an intervention (such as the "Extrinsic" arm) that attracts mostly relatively lower-skilled teachers might not be the best alternative. The opposite is true in the case of the "Identity" arm: not only it was the most effective treatment in terms of teachers' final assignment, but it also worked particularly well among the highest performing teacher candidates in the country.

7 Conclusions

In this study, we provide novel evidence on the impact of making salient certain facets of identity–altruistic and extrinsic–on employment choices. We examine this question in a high-stakes setting in which teacher candidates apply for jobs in specific schools with different levels of vulnerability. The government program we evaluate aimed to prime either teacher candidates' altruistic identity or external rewards in an effort to encourage them to apply to vacancies in more disadvantaged schools (typically understaffed and with lower-performing students). To assess the impact of this intervention, we conducted a three-arm large-scale randomized controlled trial in Peru with the 11,568 teacher candidates who participated in the 2019 teacher selection process.

We find that teachers in both treatment arms ("Identity" and "Extrinsic") are significantly more likely to apply to vacancies in disadvantaged schools and, in the case of the "Identity" treatment, we observe a significant effect on the likelihood of being assigned to disadvantaged schools in the final stage of the evaluation process. We also find suggestive evidence that the effects are driven by male teachers, who are arguably more mobile and thus more willing to work in remote areas. Importantly, our estimates reveal that the effect of both treatments on the probability of being assigned to a disadvantaged school in the final in-person evaluation is larger among high-performing teachers, particularly for those in the "Altruistic Identity" arm. This result provides crucial insight for efforts aimed at reducing teacher sorting.

Broadly, our paper shows how a well-designed low-cost behavioral strategy can enhance the resources of disadvantaged schools, fundamental to improving the equity of the education system. The results of our first treatment arm suggest that making teachers' altruistic identity salient at the right moment can be a powerful tool to reduce teacher sorting. One caveat of this study is that the "Altruistic Identity" treatment was implemented in a setting where teachers could also receive extrinsic rewards (i.e., salary increases and career advancement opportunities) to work in disadvantaged schools. Further research is needed to assess the effectiveness of priming teachers' altruistic identity in the absence of monetary incentives.

The results of our second arm show that simplifying and making more salient information about extrinsic rewards has a notable effect on employment choices. This is an important finding given the varying outcomes of differential compensation schemes and the failure of some monetary incentives to attract teachers to hard-to-staff schools (Clotfelter et al. 2008b, Maranto 2013). In other contexts, psychological frictions associated with informational complexity and confusion over incentives have been shown to influence the effectiveness of social programs (Bettinger et al. 2012, Hoxby et al. 2013, Bhargava and Manoli 2015). Our research demonstrates that low-cost interventions can reduce these cognitive barriers by providing individuals with more simplified and customized information about extrinsic rewards.

Finally, the magnitude and the scope of our results call for more comprehensive policies that improve the working conditions of teachers employed in disadvantaged schools (e.g. better infrastructure, educational inputs, transportation, and housing). Interventions such as those described in this paper can complement and improve the effectiveness of these policies. We estimate that the cost of filling a teaching vacancy in a disadvantaged school using either of the two strategies evaluated in this paper is approximately $13 per vacancy. Moreover, while any teacher in Peru who works in a disadvantaged school receives extrinsic rewards (including uncertified and temporary teachers), the program we evaluate targets more qualified teachers who passed a rigorous selection process. In a time when government budgets in many developing countries are being cut, low-cost interventions that prime candidates' intrinsic or extrinsic motivations provide a cost-effective way to further encourage teachers to apply to disadvantaged schools, thus reducing the shortage of credentialed teachers in places with high staffing needs.

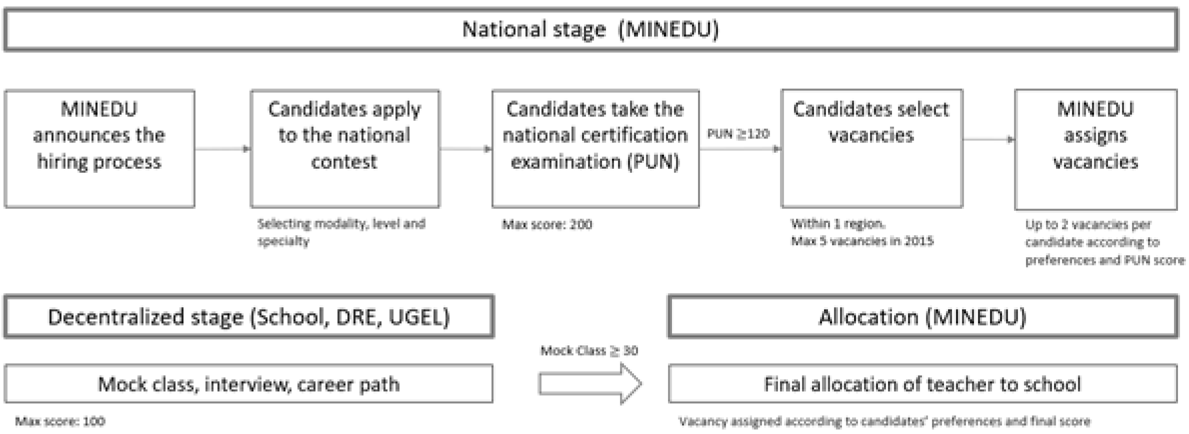
8 Tables and figures

Figure 1: Icons appearing in online vacancy selection platform

Add	Incentives	DRE/UGEL	School ID	School Name	School Type	School Management
+ Add	S/	Ugel Utcubamba	1559178	16271 - Fatima	Single-teacher	Public - Direct Management
+ Add	S/	Ugel Condorcanqui	1607027	I.E.I. N° 406 - Limon - Rio Santiago	Single-teacher	Public - Direct Management
+ Add	S/	Ugel Bagua	259002	16199	Single-teacher	Public - Direct Management
+ Add		Ugel Bongara	1303387	Iei. N° 18092 - Pomacochas	Multi-teacher	Public - Direct Management
+ Add		Ugel Condorcanqui	491811	I.E.S.M. "Nieva" - Nieva	Multi-teacher	Public - Direct Management

Note: Icons in the "Incentives" column signify the following: the green icon represents the first extrinsic reward (i.e. monetary incentives), the black icon represents the second extrinsic reward (i.e. the possibility of more rapid professional career advancement), and the red icon represents altruistic identity (i.e. being an agent of social change).

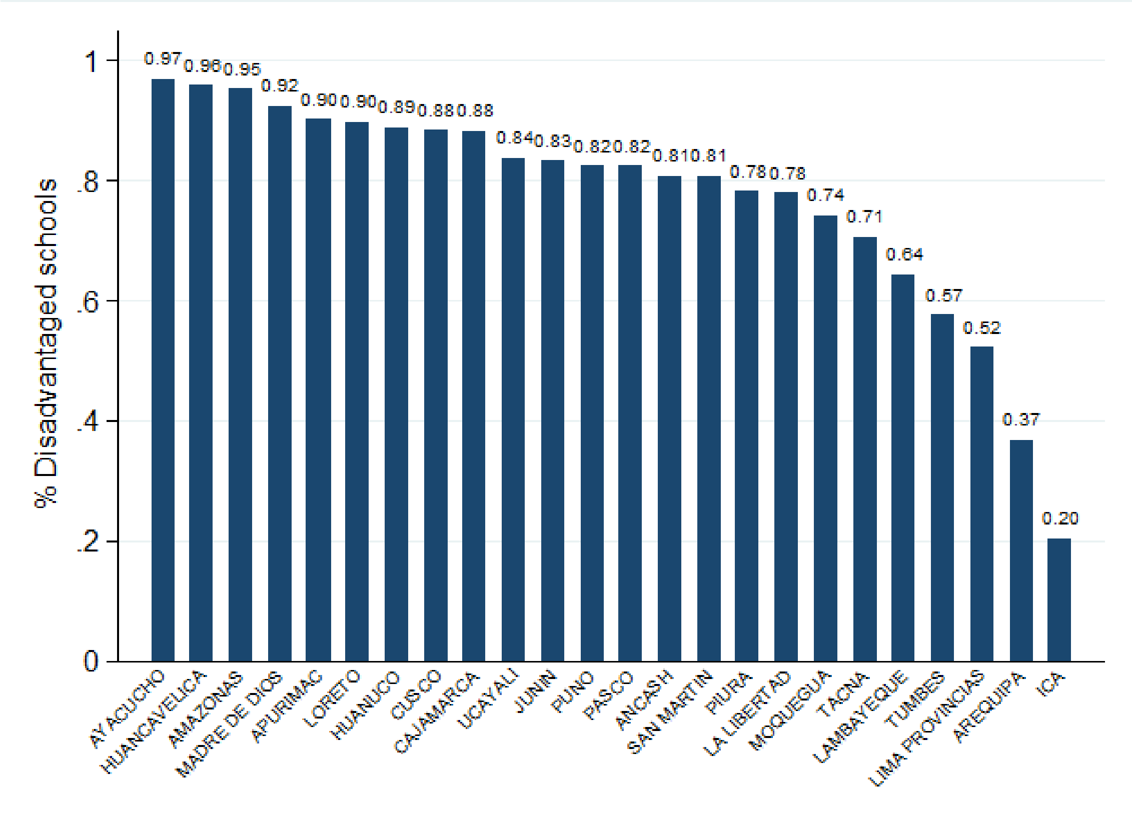
Figure 2: 2019 Teacher hiring process in Peru



Note: Ministry of Education (*Ministerio de Educación* - MINEDU). National Teacher Test (*Prueba Única Nacional* - PUN). Regional Education Directorates (*Dirección Regional de Educación* - DRE). Local Education Management Units (*Unidad de Gestión Educativa Local* - UGEL)

Source: Authors own elaboration.

Figure 3: Distribution of disadvantaged schools across regions



Source: MINEDU 2019

Note: The schools targeted by the government–referred to as "disadvantaged schools"–are those institutions that fall under the government's incentive scheme (i.e., rural of any type, in the VRAEM area, in frontier regions, bilingual, single-teacher, and/or multi-grade).

Table 1: Selected versus unselected schools

	All schools	**Selected schools (S)**	**Unselected schools (U)**	**p-value S=U**	**N.**
Characteristics associated to monetary incentives					
Most Rural (Rural 1)	0.51	0.37	0.64	0.000	12,300
Moderate Rural (Rural 2)	0.22	0.22	0.22	0.604	12,300
Least Rural (Rural 3)	0.08	0.12	0.05	0.000	12,300
VRAEM	0.08	0.06	0.11	0.000	12,300
Frontier regions	0.12	0.07	0.17	0.000	12,300
Bilingual	0.47	0.24	0.68	0.000	12,300
Single-teacher	0.28	0.19	0.36	0.000	12,300
Multigrade	0.25	0.20	0.29	0.000	12,300
Mean monetary incentives (S/)	424.16	308.85	529.63	0.000	12,300
Other characteristics					
Urban	0.19	0.30	0.09	0.000	12,300
Poverty (%)	0.50	0.46	0.53	0.000	12,172
Enrollment (100s)	111.9	155.0	72.4	0.000	12,286
Basic services	0.51	0.68	0.35	0.000	12,300
Distance from prov. capital (km)	36.8	24.4	48.1	0.000	12,262
Student test scores in Math 2018 (standardized)	-0.15	0.12	-0.58	0.000	4,820
N.	12,300	5,876	6,424		

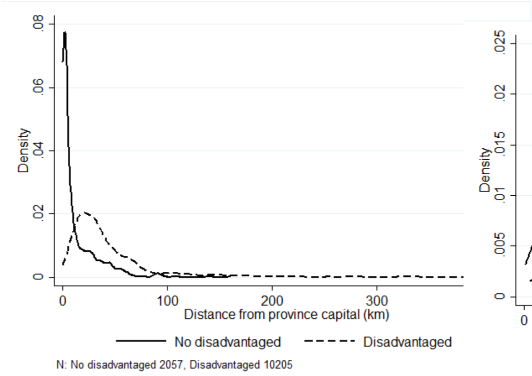
Source: Authors own elaboration.

Table 2: Structure of incentives

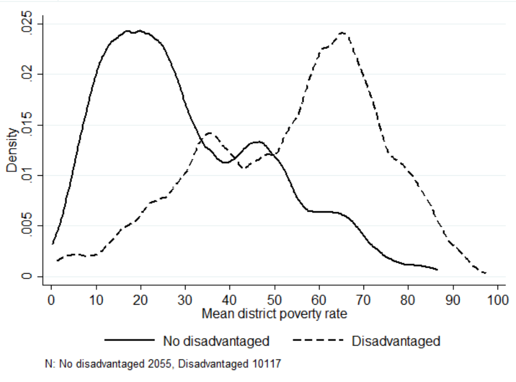
Characteristics associated to monetary incentives	**Amount (S/)**	**% of basic salary (S/ 2200)**
Location		
Most Rural (Rural 1)	500	23%
Moderate Rural (Rural 2)	100	5%
Least Rural (Rural 3)	70	3%
Frontier regions	100	5%
VRAEM	300	14%
Type of school		
Bilingual	150	7%
Single-teacher	200	9%
Multigrade	140	6%

Source: MINEDU 2019.

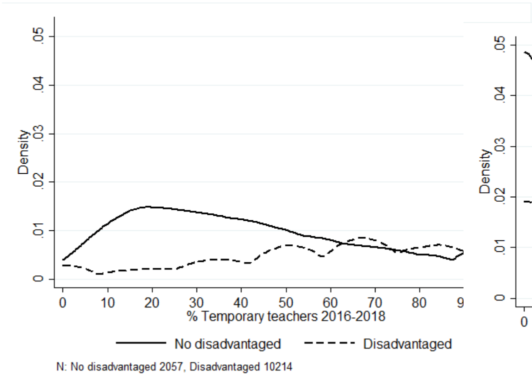
Figure 4: Disadvantaged versus non-disadvantaged schools



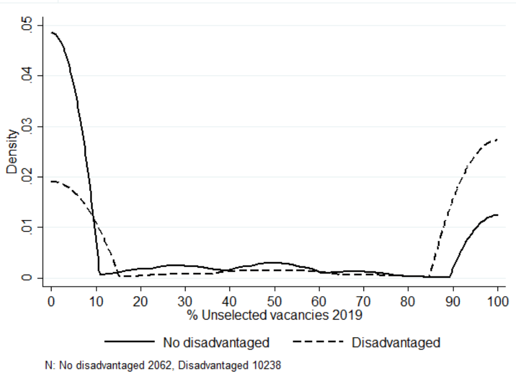
(a) Distance from prov. capital (km)



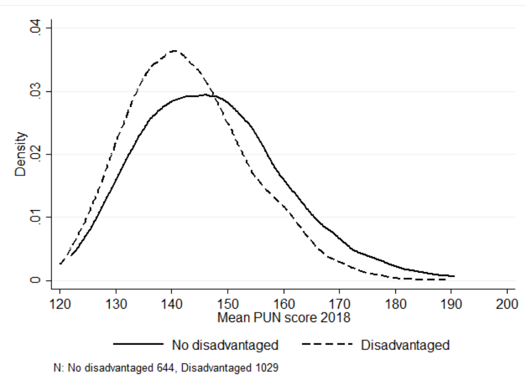
(b) District poverty rate



(c) % Temporary teachers 2016-2018



(d) % Unselected schools 2019



(e) PUN score 2019

Notes: Each graph shows the kernel density estimation of each variable for disadvantaged and not disadvantaged schools.

Table 3: Attrition and Excluded Data

Panel A. Correlation with Treatment Assignment

	Not selecting a Vacancy		Not in final sample	
	(1)	(2)	(3)	(4)
T. Extrinsic	-0.006	-0.006	-0.011	-0.010
	(0.008)	(0.008)	(0.010)	(0.010)
T. Identity	-0.002	-0.001	0.011	0.011
	(0.009)	(0.009)	(0.010)	(0.010)
Controls	NO	YES	NO	YES
N	11363	11363	9252	9252
R-Squared	0.0230	0.0238	0.0815	0.0819

Notes: Robust standard errors in parentheses.
Not selecting a vacancy: binary variable that takes a one if the teacher did not choose at least a vacancy on the platform.
Not in final sample: the outcome is a binary variable that takes a one if the teacher is excluded from the final sample because of any of these two reasons: there was no variation in terms of disadvantaged schools, or the teachers took the PUN to teach in an alternative education program. Columns (1) and (3) present the results without controls. Columns (3) and (4) control for age, gender, disability (binary), total score on the PUN and region dummies.

Panel B. Balance tests for excluded data

	Control	**Extrinsic**	**p-val C=E**	**Control**	**Identity**	**p-val C=I**	**Extrinsic**	**Identity**	**p-val E=I**
Age	35.58	36.13	0.174	35.58	35.81	0.566	36.13	35.81	0.428
Female	0.67	0.69	0.571	0.68	0.67	0.800	0.69	0.67	0.413
Disabled	0.003	0.003	0.973	0.003	0.000	0.159	0.003	0.000	0.153
PUN score									
Reading Comprehension	40.24	40.10	0.552	40.25	40.21	0.891	40.10	40.21	0.662
Logical Reasoning	36.68	36.78	0.739	36.78	36.58	0.622	36.78	36.54	0.425
Pedagogical Knowledge of Specialization	70.30	69.84	0.307	70.30	70.02	0.525	69.84	70.01	0.692
Total	144.35	144.86	0.139	144.35	144.51	0.622	144.86	144.51	0.312
N.	645	638		645	638		624	638	

Notes: P-values correspond to mean difference T-tests between the different arms. The sample includes all the observations corresponding to teachers that did not select a vacancy on the platform.

Table 4: Text messages by treatment group

N.	Date sent	Sent to	Text message
1	8/2/2019	Control	Congratulations [NAME]! You have passed the PUN. In a few days you will be able to select all the vacancies of your choice.
		Extrinsic	Congratulations [NAME]! You have passed the PUN. In a few days you will be able to select all the vacancies of your choice. Consider that in some schools you can receive up to $343 additional to your basic salary.
		Identity	Congratulations [NAME]! You have passed the PUN. In a few days you will be able to select all the vacancies of your choice. In the online platform you can identify the schools where you can generate greater changes in learning. Thank you for choosing to improve lives!
2	8/6/2019	Control	[NAME], tomorrow you will be able to select all the vacancies of your choice in your preferred region.
		Extrinsic	[NAME], tomorrow you will be able to select all the vacancies of your choice in your preferred region. Remember that schools with monetary incentives guarantee you a higher monthly income.
		Identity	[NAME], tomorrow you will be able to select all the vacancies of your choice in your preferred region. Thank you for being an agent of social change. In the online platform we will point out the schools where you can have a greater impact on the learning of your students.
3	8/7/2019*	Control	[NAME], you can now select all the vacancies of your choice in the teacher evaluation.
		Extrinsic	[NAME], you can now select all the vacancies of your choice in the teacher evaluation. Do not miss the opportunity to select rural or frontier schools that may allow you to reach a higher salary scale 1 year in advance.
		Identity	[NAME], you can now select all the vacancies of your choice in the teacher evaluation. We recognize your teacher vocation. In the online platform you can identify the schools where you can generate greater changes in student learning.
4	8/13/2019	Control	[NAME], remember to select all the vacancies of your choice in the teacher evaluation.
		Extrinsic	[NAME], remember to select all the vacancies of your choice in the teacher evaluation. Be one of the teachers who, in some schools, already receive up to 5 monetary incentives.
		Identity	[NAME], remember to select all the vacancies of your choice in the teacher evaluation. You can have a great impact on your students, especially in areas with greater needs.

Note: * Start date of vacancy selection process, closing date on 8/28/2019. Text messages in original language in Table A1). Standardized written test (*Prueba Única Nacional* – PUN)

Table 3 (cont.): Text messages by treatment group

N.	Date sent	Sent to	Text message
5	8/15/2019	All teachers who have not yet selected vacancies	[NAME], you have not yet selected the vacancies of your choice in the online platform. This is a necessary step of the teacher evaluation process.
6	8/18/2019	Control	[NAME], in 4 days the vacancies' selection process of the teacher evaluation will be closed.
		Extrinsic	[NAME], in 4 days the vacancies' selection process of the teacher evaluation will be closed. Remember that schools which provide incentives allow you a higher monthly income and the possibility to reach a higher salary scale in less time.
		Identity	[NAME], in 4 days the vacancies' selection process of the teacher evaluation will be closed. Remember that a lot of students need you to improve their learning. Thank you for choosing to improve lives!
7	8/22/2019	All teachers that passed the PUN	The vacancies' selection process of the 2019 teacher evaluation has been extended! More information on this process has been sent to your email.
8	8/26/2019	All teachers who have not yet selected vacancies	You have not yet selected the vacancies of your choice in the online platform of the teacher evaluation. Remember that if you don't complete the selection before August 28, your candidacy will be removed from the evaluation.
9	9/5/2019	Teachers with less than 2 assigned vacancies	Until September 9 you can select here: http://bit.ly/2krT0QL some vacancies of your choice among the ones that are still available for the 2019 teacher evaluation.
10	9/7/2019	Control	[NAME], until September 9 you have an additional opportunity to select vacancies of your choice in the teacher evaluation.
		Extrinsic	[NAME], until September 9 you have an additional opportunity to select vacancies of your choice in the teacher evaluation. Remember that you can select schools with monetary incentives as indicated in the online platform.
		Identity	[NAME], until September 9 you have an additional opportunity to select vacancies of your choice in the teacher evaluation. Remember that you can select schools where you have the possibility to generate greater changes in learning.

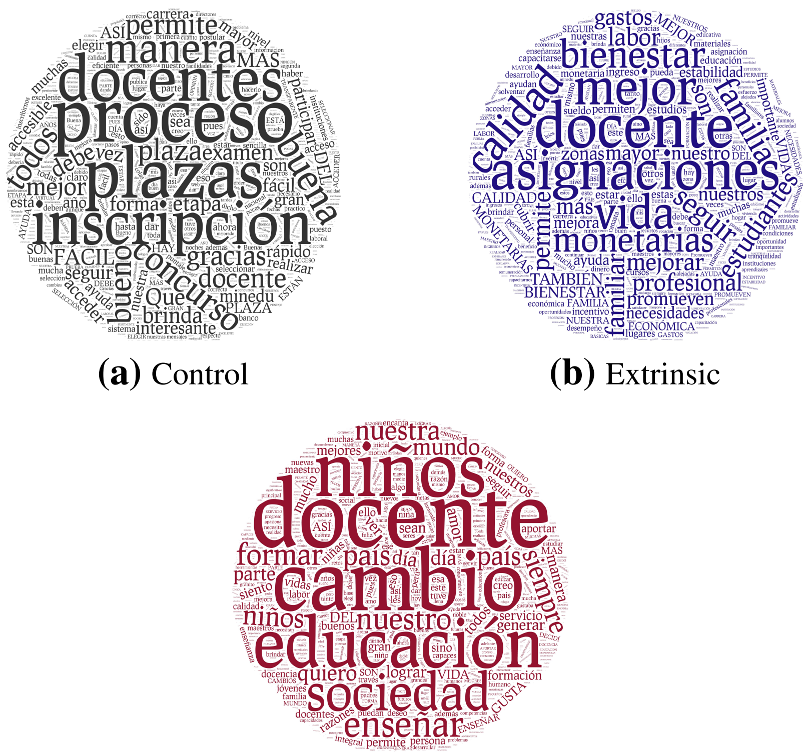
Note: * Start date of vacancy selection process, closing date on 8/28/2019. Text messages in the original language in Table A1). Standardized written test (*Prueba Única Nacional* – PUN)

Table 5: Voluntary written exercise on the online selection platform

Group	Voluntary written exercise
Control	Thank you for participating in the 2019 Teacher Evaluation. What do you think about the evaluation registration process?
Treatment Extrinsic	Thank you for participating in the teacher evaluation. How do monetary incentives promote the welfare of teachers? We would like you to take a few minutes to analyze this question and then share with us your ideas about it.
Treatment Identity	Thank you for choosing to be a teacher and help generate changes in student learning! We would like you to share with us the reasons that motivated you to become a teacher. We would like you to take a few minutes to think and then share with us the main reasons that motivated you to choose this profession.
All	Note: Your answer is very valuable to us and it will only be used for Minedu informational purposes. The answer you provide will not affect your score in the evaluation. Thanks for participating.

Note: Written exercise in original language in Table A2. Ministry of Education (*Ministerio de Educación* - MINEDU).

Figure 5: Text analysis of voluntary written exercise

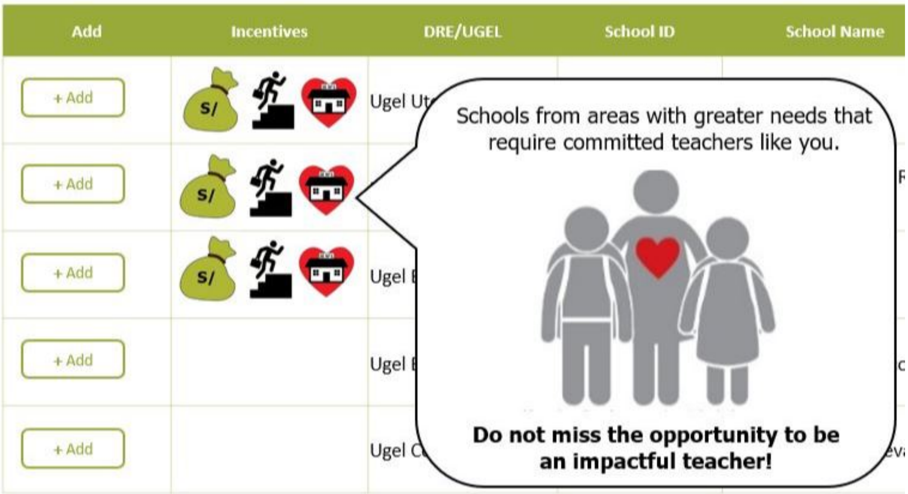


(a) Control **(b)** Extrinsic **(c)** Identity

Note: The response rate was 66% for the Control group, 66% for the Extrinsic group and 74% for the Identity group.

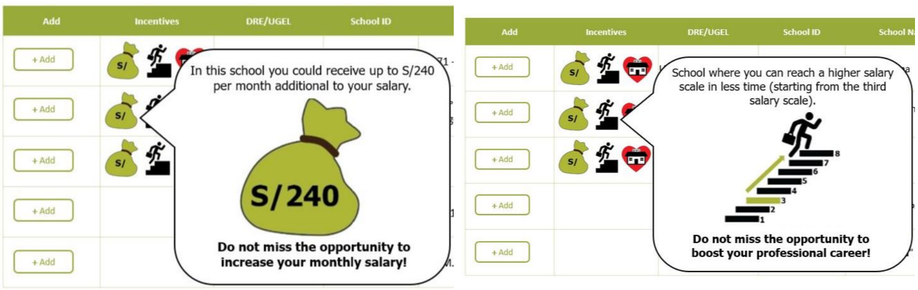
Source: Authors own elaboration.

Figure 6: Pop-up on online vacancy selection platform - Identity



Note: Pop-up in original language in Figure A1.

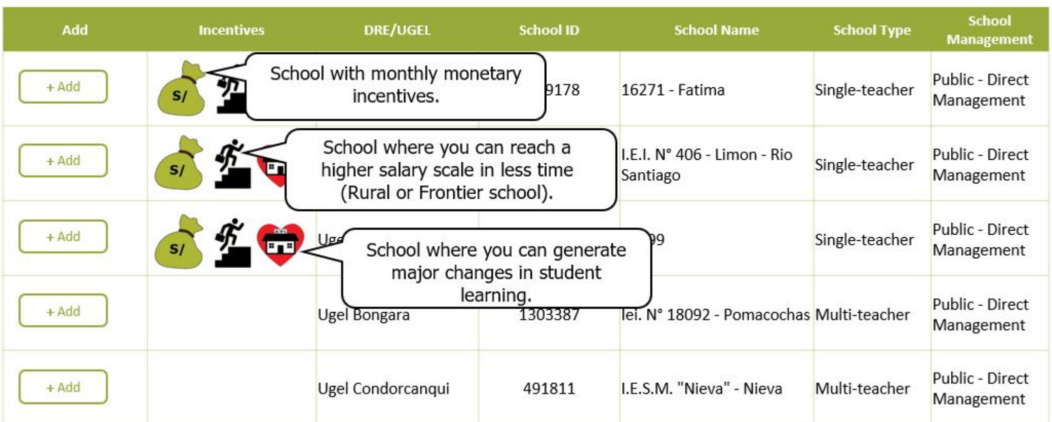
Figure 7: Pop-up on online vacancy selection platform - Extrinsic



(a) Monetary incentive **(b)** Career progression

Note: Pop-up in original language in Figure A1.

Figure 8: Pop-up on online vacancy selection platform - Control



Note: Pop-up in original language in Figure A1.

Table 6: Summary of model variables, candidate-level

	Obs	Mean	Std. Dev.	Min	Max
Candidate's attributes					
Female	7,217	0.64	0.48	0	1
Age	7,217	35.99	6.76	21	63
PUN score	7,217	144.57	11.88	120	190
Disabled	7,217	0.00	0.06	0	1
Low-performing	7,217	0.51	0.50	0	1
Outcomes					
Assigned to at least 1 vacancy	7,217	0.79	0.40	0	1
% Disadvantaged vacancies selected	7,217	0.47	0.34	0	1
Selected at least 1 disadvantaged vacancy	7,217	0.81	0.40	0	1
Assigned to a disadvantaged vacancy	7,217	0.53	0.50	0	1
% Most remote vacancies selected	7,217	0.15	0.23	0	1
Selected at least 1 most remote vacancy	7,217	0.41	0.49	0	1
Assigned to a most remote vacancy	7,217	0.21	0.41	0	1
% Poor vacancies selected	7,217	0.18	0.27	0	1
Selected at least 1 poor vacancy	7,217	0.41	0.49	0	1
Assigned to a poor vacancy	7,217	0.22	0.41	0	1

Source: Authors own elaboration.

Table 7: Balance test

	Control	**Extrinsic**	**p-val C=E**	**Control**	**Identity**	**p-val C=I**	**Extrinsic**	**Identity**	**p-val E=I**
Age	35.96	36.16	0.292	35.96	35.84	0.543	36.16	35.84	0.095
Female	0.64	0.63	0.339	0.64	0.66	0.288	0.63	0.66	0.043
Disabled	0.002	0.004	0.195	0.002	0.003	0.589	0.004	0.003	0.437
PUN score									
Reading Comprehension	39.11	39.29	0.189	39.11	39.31	0.147	39.29	39.31	0.892
Logical Reasoning	35.79	35.65	0.341	35.79	35.60	0.188	35.65	35.60	0.733
Pedagogical Knowledge of Specialization	69.44	69.92	0.039	69.44	69.60	0.484	69.92	69.60	0.171
Total	144.35	144.86	0.139	144.35	144.51	0.622	144.86	144.51	0.312
N.	2,390	2,385		2,390	2,442		2,385	2,442	

Notes: P-values correspond to mean difference T-tests between the different arms.

Table 8: Effect on Teachers' Preferences

	Full Sample		Male		Female		High PUN		Low Pun	
	Proportion	At Least One	Proportion	At Least One	Proportion	At Least One	Proportion	At Least One	Proportion	At Least One
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0201	0.0204	0.0308	0.0326	0.0154	0.0145	0.0132	0.0146	0.0249	0.0245
	(0.0086)	(0.0106)	(0.0138)	(0.0168)	(0.0109)	(0.0136)	(0.0122)	(0.0159)	(0.0120)	(0.0141)
T. Identity	0.0191	0.0177	0.0346	0.0327	0.0107	0.0101	0.0243	0.0248	0.0110	0.0059
	(0.0086)	(0.0106)	(0.0141)	(0.0171)	(0.0107)	(0.0135)	(0.0122)	(0.0159)	(0.0120)	(0.0141)
Mean(control)	0.463	0.795	0.499	0.806	0.422	0.762	0.443	0.789	0.502	0.826
N	7217	7217	2590	2590	4627	4627	3535	3535	3682	3682
R-Squared	0.2280	0.1437	0.2912	0.1527	0.1927	0.1498	0.2130	0.1584	0.2334	0.1302

Notes: Robust standard errors in parentheses.
(1) Proportion: number of disadvantaged schools included in teachers' choice set, divided by the total number of schools including in their choice set.
(2) At Least One: takes a one if there is at least one disadvantaged school in teachers' choice set.
All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median

Table 9: Effect on Teachers' Preferences: Ranking

Panel A: Full Sample

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0169	0.0188	0.0245	0.0253	0.0244
	(0.0135)	(0.0131)	(0.0125)	(0.0118)	(0.0113)
T. Identity	0.0064	0.0130	0.0118	0.0201	0.0154
	(0.0134)	(0.0131)	(0.0126)	(0.0118)	(0.0114)
Mean(control)	0.428	0.586	0.661	0.718	0.748
N	7217	7217	7217	7217	7217
R-Squared	0.1178	0.1452	0.1480	0.1523	0.1528

Panel B: Only Male

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0302	0.0209	0.0384	0.0420	0.0355
	(0.0222)	(0.0207)	(0.0195)	(0.0183)	(0.0176)
T. Identity	0.0233	0.0155	0.0309	0.0454	0.0320
	(0.0226)	(0.0212)	(0.0201)	(0.0187)	(0.0180)
Mean(control)	0.481	0.653	0.712	0.756	0.786
N	2590	2590	2590	2590	2590
R-Squared	0.1462	0.1583	0.1524	0.1489	0.1464

Panel C: Only Female

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0110	0.0177	0.0179	0.0170	0.0196
	(0.0169)	(0.0168)	(0.0160)	(0.0152)	(0.0146)
T. Identity	-0.0020	0.0107	0.0023	0.0069	0.0068
	(0.0167)	(0.0167)	(0.0160)	(0.0151)	(0.0146)
Mean(control)	0.398	0.548	0.633	0.696	0.726
N	4627	4627	4627	4627	4627
R-Squared	0.0946	0.1339	0.1491	0.1582	0.1627

Panel D: Only High PUN

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0090	0.0289	0.0236	0.0212	0.0197
	(0.0189)	(0.0190)	(0.0184)	(0.0175)	(0.0169)
T. Identity	0.0126	0.0366	0.0331	0.0384	0.0255
	(0.0189)	(0.0191)	(0.0185)	(0.0175)	(0.0170)
Mean(control)	0.370	0.523	0.604	0.671	0.706
N	3535	3535	3535	3535	3535
R-Squared	0.1139	0.1541	0.1611	0.1666	0.1671

Panel E: Only Low PUN

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0225	0.0066	0.0234	0.0271	0.0262
	(0.0192)	(0.0181)	(0.0169)	(0.0158)	(0.0152)
T. Identity	-0.0041	-0.0156	-0.0142	-0.0030	0.0007
	(0.0191)	(0.0181)	(0.0171)	(0.0160)	(0.0153)
Mean(control)	0.481	0.646	0.715	0.762	0.786
N	3682	3682	3682	3682	3682
R-Squared	0.1065	0.1303	0.1305	0.1375	0.1348

Notes: Robust standard errors in parentheses.
Each column (X, from 1 to 5) corresponds to a binary that takes a one if at least one disadvantaged schools was included up to the Xth position in the ranking of teachers' choice set. All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median

Table 10: Effect on Teachers' Allocation - Disadvantaged Schools

	Full Sample		Male		Female		High PUN		Low PUN		Male and High PUN	
	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0199	0.0102	0.0365	-0.0012	0.0124	0.0185	0.0330	0.0084	0.0039	0.0127	0.0480	0.0187
	(0.0136)	(0.0113)	(0.0221)	(0.0191)	(0.0173)	(0.0140)	(0.0197)	(0.0156)	(0.0185)	(0.0165)	(0.0329)	(0.0272)
T. Identity	0.0266	0.0130	0.0632	0.0340	0.0087	0.0042	0.0449	0.0239	0.0057	0.0018	0.0762	0.0520
	(0.0135)	(0.0112)	(0.0221)	(0.0198)	(0.0171)	(0.0135)	(0.0195)	(0.0156)	(0.0185)	(0.0161)	(0.0324)	(0.0280)
Mean(control)	0.511	0.202	0.559	0.232	0.518	0.171	0.483	0.184	0.504	0.230	0.504	0.187
N	7217	7217	2590	2590	4627	4627	3535	3535	3682	3682	1209	1209
R-Squared	0.1188	0.0739	0.1399	0.1039	0.0992	0.0675	0.1068	0.0550	0.1659	0.0903	0.1187	0.0714

Notes: Robust standard errors in parentheses.
(1): 1º stage: takes a one if the teacher was assigned to at least one disadvantaged school in the first stage (decentralized) of the process.
(2) 2º stage: takes a one if the teacher was assigned to a disadvantaged school in the second (final) stage of the process. All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median.

Table 11: Effect on Teachers' Allocation - All Schools

	Full Sample		Male		Female		High PUN		Low PUN		Male and High PUN	
	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0012	0.0102	0.0218	-0.0012	-0.0092	0.0185	0.0004	0.0084	0.0022	0.0127	0.0260	0.0187
	(0.0103)	(0.0113)	(0.0154)	(0.0191)	(0.0136)	(0.0140)	(0.0127)	(0.0156)	(0.0157)	(0.0165)	(0.0191)	(0.0272)
T. Identity	0.0081	0.0130	0.0303	0.0340	-0.0019	0.0042	0.0059	0.0239	0.0109	0.0018	0.0391	0.0520
	(0.0102)	(0.0112)	(0.0153)	(0.0198)	(0.0134)	(0.0135)	(0.0125)	(0.0156)	(0.0156)	(0.0161)	(0.0181)	(0.0280)
Mean(control)	0.475	0.203	0.532	0.237	0.518	0.171	0.444	0.184	0.450	0.221	0.891	0.464
N	7217	7217	2590	2590	4627	4627	3535	3535	3682	3682	1209	1209
R-Squared	0.2004	0.0739	0.1592	0.1039	0.2075	0.0675	0.1624	0.0550	0.2229	0.0903	0.1156	0.0714

Notes: Robust standard errors in parentheses.
(1): 1º stage: takes a one if the teacher was assigned to at least one school (disadvantaged or not) in the first stage (decentralized) of the process.
(2) 2º stage: takes a one if the teacher was assigned to a a school (disadvantaged or not) in the second (final) stage of the process. All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median.

Table 12: Effect on Final Stage Evaluations

	Show up interview		Interview Score		Class Score	
	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0290	0.0362	0.0014	-0.0153	0.0304	-0.0175
	(0.0105)	(0.0152)	(0.0301)	(0.0483)	(0.0305)	(0.0497)
T. Identity	0.0079	0.0120	-0.0160	0.0096	0.0150	-0.0420
	(0.0104)	(0.0150)	(0.0310)	(0.0477)	(0.0311)	(0.0501)
Disadvantaged		0.1316		-0.2098		-0.2678
		(0.0148)		(0.0436)		(0.0445)
T. Extrinsic*Disadvantaged		-0.0176		0.0312		0.0818
		(0.0208)		(0.0617)		(0.0627)
T. Identity*Disadvantaged		-0.0098		-0.0397		0.0938
		(0.0207)		(0.0624)		(0.0637)
T. Extrinsic + T. Extrinsic*Disadvantaged		0.0185		0.0159		0.0643*
		(0.0142)		(0.0383)		(0.0381)
T. Identity + T. Identity*Disadvantaged		0.0022		-0.0301		0.0517
		(0.0143)		(0.0402)		(0.0394)
Mean(control)	0.440	0.440	0.041	0.041	0.015	0.015
N	13452	13452	6082	6082	6084	6084
R-Squared	0.0115	0.0256	0.0033	0.0135	0.0041	0.0141

Note: Robust standard errors in parentheses
Show up interview: takes a one if the teacher took the final in-person interview after the decentralized stage. It takes a zero if the teacher was invited but did not take it.
Interview Score: Teachers' score on the in-person mock interview in the final stage. It excludes teachers that did not take the interview.
Class Score: Teachers' score on the in-person test in the final stage. It excludes teachers that did not take the test.
Columns (1): Presents treatment effects with no interactions.
Columns (2): Include a "disadvantaged" dummy that takes a one if the school is disadvantaged and the interaction between that dummy and each treatment dummy.
T.Extrinsic + T.Extrinsic*Disadvantaged and T.Intrinsic + T.Intrinsic*Disadvantaged are total effects on the subgroup of disadvantaged schools.
All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.

Table 13: Effect on being an active teacher in 2020

	Full		Male		Female		High PUN		Low PUN	
	Teacher is Active in 2020									
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0148	0.0373	0.0272	0.0570	0.0080	0.0267	0.0308	0.0569	0.0038	0.0338
	(0.0121)	(0.0165)	(0.0199)	(0.0251)	(0.0155)	(0.0223)	(0.0151)	(0.0221)	(0.0185)	(0.0237)
T. Identity	0.0098	0.0198	0.0324	0.0444	-0.0028	0.0085	0.0158	0.0332	0.0098	0.0196
	(0.0123)	(0.0176)	(0.0203)	(0.0270)	(0.0160)	(0.0245)	(0.0158)	(0.0232)	(0.0189)	(0.0258)
School	All	Disad.	All	Disad.	All	Disad.	All	Disad.	All	Disad.
Mean(control)	0.921	0.904	0.911	0.905	0.928	0.905	0.937	0.926	0.907	0.889
N	2571	1513	1002	628	1569	885	1275	673	1296	840
R-Squared	0.0469	0.0475	0.0353	0.0215	0.0506	0.0533	0.0249	0.0333	0.0864	0.0691

Note: Robust standard errors in parentheses
Columns (1): The outcome is "being an active teacher in any school in 2020" and takes a one if the teacher was actively teaching in any school (disadvantaged or not) by the end of 2020. The sample includes only teachers that were offered a vacancy in the 2019 process.
Columns (2): The outcome is "being an active teacher in a disadvantaged school in 2020" and takes a one if the teacher was actively teaching in a disadvantaged school by the end of 2020. The sample includes only teachers that were offered a vacancy in a disadvantaged school in the 2019 process.
All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median.

Figure 9: Platform in 2018

Resultados de la búsqueda de institución educativa

Región: **AREQUIPA** - Grupo de inscripción: **EBR Secundaria Educación para el Trabajo**

Recuerde que puede seleccionar todas las instituciones educativas que contengan la plaza de su interés de acuerdo a su grupo de inscripción.

Seleccione la(s) IE a la(s) que postula:

Agregar	DRE/UGEL	Código modular	Nombre de IE	Tipo de IE	Ámbito	Bilingue	Lengua	Frontera	Vraem	Gestión	Familia
+ Agregar	UGEL AREQUIPA SUR	0309468	SAN MARTIN DE SOCABAYA	POLIDOCENTE		No	-	No	No	Pública de gestión directa	MECÁNICA Y METALES
+ Agregar	UGEL AREQUIPA SUR	0579623	PIO XII (CIRCA)	POLIDOCENTE		No	-	No	No	Pública de gestión privada	COMPUTACIÓN E INFOR
+ Agregar	UGEL AREQUIPA SUR	0636019	RAFAEL LOAYZA GUEVARA	POLIDOCENTE		No	-	No	No	Pública de gestión directa	CONSTRUCCIÓN
+ Agregar	UGEL AREQUIPA SUR	0636217	SAN ANTONIO MARIA CLARET (CIRCA)	POLIDOCENTE		No	-	No	No	Pública de gestión privada	COMPUTACIÓN E INFOR
+ Agregar	UGEL CAMANÁ	0309351	NUESTRA SEÑORA DE LA CANDELARIA	POLIDOCENTE		No	-	No	No	Pública de gestión privada	COMPUTACIÓN E INFOR
+ Agregar	UGEL CARAVELI	0309583	HORTENCIA PARDO MANCEBO	POLIDOCENTE		No	-	No	No	Pública de gestión directa	COMPUTACIÓN E INFOR

Página 1 de 2 10 ▾ Mostrando 1 - 10 de 19

Source: MINEDU 2018

Figure 10: Platform in 2019

Resultados de la búsqueda de institución educativa

Selecciona **todas las IE de tu preferencia** haciendo clic en el botón "Agregar". **A mayor cantidad de IE seleccionadas, tendrás mayor probabilidad de competir por una plaza.**

Cuando termines de agregar tus IE, ubícate al final de la pantalla para visualizar el listado de IE seleccionadas.

Seleccione la(s) IE a la(s) que postula:

PARA MÁS INFORMACIÓN SOBRE LOS BENEFICIOS DE LAS PLAZAS, PASA EL CURSOR SOBRE LOS ÍCONOS.

2 IE seleccionadas

Agregar	Beneficios	DRE/UGEL	Provincia	Distrito	Nombre de IE	Código modular	Cantidad de plazas	Gestión	Tipo de IE	Ámbito
+ Agregar	S/	UGEL BAGUA	BAGUA	ARAMANGO	235	0767939	2	Pública de gestión privada	POLIDOCENTE MULTIGRADO	Rural 2
+ Agregar		UGEL BAGUA	BAGUA	BAGUA	16192	1307438	2	Pública de gestión directa	POLIDOCENTE COMPLETA	Urbano prueba
+ Agregar	S/	UGEL BAGUA	BAGUA	ARAMANGO	282	1546209	1	Pública de gestión directa	UNIDOCENTE	Rural 2
+ Agregar	S/	UGEL BAGUA	BAGUA	ARAMANGO	279	1546175	1	Pública de gestión directa	UNIDOCENTE	Rural 1
+ Agregar	S/	UGEL BAGUA	BAGUA	ARAMANGO	280	1546183	1	Pública de gestión directa	UNIDOCENTE	Rural 1

Página 1 de 62 5 ▾ Mostrando 1 - 5 de 310

Source: MINEDU 2019

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Appendix - Tables

Table A1: Text messages in original language by treatment group

N.	Date sent	Sent by	Sent to	Text message (Original)
1	8/2/2019	IDB	Control	¡Felicitaciones [NOMBRE]! Has aprobado la PUN. En pocos días podrás seleccionar todas las plazas de tu preferencia.
			Extrinsic	¡Felicitaciones [NOMBRE]! Has aprobado la PUN. En pocos días podrás seleccionar todas las plazas de tu preferencia. Considera que en algunas instituciones educativas puedes recibir asignaciones mensuales de hasta 1150 soles adicionales a tu remuneración.
			Identity	¡Felicitaciones [NOMBRE]! Has aprobado la PUN. En pocos días podrás seleccionar todas las plazas de tu preferencia. En el aplicativo podrás ver las instituciones educativas donde puedes generar mayores cambios en los aprendizajes. ¡Gracias por elegir mejorar vidas!
2	8/6/2019		Control	[NOMBRE], mañana ya podrás seleccionar todas las plazas de tu interés en la región de tu preferencia.
			Extrinsic	[NOMBRE], mañana ya podrás seleccionar todas las plazas de tu interés en una región del Perú. Recuerda que las instituciones educativas con asignaciones te garantizan un mayor ingreso mensual.
			Identity	[NOMBRE], mañana ya podrás seleccionar todas las plazas de tu interés en la región de tu preferencia. Gracias por ser un agente de cambio social. En el aplicativo te señalaremos las instituciones educativas donde podrás lograr mayor impacto en los aprendizajes de tus estudiantes.
3	8/7/2019*		Control	[NOMBRE], ya puedes seleccionar todas las plazas de tu interés en el concurso de nombramiento.
			Extrinsic	[NOMBRE], ya puedes seleccionar todas las plazas de tu interés en el concurso de nombramiento. No pierdas la oportunidad de seleccionar instituciones educativas rurales o de frontera que te pueden permitir subir de escala magisterial 1 año antes.
			Identity	[NOMBRE], ya puedes seleccionar todas las plazas de tu interés en el concurso de nombramiento. Reconocemos tu vocación docente. En el aplicativo podrás identificar las instituciones educativas donde puedes generar mayores cambios en los aprendizajes de los estudiantes.
4	8/13/2019		Control	[NOMBRE], recuerda seleccionar todas las plazas de tu interés en el concurso de nombramiento.
			Extrinsic	[NOMBRE], recuerda seleccionar todas las plazas de tu interés en el concurso de nombramiento. Sé uno de los docentes que ya reciben hasta 5 asignaciones monetarias en algunas instituciones educativas.
			Identity	[NOMBRE], recuerda seleccionar todas las plazas de tu interés en el concurso de nombramiento. Tú puedes tener un gran impacto en tus estudiantes, especialmente en ámbitos con mayores necesidades.
5	8/15/2019		All teachers who have not yet selected vacancies	[NOMBRE], aun no has seleccionado las plazas de tu interes en el aplicativo. Este es un paso fundamental para continuar participando del concurso de nombramiento.

Note: * Start date of vacancy selection process, closing date 8/28/2019. Inter-American Development Bank (IDB), Ministry of Education (*Ministerio de Educación* - MINEDU), standardized written test (*Prueba Única Nacional* – PUN).

Table A1 (cont.): Text messages in original language by treatment group

N.	Date sent	Sent by	Sent to	Text message (Original)
6	8/18/2019	IDB	Control	[NOMBRE], en 4 días culminará la etapa de selección de plazas en el concurso de nombramiento.
			Extrinsic	[NOMBRE], [NOMBRE], en 4 días culminará la etapa de selección de plazas en el concurso de nombramiento. Recuerda que las instituciones educativas con asignaciones te permiten un mayor ingreso mensual y la posibilidad de subir de escala magisterial en menos tiempo.
			Identity	[NOMBRE], en 4 días culminará la etapa de selección de plazas en el concurso de nombramiento. Recuerda que hay muchos estudiantes que te necesitan para mejorar sus aprendizajes. ¡Gracias por elegir mejorar vidas!
7	8/22/2019	MINEDU	All teachers that passed the PUN	¡Se amplio la etapa de seleccion de plazas del Concurso de Nombramiento 2019! Mas informacion de su interes para esta etapa en su correo electronico.
8	8/26/2019	IDB	All teachers who have not yet selected vacancies	Aun no has seleccionado las plazas de tu interes en el aplicativo del concurso de nombramiento. Recuerda que de no hacerlo hasta el 28 de agosto, quedarás fuera del concurso
9	9/5/2019	MINEDU	Teachers with less than 2 assigned vacancies	Hasta el 9 set puede seleccionar aqui: http://bit.ly/2krT0QL alguna plaza de su interes con espacio disponible para el Concurso de Nombramiento 2019.
10	9/7/2019	IDB	Control	[NOMBRE], hasta el 9 de set tienes una nueva oportunidad para seleccionar plazas de tu interes en el aplicativo del concurso.
			Extrinsic	[NOMBRE], hasta el 9 de set tienes una nueva oportunidad para seleccionar plazas de tu interes en el concurso. Recuerda que puedes seleccionar escuelas con asignaciones monetarias señaladas en el aplicativo.
			Identity	[NOMBRE], hasta el 9 de set tienes una nueva oportunidad para seleccionar plazas de tu interes en el aplicativo del concurso. Recuerda que puedes seleccionar escuelas donde tienes la posibilidad de generar mayores cambios en los aprendizajes.

Note: * Start date of vacancy selection process, closing date 8/28/2019. Inter-American Development Bank (IDB), Ministry of Education (*Ministerio de Educación* - MINEDU), standardized written test (*Prueba Única Nacional* – PUN).

Table A2: Voluntary written exercise on the online selection platform in original language

Group	Voluntary written exercise (Original)
Control	Gracias por participar en el Concurso de Nombramiento Docente 2019. ¿Qué opinas sobre el proceso de inscripción al concurso?
Extrinsic	Gracias por participar en el concurso de nombramiento. ¿De qué manera las asignaciones monetarias promueven el bienestar de los docentes? Nos gustaría que te tomes unos minutos para analizar esta pregunta y luego compartas con nosotros tus ideas al respecto.
Identity	¡Gracias por elegir ser docente y ayudar a generar cambios en los aprendizajes de los estudiantes! Quisiéramos que compartas con nosotros las razones por las que elegiste ser docente. Nos gustaría que te tomes unos minutos para pensar y luego compartas con nosotros las principales razones que te motivaron a elegir esta profesión.
All	Nota: Tu respuesta es muy valiosa para nosotros y solo se utilizará para fines informativos del Minedu. La respuesta que brindes no afectará tu puntaje en el concurso. Gracias por participar.

Table A3: Effect on Teachers' Preferences

	Full Sample		Male		Female		High PUN		Low Pun	
	Proportion	At Least One	Proportion	At Least One	Proportion	At Least One	Proportion	At Least One	Proportion	At Least One
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0177	0.0164	0.0319	0.0312	0.0092	0.0074	0.0174	0.0221	0.0173	0.0106
	(0.0083)	(0.0104)	(0.0133)	(0.0165)	(0.0104)	(0.0133)	(0.0117)	(0.0155)	(0.0116)	(0.0138)
T. Identity	0.0117	0.0145	0.0367	0.0255	-0.0020	0.0086	0.0179	0.0237	0.0024	0.0006
	(0.0083)	(0.0105)	(0.0137)	(0.0168)	(0.0104)	(0.0134)	(0.0117)	(0.0157)	(0.0117)	(0.0139)
Mean(control)	0.454	0.710	0.493	0.739	0.422	0.762	0.392	0.643	0.519	0.780
N	9469	9469	3360	3360	6109	6109	4825	4825	4644	4644
R-Squared	0.2492	0.1455	0.3104	0.1793	0.2167	0.1354	0.2194	0.1399	0.2594	0.1361

Notes: Robust standard errors in parentheses.
(1) Proportion: number of disadvantaged schools included in teachers' choice set, divided by the total number of schools including in their choice set.
(2) At Least One: takes a one if there is at least one disadvantaged school in teachers' choice set.
All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median
This table uses the unrestricted sample (see Section 4).

Table A4: Effect on Teachers' Preferences: Ranking - No sample restriction

Panel A: Full Sample

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0161	0.0171	0.0206	0.0214	0.0207
	(0.0114)	(0.0113)	(0.0110)	(0.0108)	(0.0106)
T. Identity	0.0009	0.0079	0.0088	0.0162	0.0125
	(0.0115)	(0.0114)	(0.0112)	(0.0110)	(0.0108)
Mean(control)	0.429	0.551	0.609	0.652	0.675
N	9469	9469	9469	9469	9469
R-Squared	0.1576	0.1763	0.1765	0.1684	0.1631

Panel B: Only Male

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0301	0.0224	0.0348	0.0384	0.0328
	(0.0192)	(0.0183)	(0.0178)	(0.0172)	(0.0169)
T. Identity	0.0273	0.0172	0.0265	0.0360	0.0255
	(0.0194)	(0.0187)	(0.0182)	(0.0175)	(0.0172)
Mean(control)	0.480	0.616	0.664	0.699	0.723
N	3360	3360	3360	3360	3360
R-Squared	0.1894	0.1944	0.1849	0.1844	0.1797

Panel C: Only Female

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0082	0.0119	0.0109	0.0105	0.0130
	(0.0142)	(0.0143)	(0.0140)	(0.0137)	(0.0136)
T. Identity	-0.0124	0.0025	-0.0010	0.0052	0.0053
	(0.0143)	(0.0144)	(0.0142)	(0.0140)	(0.0138)
Mean(control)	0.402	0.516	0.580	0.627	0.650
N	6109	6109	6109	6109	6109
R-Squared	0.1344	0.1635	0.1739	0.1631	0.1593

Panel D: Only High PUN

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0159	0.0307	0.0274	0.0272	0.0255
	(0.0157)	(0.0160)	(0.0159)	(0.0158)	(0.0157)
T. Identity	0.0084	0.0274	0.0266	0.0321	0.0230
	(0.0157)	(0.0161)	(0.0161)	(0.0159)	(0.0158)
Mean(control)	0.354	0.466	0.527	0.575	0.601
N	4825	4825	4825	4825	4825
R-Squared	0.1468	0.1731	0.1756	0.1682	0.1618

Panel E: Only Low PUN

	Until the nth vacancy				
	(1)	(2)	(3)	(4)	(5)
T. Extrinsic	0.0164	0.0021	0.0131	0.0149	0.0144
	(0.0166)	(0.0159)	(0.0152)	(0.0146)	(0.0143)
T. Identity	-0.0100	-0.0173	-0.0143	-0.0049	-0.0027
	(0.0168)	(0.0161)	(0.0155)	(0.0149)	(0.0146)
Mean(control)	0.498	0.634	0.691	0.728	0.748
N	4644	4644	4644	4644	4644
R-Squared	0.1459	0.1597	0.1576	0.1517	0.1444

Notes: Robust standard errors in parentheses.
Each column (X, from 1 to 5) corresponds to a binary that takes a one if at least one disadvantaged schools was included up to the Xth position in the ranking of teachers' choice set. All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median
This table uses the unrestricted sample (see Section 4).

Table A5: Effect on Teachers' Allocation - Disadvantaged Schools - No sample restriction

	Full Sample		Male		Female		High PUN		Low PUN		Male and High PUN	
	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0186	0.0110	0.0363	-0.0048	0.0097	0.0197	0.0331	0.0138	0.0022	0.0087	0.0472	0.0176
	(0.0115)	(0.0097)	(0.0191)	(0.0168)	(0.0145)	(0.0118)	(0.0164)	(0.0129)	(0.0160)	(0.0146)	(0.0286)	(0.0235)
T. Identity	0.0215	0.0061	0.0528	0.0255	0.0067	-0.0018	0.0349	0.0142	0.0045	-0.0028	0.0528	0.0403
	(0.0116)	(0.0096)	(0.0192)	(0.0172)	(0.0146)	(0.0115)	(0.0164)	(0.0128)	(0.0162)	(0.0144)	(0.0278)	(0.0233)
Mean(control)	0.475	0.203	0.532	0.237	0.518	0171	0.449	0.502	0.507	0.163	0.244	0.183
N	9469	9469	3360	3360	6109	6109	4825	4825	4644	4644	1608	1608
R-Squared	0.1544	0.1027	0.1844	0.1251	0.1295	0.0999	0.1338	0.0849	0.2008	0.1143	0.1556	0.0925

Notes: Robust standard errors in parentheses.
(1): 1º stage: takes a one if the teacher was assigned to at least one disadvantaged school in the first stage (decentralized) of the process.
(2) 2º stage: takes a one if the teacher was assigned to a disadvantaged school in the second (final) stage of the process. All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median.
This table uses the unrestricted sample (see Section 4)

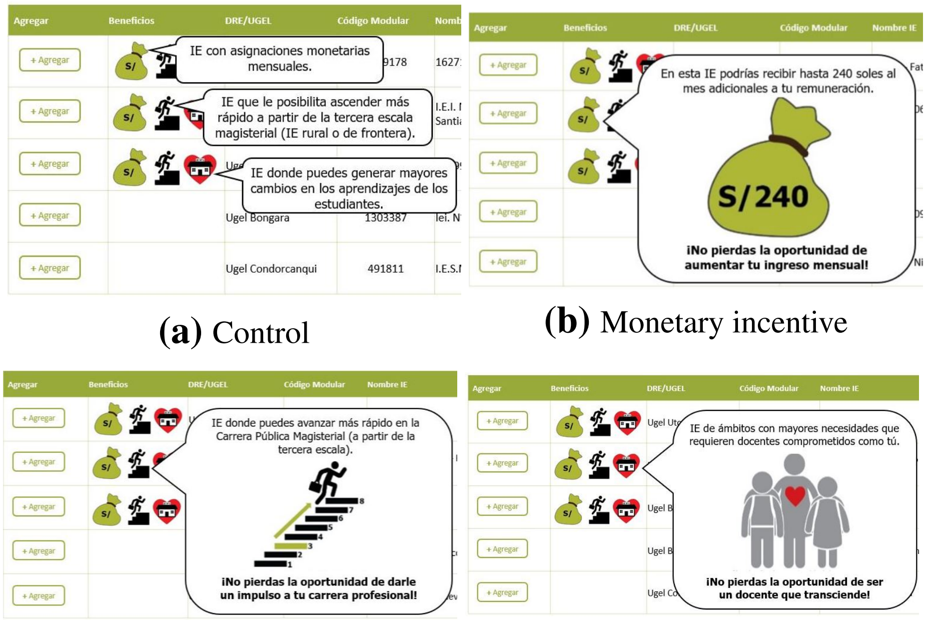
Table A6: Effect on Teachers' Allocation - All Schools - No sample restriction

	Full Sample		Male		Female		High PUN		Low PUN		Male and High PUN	
	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage	1º stage	2º stage
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
T. Extrinsic	0.0041	0.0226	0.0189	0.0228	-0.0041	0.0228	0.0056	0.0472	0.0029	-0.0024	0.0177	0.0824
	(0.0095)	(0.0113)	(0.0142)	(0.0196)	(0.0125)	(0.0136)	(0.0125)	(0.0157)	(0.0142)	(0.0161)	(0.0183)	(0.0285)
T. Identity	0.0093	0.0157	0.0207	0.0236	0.0040	0.0136	0.0120	0.0426	0.0080	-0.0116	0.0169	0.0859
	(0.0095)	(0.0112)	(0.0143)	(0.0198)	(0.0124)	(0.0136)	(0.0125)	(0.0157)	(0.0142)	(0.0160)	(0.0188)	(0.0183)
Mean(control)	0.761	0.334	0.824	0.368	0.856	0.312	0.803	0.717	0.875	0.295	0.374	0.307
N	9469	9469	3360	3360	6109	6109	4825	4825	4644	4644	1608	1608
R-Squared	0.1806	0.1161	0.1324	0.0861	0.1850	0.1438	0.1566	0.1005	0.2089	0.1492	0.1136	0.0683

Notes: Robust standard errors in parentheses.
(1): 1º stage: takes a one if the teacher was assigned to at least one school (disadvantaged or not) in the first stage (decentralized) of the process.
(2) 2º stage: takes a one if the teacher was assigned to a a school (disadvantaged or not) in the second (final) stage of the process. All regressions control for age, gender, disability (binary), total score on the PUN and region dummies.
Low (High) PUN: teacher's score in the PUN was below (above) the sample median.
This table uses the unrestricted sample (see Section 4).

Appendix - figures

Figure A1: Pop-ups on online vacancy selection platform in original language



(a) Control

(b) Monetary incentive

(c) Career progression

(d) Identity