Does Rewarding Pedagogical Excellence Keep Teachers in the Classroom? Evidence from a Voluntary Award Program*

Samuel Berlinski
Inter-American Development Bank and IZA

Alejandra Ramos
Trinity College Dublin

August 31, 2017

Abstract

We analyze the effects on teacher retention and between school mobility of a program that rewards excellence in pedagogical practice in Chile. Teachers apply voluntarily for the award and those who succeed on a set of assessments receive a 6 percent annual wage increase for up to 10 years. We use a sharp regression discontinuity design to identify the causal effect of receiving the award. Using administrative data over several cohorts of applicants, our estimates indicate that locally the award does not alter transitions out of the school system. We interpret this finding with a simple model of teachers' quit behavior. Teachers that marginally fail to receive the award value their jobs more than their outside option. We observe, however, an increase in mobility within the school system among teachers that receive the award. Some of these mobility patterns are consistent with the award providing a signal of teacher ability.

Keywords: Teacher mobility, Teacher compensation, Teacher labor market, Chile
JEL Classification: I28, J33, J45

*We thank Esteban Aucejo, Luca Flabbi, Giacomo De Giorgi, Dany Elias Jaimovich, Rafael Lalive, Alessandro Tarozzi and seminar participants at ENTER Jamboree 2016 (Universidad Carlos III), Goethe University, IFPRI, Universidad Catolica de Chile, Universite de Laussane, and SWIPS Seminar (University College London). We also thank the Ministerio de Educación in Chile and its Centro de Estudios for sharing the data and knowledge about the program with us. The views expressed herein are those of the authors and should not be attributed to the Inter-American Development Bank, its Executive Directors, or the governments they represent. Authors' emails: samuelb@iadb.org; alejandra.ramosmoreno@gmail.com

1 Introduction

Successful public schools systems retain the best teachers in their classrooms. Yet compensation policies in many countries do not provide much help in achieving this goal. In the US, for example, teachers earn 67 percent of what they could have earned in other career paths (OECD, 2013). Not surprisingly, seven percent of US teachers leave the profession every year, presumably with relatively higher separation rates among those with better outside options.[1] Because wage schedules are traditionally based on factors that are not necessarily related to classroom performance (e.g., education, experience, hours worked), they are not flexible enough to reward the best teachers.

A large literature in personnel economics focuses on the role that wages play in motivating, retaining and recruiting workers.[2] Tying wages to a performance measure may both motivate workers and allow firms to retain its most productive workers. These personnel policies crucially depend on workers knowing their ability/type and on higher ability workers being able to sort themselves at a relatively lower cost than lower ability ones. If ability can be revealed through observation and testing at a reasonable cost for schools and teachers, it may provide a suitable tool to keep the best teachers in the classroom.

In this paper, we analyze the effects on teachers' retention and between school mobility of a program that rewards excellence in pedagogical practice in Chilean primary and secondary schools (a country with comparable teacher turnover rate to the US). The Pedagogical Excellence Award initiative aims to identify good teachers, prevent them from leaving the public school system, and allocate them where they are needed the most (Araya-Ramirez et al., 2012; Rodriguez et al., 2015). Teachers apply voluntarily for the award which is allocated on the basis of teachers' knowledge of their field and their pedagogical skills. In order to receive the award, teachers must prepare a teaching portfolio and take a knowledge test. The results of both assessments are combined in a final score and only those scoring above a certain cut-off receive the award. The teachers that succeed on the assessments are awarded the equivalent of a six percent yearly wage increase for up to ten years, after which they need to re-apply for the program.

We formalize our identification conditions using a simple model of quit behavior (Guasch and Weiss, 1980, 1981) and teacher testing (Angrist and Guryan, 2004). Teachers decide whether or not to take the test and, after observing the results, they decide whether or not to quit. The retention effect depends on the test difficulty. The easier is the test, the more likely it is that teachers scoring around the threshold are being paid above their reservation wage and that they will be willing to stay in the school system

[1]Statistics from the U.S. Department of Education. http://nces.ed.gov/pubs2014/2014077.pdf
[2]See Prendergast (1999) for a review.

irrespectively of receiving the award. In contrast, when the test is rather difficult the award can alter teachers' decisions to quit at all margins.

Using administrative data over nine cohorts of applicants, our estimates indicate that locally the award does not alter transitions out of the school system. This suggests that teachers marginally failing to receive the award value their jobs more than their outside option. We observe, however, an increase in mobility within the school system among teachers that receive the award. Some of these mobility patterns are consistent with the award providing a signal of teacher ability. Contrary to the spirit of the policy, awardees in schools with relatively low performing students and working conditions tend to move after receiving the award.

To our knowledge this is the first paper that provides estimates of the impact on teacher mobility of a voluntary award system that ties wages to an input measure of classroom performance. The education literature suggests that teacher separation responds to changes in basic compensation (Dolton and Van der Klaauw, 1995, 1999; Clotfelter et al., 2008; Falch, 2011) and that teachers' effort increases when compensation is tied to student performance (Lavy, 2002, 2009; Muralidharan and Sundararaman, 2011). Our paper is also related to the literature on occupational licensing. Compulsory licensing imposes a barrier to entry, which reduces the supply of labor and increases labor costs.[3] The available evidence for the education sector suggests that teachers are not an exception. Using data from the Schools and Staffing Survey in the US, Angrist and Guryan (2004, 2008) find that state's licensing requirements do not improve teacher quality while they do increase wages.[4] The literature is mute on the effect of compulsory certification on teachers' turnover.

The rest of the paper is organized as follows. In Section 2 we provide some background on the Chilean education system and the design of the program. Section 3 describes the data used. In Section 4 we model the decision to quit teaching and study the margins at which a program with the basic features of the Chilean Pedagogical Excellence Award program can affect behavior. In section Section 5 we present our identification strategy and relate it to the model presented in Section 4. In Section 6 we present our results. Section 7 concludes.

2 Background

Primary and secondary education in Chile is provided by three type of institutions: municipal or public schools, private-subsidized schools, and private schools. Municipal

[3]See (Kleiner, 2000) for a thorough discussion on occupational licensing.

[4]See Hanushek and Rivkin (2010); Wiswall (2007); Kane et al. (2008); Harris and Sass (2009) for further evidence.

schools are non-profit institutions that offer instruction to students for free. They receive a per-student subsidy from the Ministry of Education and are administered by municipalities. Private schools are for profit institutions that charge tuition to students. They receive no subsidies from the government and are administered as private corporations. Private-subsidized schools are run like private schools, they receive the same per-student subsidy than municipal schools and can also charge a tuition (Mizala and Schneider, 2014; Hsieh and Urquiola, 2006).[5] We refer to municipal and private-subsidized schools as the Voucher School System.

The contractual arrangements for teachers are different in the three type of providers.[6] In Figure 1, we use data on wages, age category and type of school to construct wage-age profiles for teachers. The data comes from *Encuesta Longitudinal Docente 2005: Análisis y Principales Resultados*, a national representative survey of that collects information on socio-demographic characteristics and employment history of 6,000 Chilean teachers. As one will expect, wages increase with age. Wages in the private sector are uniformly higher. For younger teachers, wages in private-subsidized schools are higher than in the municipal sector but wages increase faster in the municipal sector. In fact, the level of wages is practically equal for the 41-50 age group. After this age, municipal school teachers are paid a higher per hour wage rate than private-subsidized schools.

In Figure 2 we present the share of students enrolled and teachers employed in primary and secondary schools during 2004-2013. Enrollment in the Voucher System over this period is pretty stable at around 93 percent. However, there have been large compositional changes between municipal and private-subsidized schools. In 2004, 50.4 percent of the students were enrolled in municipal schools; while in 2013, it was only 39 percent. This has, of course, caused a commensurate shift in the share of teachers employed in municipal and private-subsidized schools.

In Chile, like in the US (Hanushek et al., 2004), there is considerable teacher turnover, particularly among the least experienced teachers. As we show in Table 1, from all teachers employed in 2003, two years later 12 percent were no longer teaching and 9 percent have changed schools. These figures are even larger for those with less than 11 years of experience (18 and 15 percent, respectively).

The Chilean government perceived that many good teachers were leaving the profes-

[5] The fees that these schools can charge to students are regulated.

[6] The employment of teachers in municipal schools follows a union negotiated teacher statute. In the private sector, employment follows the standards established by common labor law. Employment of teachers in private-subsidized schools retain some aspects of the municipal school system (Mizala and Romaguera, 2005; Santiago et al., 2013). For example, minimum wages, bonuses, and maximum working hours are determined by the Teachers Statute. Yet, after reaching the retirement age (60 years for women and 65 for men) teachers are no longer allowed to teach in municipal schools, but they can still teach in private-subsidized institutions.

sion and introduced a voluntary award program designed to reward, both economically and socially, excellence in teaching practice: The Pedagogical Excellence Award (*Asignación a la Excelencia Pedagógica*) or AEP (following its Spanish acronym).[7] Starting in 2002, teachers employed in municipal schools and private-subsidized schools could apply for this award. Eligible candidates must teach at least 20 hours a week during the academic year in Voucher System schools. The award entitles beneficiaries with a 6 percent annual salary increase for up to ten years.[8,9] The magnitude of the bonus varies at four levels of experience: 0-11 years, 12-21 years, 22-30 years, and 31 plus years. In addition, those awarded the AEP are invited to become mentors of other teachers in the Network of Teachers of Teachers (*Red Maestro de Maestros*).[10] The awards are presented in a ceremony with local authorities and media coverage. Teachers can apply for an award only twice within each level of experience.

To receive the AEP award, teachers must prepare a teaching portfolio and take a written test in their main area of expertise. In the portfolio, teachers must demonstrate their teaching practices. This assessment requires a learning plan for the students, an evaluation strategy, a pedagogical reflection and a recording of a class. In the written test, teachers are evaluated on grounds of their knowledge. The results of these two assessments are combined in a final score ranging from 100 to 400. For the AEP rounds taking place between 2002 and 2011, the final score was a weighted average with 70 percent of the weight given to the portfolio and 30 percent to the written test. Only teachers with a final score of at least 275 receive the award.[11]

The application process for the AEP begins in April. The portfolio is prepared from July to October, and the written examination takes place in November. The school year starts in March and teachers learn about their score in April. For those who are successful, payments are done twice a year with the first installment in July. We present this time line in Figure 3.

There are other incentive mechanisms built into the Chilean education system. In 1996, the National System for Performance Evaluation (*Sistema Nacional de Evaluación del Desempeño*) or SNED (following its Spanish acronym) introduced collective

[7] AEP was established by law in 2001 (Law 19715). Modifications to the law were introduced in 2006 (Law 20158) and 2011 (Law 20501).

[8] AEP bonus is equivalent to 70 percent of a monthly salary.

[9] After 2011, the AEP award period was reduced to four years.

[10] AEP awardees willing to become members of the Network of Teachers of Teachers are required to present another portfolio. If they score above a certain threshold, they become permanent members of the Network. Teachers who are not selected can reapply every three years for as many times as desired. Members of the Network receive an additional monetary incentive tied to the hours worked. 40 percent of the AEP awardees become members of the Network at some point after receiving the award.

[11] This cut-off point was identified by inspecting the data and was confirmed by the *Centro de Perfeccionamiento, Experimentación e Investigaciones Pedagógica* (CPEIP) in internal correspondence. To our knowledge, there is no official document where the threshold is stated.

performance incentives in the Voucher School System. Every two years, SNED gathers information about schools' performance at a standardized national examination, repetition and dropout rates, educational activities provided, parental participation in school activities, and overall working conditions. After grouping schools in sets with similar students' socioeconomic characteristics, SNED ranks schools using an aggregate index that combines the factors described. The best schools in each group (accounting for up to 35 percent of the enrollment in the set) receive a monetary transfer for two years. That transfer is distributed among teachers and accounts for a 50 percent to 70 percent of a monthly salary (Mizala and Urquiola, 2013).

In 2004 the Ministry of Education implemented a compulsory examination for municipal school teachers. Every 4 years, teachers of municipal schools are assessed through a written examination (*Evaluación Docente* (EV)).[12] Municipal school teachers with an outstanding evaluation can apply to a performance award: *Asignación Variable al Desempeño Individual* or AVDI (following its Spanish acronym). For this purpose, teachers must take the same knowledge test than for AEP. Teachers can receive both the AEP and the AVDI award, and can apply to them simultaneously (although not many do). We focus the main body of the paper on the AEP as the data suggests that the conditions for identification using a regression discontinuity design are not fulfilled for AVDI. For completeness, we provide the analysis of AVDI along the lines of our work for AEP in an online appendix.

3 Data

We use administrative data from all teachers in the school system published yearly by the Ministry of Education. The data set starts in 2003 and contains information on basic demographics, educational qualifications, experience, place and hours of work. We match it with the scores and award status of individual applicants to AEP and AVDI and with school level data from SNED. Figure 4 presents a sample flowchart. We start with the 13,098 teachers that applied for the first time for an AEP award between 2003 and 2011.[13] Further, we restrict to individuals who applied for an award as primary or secondary school teachers.[14] We match this data with administrative records and restrict our analysis to individuals that at the time of application were at least four

[12] Teachers failing the test can retake it up to three times. After a third failure, teachers are fired from the Voucher System. From 2004 to 2013, around 1.5 percent of the teachers that took the test fail it at the first attempt but less than 0.1 percent took the examination more than twice.

[13] We eliminate 2002 AEP applicants because of lack of administrative data.

[14] We eliminate those applying for the award in pre-primary education, adult education and special education as they face radically different inside and outside options that teachers in primary and secondary schools.

years away from the retirement age (i.e., 56 for females and 61 for males). For brevity, our main results focus on the sample of 9,311 teachers that are not concurrently applying to AVDI.

We start by showing that the assignment rule was strictly enforced. In Figure 5, we plot the mean of a variable that takes the value of 1 if an individual has an AEP award and 0 otherwise for each possible score cell (circles). There is clearly a sharp discontinuity. Those who obtained the award have an aggregate score of 275 or more. In Table 2, we present the awardee rate and final scores by year. We divide the data in two samples, Panel A has the 9,311 teachers from our benchmark sample and Panel B has the 13,098 first time applicants. The table confirms the information on the graph: compliance with the allocation rule is above 99 percent regardless of the application wave or sample. Focusing on Panel A, 28 percent of the teachers that apply for an AEP obtained it. There are significant differences, however, in the passing rates over time; while 44 percent of the 2003 applicants received the award, less than 22 percent did so after 2007. Finally, the awardee rates in Panel B are slightly smaller than in Panel A, but we cannot detect systematic differences in the final score.

In the first column of Table 3, we present average information for all employed teachers in the Voucher School System during the 2003-2014 period. In the second column, we present the same information but only for those who have applied to AEP during the 2003-2011 window. Beginning with basic demographic and qualification variables, we observe that over the 2003-2014 period, the average Chilean teacher is a 44 years old woman with a degree in education and 17 years of teaching experience. Teachers work on average 35 hours a week, around 10 percent work in more than one school, 75 percent work as primary school teachers, 10 percent hold a managerial position, and 40 percent work at private-subsidized schools. Every year, 12 percent of the teachers change schools and 7 percent move to a different municipality. Around 42 percent of the teachers work in municipalities considered as isolated and are monetarily compensated with an allowance.[15] We average schools' working conditions and students' performance using information from SNED between 2003 and 2014, and rank the schools based on these variables. Around 40 percent of the teachers work in schools ranked in the top 50 percentile in terms of working conditions and 63 percent in schools ranked in the top 50 percentile in terms of student performance.

Of the employed teachers, 6.5 percent applied to AEP at some point between 2003 and 2011. From these applicants, 42 percent also applied to AVDI. Only 1.2 percent

[15]In Chile, the *D.L. 249* of the Fiscal Sector establishes a percentage increase in the RMBN for civil servants working in zones considered as isolated or with high cost of living. We extract allowance information at the municipality level from the *Ley 19.354* of 1994 and use those percentages along the 2003-2014 period.

of the teachers are recipients of the AEP award and 2.6 percent are AVDI recipients. Relative to the average Voucher System teachers, AEP applicants are slightly younger, more likely to have a degree in education, and more likely to work in a school with top-performing students. In the third and fourth column of Table 3, we describe the sample at the first time of application to AEP and two-years after. Two-years after applying to AEP, 4 percent of the teachers are not employed in the school system[16], 1 percent work in a private school, 10 percent change from municipality, and 16 percent moved to a different school from the one they were at when applying.[17] The number of contract hours, the rurality of the school, the percentage working in subsidized-private schools, the percentage working in school with better working conditions and student performance all fall relative to the baseline measure.

4 A Model of Teachers' Quit Behavior

One of the goals of AEP is to prevent good teachers from leaving the profession (Araya-Ramirez et al., 2012). With this aim, the program entitles whomever pass the assessment with a fix monetary award and a token of social recognition. These incentives increase the marginal benefit of being in the profession and raise the opportunity cost of quitting. In this section, we provide a simple model that captures these features and speaks to the margin of behavior that the identification strategy described in Section 5 is able to capture.

Similar to Guasch and Weiss (1980, 1981) and Angrist and Guryan (2004), we consider a continuum of teachers i, characterized by their productivity as teachers or ability, ω_i, where $\omega_i \in [0,1]$. Teachers are risk neutral, and their productivity is distributed following $\omega_i \sim f(\omega)$. Teachers observe their productivity upon entering the profession, but the school system only observes the overall distribution.

Assume that ω_i also captures teachers' reservation wage. Teaching pays a fixed wage w. Without lost of generality assume that $E(\omega_i) \leq w$. A teacher i with reservation wage ω_i will stay in the profession if and only if

$$w \geq \omega_i.$$

The government wants to retain all teachers of at least productivity $\widetilde{\omega} > E(\omega_i)$, without increasing the base salary. Even if productivity cannot be directly observed, the government can design a test where the score, s_i, is an increasing function of teachers'

[16]This variable takes a value of zero for those teachers who have dropped from the sample.

[17]For example, someone without a contract one year after applying but with a contract two years after applying is classified not at work in the first year and at work in the second year.

productivity, ω_i, and some measurement error, ν_i. We assume that the measurement error follows a distribution $\nu_i \sim g(\nu)$, is symmetrically distributed around a mean of zero and orthogonal to ability. Furthermore,

$$s_i = \omega_i + \nu_i. \tag{1}$$

Taking the test is costly for teachers and we define this cost, in monetary terms, as c. To create incentives for more productive teachers to stay in the school system, the government pays a bonus b to all teachers that voluntarily take the test (i.e., pay the cost c) and score above the cut-off $\widetilde{\omega}$.

A teacher whose reservation wage is at most the fix wage, $\omega_i \leq w$, will sit the exam if the expected pay-off of taking the test is at least the fixed wage. In other terms,

$$\begin{aligned} p(\omega_i)\,(w+b-c) + (1-p(\omega_i))\,(w-c) &\geq w, \\ p(\omega_i) &\geq \frac{c}{b}, \end{aligned} \tag{2}$$

where $p(\omega_i)$ is the probability of passing the exam for a teacher of productivity ω_i. Likewise, a teacher with reservation wage above the fix wage, $\omega_i > w$, will sit the exam if the expected pay-off is at least as high as her reservation wage

$$\begin{aligned} p(\omega_i)\,(w+b-c) + (1-p(\omega_i))\,(\omega_i-c) &\geq \omega_i, \\ p(\omega_i) &\geq \frac{c}{w+b-\omega_i}. \end{aligned} \tag{3}$$

We can now characterize the teachers' decision to quit around the cut-off $\widetilde{\omega}$. Using equations (2) and (3), we define the probability of receiving the award for the lowest, $\underline{\omega}$, and highest, $\overline{\omega}$, productivity teachers that take the exam as:

$$\begin{aligned} p(\underline{\omega}) &= \frac{c}{b} \quad \text{and} \\ p(\overline{\omega}) &= \frac{c}{w+b-\overline{\omega}}. \end{aligned}$$

For a teacher of productivity ω_i, the probability of receiving the award is:

$$\begin{aligned} p(\omega_i) &= \begin{cases} 1 & \text{if } \omega_i + \nu_i \geq \widetilde{\omega} \\ 0 & \text{if } \omega_i + \nu_i < \widetilde{\omega} \end{cases} \\ &= \Pr(\omega_i + \nu_i \geq \widetilde{\omega}) = 1 - \Pr(\widetilde{\omega} - \omega_i \geq \nu_i) \\ &= 1 - G(\widetilde{\omega} - \omega_i) = G(\omega_i - \widetilde{\omega}), \end{aligned}$$

where $G(.)$ is the CDF of the measurement error term. Therefore, $\underline{\omega}$ and $\overline{\omega}$ can be expressed as,

$$\begin{aligned} G(\underline{\omega} - \widetilde{\omega}) &= \frac{c}{b} \quad \text{and} && (4) \\ G(\overline{\omega} - \widetilde{\omega}) &= \frac{c}{w + b - \overline{\omega}}. && (5) \end{aligned}$$

Let $q(\omega_i)$ be the probability that a teacher of productivity ω_i stays in the profession. Notice that $q(\omega_i)$ depends both on the probability of taking the exam and the probability of passing it. In particular,

$$q(\omega_i) = \begin{cases} 1 & \text{if } \omega_i \leq w \\ p(\omega_i) & \text{if } w < \omega_i \leq \overline{\omega} \\ 0 & \text{if } \omega_i > \overline{\omega}. \end{cases} \qquad (6)$$

Consider the case where b, c and $\widetilde{\omega}$ are such that equations (2) and (3) hold for a positive mass of teachers. In other words, some teachers whose outside option is below the current teacher wage apply for the award and some teachers who in the absence of the award will quit sit for the exam as well (i.e., $\underline{\omega} \leq w < \overline{\omega}$). It is worth pointing out that these set of conditions do not pose any restrictions on the relation between the difficulty of the test and the fixed teachers wage (this can be seen by manipulating equation (4)).[18]

Define an interval ϵ around the cut-off $\widetilde{\omega}$ and call $\Delta_\epsilon^{\widetilde{\omega}}$ the difference between the mass of non quitters above and below the cut-off.

$$\Delta_\epsilon^{\widetilde{\omega}} = \int_{\widetilde{\omega}}^{\widetilde{\omega}+\epsilon} q(\omega_i) f(\omega_i) d\omega_i - \int_{\widetilde{\omega}-\epsilon}^{\widetilde{\omega}} q(\omega_i) f(\omega_i) d\omega_i$$

Let $\widetilde{\omega}_L$ denote a test such that $\widetilde{\omega}_L \leq w$ and $\widetilde{\omega}_H$ denote a test such that $w < \widetilde{\omega}_H$. We now prove that the capacity of the award to affect teachers' quit behavior around the threshold depends on the difficulty of the test.

Proposition 1. *For any* $0 < \epsilon < \min\{w - \widetilde{\omega}_L, \widetilde{\omega}_H - w\}$ *such that* $\int_{\widetilde{\omega}}^{\widetilde{\omega}+\epsilon} f(\omega_i) d\omega_i = \int_{\widetilde{\omega}-\epsilon}^{\widetilde{\omega}} f(\omega_i) d\omega_i$*,* $\Delta_\epsilon^L = 0$ *and* $\Delta_\epsilon^H > 0$*.*

[18] Equation (4) and $\underline{\omega} \leq w$ imply that

$$\begin{aligned} \underline{\omega} = \widetilde{\omega} + G^{-1}\left(\frac{c}{b}\right) &\leq w, \\ G^{-1}\left(\frac{c}{b}\right) &\leq w - \widetilde{\omega}. \end{aligned}$$

As $g(\nu)$ is symmetric around 0, $G^{-1}\left(\frac{c}{b}\right) \leq 0 \iff \frac{c}{b} < G(0) = \frac{1}{2}$. Therefore, if $2c \leq b$, $w \gtreqless \widetilde{\omega}$.

Proof. For relatively easy test, $q(\omega_i) = 1$ for all $\omega_i \in (\widetilde{\omega} - \epsilon, \widetilde{\omega} + \epsilon)$, so that

$$\Delta_\epsilon^L = \int_{\widetilde{\omega}}^{\widetilde{\omega}+\epsilon} f(\omega_i) d\omega_i - \int_{\widetilde{\omega}-\epsilon}^{\widetilde{\omega}} f(\omega_i) d\omega_i.$$

It is straight forward that, whenever the distribution productivity is smooth around the cut-off, $\Delta_\epsilon^L = 0$. For a relatively difficult test, $q(\omega_i) = p(\omega_i)$ for all $\omega_i \in (\widetilde{\omega} - \epsilon, \widetilde{\omega} + \epsilon)$, so that

$$\Delta_\epsilon^H = \int_{\widetilde{\omega}}^{\widetilde{\omega}+\epsilon} p(\omega_i) f(\omega_i) d\omega_i - \int_{\widetilde{\omega}-\epsilon}^{\widetilde{\omega}} p(\omega_i) f(\omega_i) d\omega_i.$$

As the measurement error is independent of productivity,

$$\Delta_\epsilon^H = \left[\int_{\widetilde{\omega}}^{\widetilde{\omega}+\epsilon} p(\omega_i) d\omega_i - \int_{\widetilde{\omega}-\epsilon}^{\widetilde{\omega}} p(\omega_i) d\omega_i \right] \int_{\widetilde{\omega}}^{\widetilde{\omega}+\epsilon} f(\omega_i) d\omega_i > 0$$

The first term on the RHS is positive as $p(\omega_i)$ is increasing in ω_i. Formally, let $h : [0, \epsilon] \to \mathbb{R}$ such that $h(x) = p(\widetilde{\omega} + x)$, and $k : [0, \epsilon] \to \mathbb{R}$ such that $k(x) = p(\widetilde{\omega} - x)$. Since $p(\omega_i)$ is strictly increasing in ω_i, $h > k$. Then, by monotonicity,

$$\int_{[0,\epsilon]} h(x) dx > \int_{[0,\epsilon]} k(x) dx \iff \int_{\widetilde{\omega}}^{\widetilde{\omega}+\epsilon} p(\omega_i) d\omega_i > \int_{\widetilde{\omega}-\epsilon}^{\widetilde{\omega}} p(\omega_i) d\omega_i$$

□

Proposition 1 is intuitive: if the difficulty of the test is rather low ($\widetilde{\omega}_L \leq w$), teachers around the threshold are currently being paid above their reservation wage and they will stay in the school system irrespectively of receiving the award. The decision of teachers that are not infra-marginal for a low difficulty test can be affected as long as the bonus b (relative to the cost c) is large enough (see equation (3)). In contrast, when the test is rather difficult ($w < \widetilde{\omega}_H$) the award can alter teachers' decisions to quit at all margins.

When the test difficulty is low, there is potential room to capture some of the rents of teachers with relatively low reservation wages by increasing the difficulty of the assessment. To see it clearly, we characterize the lowest and the highest productivity teachers taking the exam in terms of its difficulty. Differentiating equations (4) and (5) with respect to $\widetilde{\omega}$, we obtain

$$\frac{\partial \underline{\omega}}{\partial \widetilde{\omega}} = 1 \quad \text{and}$$
$$\frac{\partial \overline{\omega}}{\partial \widetilde{\omega}} = \frac{cg(\overline{\omega}-\widetilde{\omega})}{cg(\overline{\omega}-\widetilde{\omega}) - G^2(\overline{\omega}-\widetilde{\omega})}.$$

Therefore, if the cost is sufficiently low, increasing the difficulty of the test *deters* low productivity teachers from applying more than what it *deters* higher productivity ones $\left(\text{i.e. } \left|\frac{\partial \overline{\omega}}{\partial \widetilde{\omega}}\right| < \left|\frac{\partial \underline{\omega}}{\partial \widetilde{\omega}}\right|\right)$.[19] The remaining funds can be used to increase the bonus which, *ceteris paribus*, may prevent teachers with the highest outside options from leaving the educational system. Differentiating equations (4) and (5) with respect to b, we obtain

$$\frac{\partial \underline{\omega}}{\partial b} = -\frac{1}{b}\frac{G(\underline{\omega}-\widetilde{\omega})}{g(\underline{\omega}-\widetilde{\omega})} \quad \text{and}$$
$$\frac{\partial \overline{\omega}}{\partial b} = \frac{G^2(\overline{\omega}-\widetilde{\omega})}{G^2(\overline{\omega}-\widetilde{\omega}) - cg(\overline{\omega}-\widetilde{\omega})}.$$

The larger the bonus, the higher the incentives for teachers to take the exam.[20] Yet, if the bonus is sufficiently high, the *entry* effect dominates for high productivity teachers.[21]

Finally, the model speaks only to the decision to leave the school system. If passing the assessment for the award provides an otherwise unobservable signal of ability, the program may also boost mobility within the school system. To the extent that competition in wages among schools is coerced by wage rules, schools may still be available to compete for teachers in amenities (e.g., working conditions, students ability, etc). Therefore, we will expect that independently of the quit decision the program may increase mobility between schools.

5 Identification Strategy

Our goal is to measure the causal effect of obtaining an award on teachers' retention and between school mobility. AEP is assigned using a performance measure which is likely to be associated with other determinants of teacher behavior. Therefore, a naive comparison of the outcomes of awardees versus non-awardees will provide biased and inconsistent estimates of the causal effect of the program. We tackle this issue by using a regression-discontinuity approach. We exploit the sharp discontinuity in the allocation

[19]The referred condition is $2c < \frac{G^2(\overline{\omega}-\widetilde{\omega})}{g(\overline{\omega}-\widetilde{\omega})}$.

[20]Notice $\frac{\partial \underline{\omega}}{\partial b} < 0$ for any set of parameters b,c, $\widetilde{\omega}$. For $\frac{\partial \overline{\omega}}{\partial b} > 0$, we require $c < \frac{G^2(\overline{\omega}-\widetilde{\omega})}{g(\overline{\omega}-\widetilde{\omega})}$.

[21]The referred condition is $\frac{1}{b} < \frac{g(\underline{\omega}-\widetilde{\omega})}{G(\underline{\omega}-\widetilde{\omega})} + \frac{g(\overline{\omega}-\widetilde{\omega})}{G(\overline{\omega}-\widetilde{\omega})}\frac{G(\underline{\omega}-\widetilde{\omega})}{G(\overline{\omega}-\widetilde{\omega})}$.

of the award for teachers with 275 points or more in the aggregate evaluation score. In the absence of manipulation around the cut-off, teachers that obtained 275 should be similar to those that obtained 274.[22] As a result, any systematic differences in behavior after the award is granted could be attributed to the program.

We implement the regression discontinuity design using the following estimating equation for a teacher i who applied to AEP in wave τ:

$$Y_{i\tau}^{t} = \alpha + \beta D_{i\tau} + \gamma_{\tau} f(s_{i\tau}) + \delta_{\tau} D_{i\tau} \times f(s_{i\tau}) + \lambda_{\tau} + \varepsilon_{i\tau}^{t}. \quad (7)$$

$Y_{i\tau}^{t}$ is the outcome variable of interest t years after the candidate applied for the award (e.g., weekly hours of work in the voucher school system), $D_{i\tau}$ is a variable equal to 1 if the teacher composite score at the exam was at least 275 and 0 otherwise, $s_{i\tau}$ is the teacher's score centered around the 275 cut-off, $f(s_{i\tau})$ is a suitable polynomial function of the composite score and λ_{τ} is a set of wave fixed effects. We allow the effect of the running variable to differ across waves as well as at both sides of the cut-off.[23]

We are interested in the parameter β. Under suitable assumptions, β provides a local measure of the causal impact of obtaining the AEP award. The basic identifying assumption is that there is no systematic manipulation of the running variable around the cut-off. There are at least two strategies to test the plausibility of this assumption (Bloom, 2012; Hahn et al., 2001; Imbens and Lemieux, 2008; Lee and Card, 2008; Lee and Lemieux, 2010). First, there should be no kinks in the density of the score around the discontinuity. Second, predetermined factors ought to vary smoothly around the 275 cut-off.

In Figure 6, we plot the histogram of the final score for the pooled sample of applicants. In column one of Table 4, we present the results of testing for a discontinuity for the pooled sampled using the McCrary (2008) test and Frandsen (2014)'s approach for variables with discrete support. In the remaining columns we presents the McCrary (2008) and Frandsen (2014)'s p-values for each AEP wave. These tests do not reject the null hypothesis either yearly or pooling all the years together. As the estimated densities to the left and to the right of the discontinuity overlap, we cannot reject the no discontinuity hypothesis.

In Table 5 we provide evidence on the continuity of baseline characteristics around the threshold. We estimate equation (7) using as outcome variables the characteristics

[22]See Hahn et al. (2001); Lee (2008) for an interpretation of the regression discontinuity approach as a local randomization.

[23]The estimated regression functions do not fully saturate the model. Lee and Card (2008) show that one can interpret the deviation between the true conditional expectation function and the estimated regression function as random specification error that introduces a group structure into the standard errors for the estimated treatment effect. Thus, we always report standard errors clustered by test score integer bins.

of the teachers and their schools, at the time of application to AEP. The number of the column in this table indicates the order of the piece-wise polynomial of the score used in each specification. In general, there are few statistically significant differences and these differences are small in magnitude with respect to the mean of the variables involved. The second degree order polynomial seems to do best at eliminating individual differences in baseline characteristic between AEP awardees and non-awardees. We cannot reject the null hypothesis of continuity for the 15 variables presented, either using individual tests or a joint (Wald) test. Therefore, we adopt a polynomial of degree two as our benchmark specification. Additionally, we present specifications that control for baseline variables interacted with wave fixed effects.

6 Main Results

6.1 Teacher Retention and Labor Supply

We look now at the effect of receiving an AEP award on teacher retention.[24] As we showed in Section 4, the presence or absence of a local effect of an AEP award on teacher quitting behavior reflects the difficulty of the test relative to the fix wage. If we observe that the AEP award has no effect on quitting at the threshold, this would suggests that teachers marginally failing to receive the award value their jobs more than their outside option. In contrast, if we do observe an effect in teacher turnover, it is the case that teachers at the threshold were about to quit in the absence of the program.

In Figure 7, we summarize the relationship between the AEP aggregate score and teacher turnover, two years after applying for an AEP award. The circles represent the un-adjusted mean of this variable within bins of the score. The superimposed lines are fitted values from a piece-wise linear specification on the score. There is no visual evidence of breaks around the cut-off. In the light of the model presented in Section 4, this implies that the marginal teacher who obtains the award is receiving a rent as she was not at risk of quitting, even in the absence of the award.

The program may have affected, however, other margins of labor supply. For example, the AEP award is independent of the hours that the teacher works beyond a minimum of 20 hours. In a static labor supply framework, without restrictions on hours worked, the pure income effect of the award will reduce hours worked. In practice, teachers may have a coarse choice set on the hours they can work and reducing hours may

[24]This is clearly a sharp regression-discontinuity design and therefore receiving the award is the same than scoring above the cut-off. Indeed, looking at Figure 5 is not surprising that estimating equation (7) using the AEP award variable as a dependent variable, pooling all years or year-by-year, we cannot reject the null hypothesis that the cut-off coefficient is equal to one. The results are available upon request from the authors.

be unfeasible. Yet teachers can adapt their labor supply by adjusting the number of schools they teach at. There are 1,457 teachers working in more than one school at the time of application. If wages across schools are the same and there are some minimal transportation costs, it must be the case that these teachers cannot get enough working hours in one school. In such case, a strong income effect may induce teachers to reduce hours of work mainly by providing incentives to drop second jobs.[25]

In Table 6, we present OLS estimates of equation (7) for the total hours worked and teaching at more than one school recorded two years after applying for an AEP award. We focus on the sample of teachers who are in the school system as we found not evidence of an impact of AEP at the extensive margin.[26,27] We show estimates by experience levels using the brackets designated by AEP to determine the size of the bonus: 0-11 years, 12-21 years and 22 or more years of experience.[28] The odd-columns in the table are the results of estimating equation (7). In the even columns we add controls for demographics, qualifications, labor outcomes, and main school's characteristics at the time of application.

The estimates are very small and mostly non-statistically significant. For example, looking at the sample of all teachers and excluding additional covariates (first column), we find that receiving the award increases the chance of not working in the school system by 0.0038 percentage points (p-value 0.66), reduces hours of work by 0.6344 hours a week (p-value 0.06) and decreases the likelihood of working in more than one school by 0.0047 percentage points (p-value 0.75). Finally, looking by experience levels we can see a stronger fall in hours worked for more experienced teachers of 1.6 hours a week (p-value 0.02) but no other systematic differences.

Figure 8 shows estimates of the parameters of interest separately for each of the nine waves. In general, we cannot reject the null hypotheses that all the coefficients are zero.[29] In Figure 9 we explore different time windows for the outcomes of interest (the year previous to the program, the year of application to the program, one year after, two years after and three years after). Looking at Figure 9, is reassuring that previous to the application and in the year of application for the award there are no effects.[30]

[25]The award may also affect the desirability of taking managerial positions within the school system that take teachers outside the classroom. We find no evidence of such effect. The results are available from the authors upon request.

[26]We have also estimated models including zeros in the dependent variable for those who are not working in the school system. The results are similar and are available from the authors upon request

[27]We also separate the sample between female and male teachers but we find no systematic differences in our results. These estimates are available from the authors upon request.

[28]For each column, we estimate equation 7 in the sub-sample of teacher within the corresponding age range.

[29]Only the coefficient for *Working at more than one school* in the 2004 wave is statistically different from zero.

[30]Administrative data only starts in 2003. Therefore, the information in the years previous to the

Looking at the one year window or the three year window does not change the initial assessment from Table 6.

6.2 Between-School Mobility

There is no evidence that the program has locally affected teachers' decisions to leave the profession. But, has the award led to any changes in the way teachers sort themselves between schools? Due to the selective nature of the award process, AEP can provide a signal of ability and those receiving the award may use it to improve the overall deal they get from working in the school system. Hence, are teachers changing schools after receiving an award? Who are those teachers? Where are they moving?

In Figure 10, we look for breaks in teachers' mobility. Teachers receiving the award seem to have higher chances of moving to a new school. The first row of Table 7 confirms this insight. Two years after receiving the award, teachers are 0.0447 percentage points (p-value 0.01) more likely to move to a new school (first column, first row). With 12 percent of the teachers changing schools every year, the point estimate implies that the AEP award contributes towards more than a 30 percent boost in mobility.

Can we detect any systematic patterns of between school mobility among those that receive the award? We explore this question in rows (2) to (7) of Table 7 where we study mobility in the school system independently of the characteristics of the school the teacher is employed when applying to the program. Teachers with 0 to 11 years of experience are 0.0799 percentage points (p-value 0.08) less likely to teach in private-subsidized schools, without necessarily being more prone to teach in private schools (third column). In contrast, awardees with 12 to 21 years of experience are 0.0242 percentage points (p-value 0.00) more likely to teach in private schools, without being less prone to teach in private-subsidized schools (fifth column). This evidence is consistent with the program contributing to equalize wages for municipal and private-subsidized schools at an earlier stage of the teaching career.[31] Finally, there is some evidence that the receiving the award increases the likelihood of working a rural school but no evidence that, independently of initial conditions, teachers are searching for schools located in municipalities where they could receive higher compensation or in schools with better working conditions.

---

application for the 2003 applicants is missing

[31] Moreover, we can show (results available from the authors upon request) that the probability of applying to AVDI and receiving the AVDI award 1 year after applying to AEP increases. Indeed, the point estimates suggests that teachers receiving the AEP award are 0.0269 percentage points more likely to apply to AVDI (p-value 0.00). The effect is concentrated among teachers in the first decade of their careers, who are 0.0382 percentage points more likely to become AVDI awardees (p-value 0.00). As AVDI is exclusively available for municipal school teachers, this evidence is consistent with the wage equalization occurring at an earlier stage of the teaching career.

If teachers use the AEP award as a signal of otherwise hard to observe quality, those who were initially working at under-performing schools are more likely to experience higher mobility. In Table 8 we look for heterogeneous effects of the AEP on teachers' mobility two years after application. Because teachers preferences for school may vary, Table 8 explores alternative definitions of school quality: good working conditions or high student performance. In each column of Table 8 we present the OLS estimates of equation (7), estimated separately for teachers of *bad* schools (i.e., with characteristics below the median) and *good* schools (i.e., with characteristics above the median) at the time of application. As hypothesized, the mobility effect is only present for teachers that were at *bad* schools at the time of application. AEP awardees teaching at schools with working conditions or student performance below the median at the time they applied for the award are 0.0753 (p-value 0.00) and 0.0966 (p-value 0.02) percentage points more likely to be teaching at a different school two years after. This type of mobility, goes against the spirit of the program and may harm disadvantaged schools.[32,33]

The absence of statistically significant findings is not an artifact of low power. In Table A1 we present the minimum detectable effects for the specifications in the odd columns of Tables 6 and 7. For example, the minimum detectable effect for teacher turnover is 0.024. With an average of teacher turnover of 12 percent and a 6 percent wage increased induced by AEP, we would be able to identify a separation elasticity of teachers of about -3.3. This number lies within the -3 to -4 range previously identified in literature (Clotfelter et al., 2008; Ransom and Sims, 2010; Falch, 2011). In a similar fashion, the implied elasticity for the minimum detectable effect for teaching hours is around -0.4, which is consistent with the income elasticities reported in Blundell and Macurdy (1999). In Figures A5 and A6 we depict the power analysis for all the variables in out specification.

6.3 Robustness Checks

In this section we study how robust are our results. First, we analyze the sensitivity of our estimates to alternative bandwidths. In Figure A1 and Figure A2, we provide graphical evidence on the effects of the program using the optimal bandwidth obtained with Imbens and Kalyanaraman (2011)'s criteria and a piece-wise linear polynomial of the score.[34] The results are consistent with those of the full window presented in Figures

[32]Unfortunately, even in the absence of quitting effects, student test-score information is available only for the 4th and 8th grade so it is no possible to analyze the effect of a teacher/school receiving the award on student outcomes.

[33]We find no evidence of systematic movement towards schools in the top fifteeth percentile (results available upon request).

[34]Our benchmark estimation uses the entire window size. As a result, the optimal IK bandwidth is always smaller.

7 and 10.

Second, we estimate the effects of an AEP award using a fully non-parametric specification combined with several bandwith sizes. In Figures A3 and A4, we plot the estimated impacts of the program for each bandwidth. Our benchmark findings are consistent with this approach. The only statistically significant effect is the increased likelihood that teachers will switch schools after receiving the award.

Third, we replicate Table 6 and Table 7 clustering both at the score-bin and at the school level following Cameron et al. (2011). As it can be seen in Tables A2 and A3, there is almost no variation in the standard errors.[35]

7 Conclusions

Successful public schools systems can retain the best teachers in their classrooms. We analyze the effects on retention and between school mobility of a program that rewards excellence in pedagogical practice in Chile. Teachers apply voluntarily for the award and those who succeed on a set of assessments receive a six percent annual wage increase for up to ten years.

We use a sharp regression discontinuity design to identify the causal effect of receiving an award for primary and secondary school teachers. Using administrative data over nine cohorts of applicants, our estimates indicate that locally the award does not alter transitions out of the school system. This suggests that teachers marginally failing to receive the award value their jobs more than their outside option.

We observe, however, an increase in mobility within the school system among teachers that receive the award. Some of these mobility patterns are consistent with the award providing a signal of teacher ability. For example, movements are concentrated among teachers working at lower performing schools at the time of application.

We also find evidence that teachers in the first decade of their careers that receive the award move out from private-subsidized schools to municipal schools. These movements are consistent with the economic incentives that are present in the system.

In sum, the evidence in these paper suggests that teachers respond to economic incentives but that the design of the program leaves rents to the teachers that marginally pass the assessment. As our model suggests, there is potential room to capture some

[35]Because we are testing for the effects of obtaining the award in 10 different outcome variables, ideally we should implement some error correction method for multiple testing. However, since we only have one outcome variable whose effect is statistically different from zero, any step-up procedure such as Hochberg (1988)'s correction will give the Bonferroni's standard errors for the statistically significant outcome and make all of the other standard errors even larger. As for the Bonferroni's correction, with an un-adjusted p-value of 0.01 (Table 7, first column), the significance of the results depends of the choice of the relevant family of outcome variables.

of these rents by increasing the difficulty of the assessment. The remaining funds can be used to increase the bonus which *ceteris paribus* may prevent those teacher with the highest outside options from leaving the educational system.

References

Angrist, J. D. and Guryan, J. (2004). Teacher testing, teacher education, and teacher characteristics. *American Economic Review*, 94(2):241–246.

Angrist, J. D. and Guryan, J. (2008). Does teacher testing raise teacher quality? evidence from state certification requirements. *Economics of Education Review*, 27(5):483–503.

Araya-Ramirez, C., Taut, S., Santelices-Etchegaray, V., Manzi-Astudillo, J., and Mino-Flores, F. (2012). The theory underlying a certification of teaching excellence program in chile. *Revista de Educacion*, (359).

Bloom, H. S. (2012). Modern regression discontinuity analysis. *Journal of Research on Educational Effectiveness*, 5(1):43–82.

Blundell, R. and Macurdy, T. (1999). Chapter 27 - labor supply: A review of alternative approaches. volume 3, Part A of *Handbook of Labor Economics*, pages 1559 – 1695. Elsevier.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2):238–249.

Clotfelter, C., Glennie, E., Ladd, H., and Vigdor, J. (2008). Would higher salaries keep teachers in high-poverty schools? evidence from a policy intervention in north carolina. *Journal of Public Economics*, 92(5-6):1352–1370.

Dolton, P. and Van der Klaauw, W. (1995). Leaving teaching in the uk: A duration analysis. *The Economic Journal*, 105(429):pp. 431–444.

Dolton, P. and Van der Klaauw, W. (1999). The turnover of teachers: A competing risks explanation. *The Review of Economics and Statistics*, 81(3):pp. 543–550.

Falch, T. (2011). Teacher mobility responses to wage changes: Evidence from a quasi-natural experiment. *American Economic Review*, 101(3):460–65.

Frandsen, B. R. (2014). Party bias in union representation elections: Testing for manipulation in the regression discontinuity design when the running variable is discrete.

Guasch, J. L. and Weiss, A. (1980). Wages as Sorting Mechanisms in Competitive Markets with Asymmetric Information: A Theory of Testing. *The Review of Economic Studies*, 47(4):653–664.

Guasch, J. L. and Weiss, A. (1981). Self-Selection in the Labor Market. *The American Economic Review*, 71(3):275–284.

Hahn, J., Todd, P., and Klaauw, W. V. d. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, 69(1):pp. 201–209.

Hanushek, E., Kain, J., and Rivkin, S. (2004). Why public schools lose teachers. *The Journal of Human Resources*, 39(2):326–354.

Hanushek, E. A. and Rivkin, S. G. (2010). The quality and distribution of teachers under the no child left behind act. *Journal of Economic Perspectives*, 24(3):133–50.

Harris, D. N. and Sass, T. R. (2009). The effects of nbpts-certified teachers on student achievement. *Journal of Policy Analysis and Management*, 28(1):55–80.

Hochberg, Y. (1988). A sharper bonferroni procedure for multiple tests of significance. *Biometrika*, 75(4):800–802.

Hsieh, C.-T. and Urquiola, M. (2006). The effects of generalized school choice on achievement and stratification: Evidence from chile's voucher program. *Journal of Public Economics*, 90(8-9):1477–1503.

Imbens, G. and Kalyanaraman, K. (2011). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies.*

Imbens, G. W. and Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2):615 – 635.

Kane, T. J., Rockoff, J. E., and Staiger, D. O. (2008). What does certification tell us about teacher effectiveness? evidence from new york city. *Economics of Education Review*, 27(6):615 – 631.

Kleiner, M. M. (2000). Occupational licensing. *Journal of Economic Perspectives*, 14(4):189–202.

Lavy, V. (2002). Evaluating the effect of teachers' group performance incentives on pupil achievement. *Journal of Political Economy*, 110(6):1286–1317.

Lavy, V. (2009). Performance pay and teachers' effort, productivity, and grading ethics. *American Economic Review*, 99(5):1979–2011.

Lee, D. S. (2008). Randomized experiments from non-random selection in u.s. house elections. *Journal of Econometrics*, 142(2):675 – 697.

Lee, D. S. and Card, D. (2008). Regression discontinuity inference with specification error. *Journal of Econometrics*, 142(2):655 – 674.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2):281–355.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2):698 – 714.

Mizala, A. and Schneider, B. R. (2014). Negotiating education reform: Teacher evaluations and incentives in chile (1990-2010). *Governance*, 27(1):87–109.

Mizala, A. and Urquiola, M. (2013). School markets: The impact of information approximating schools' effectiveness. *Journal of Development Economics*, 103(C):313–335.

Muralidharan, K. and Sundararaman, V. (2011). Teacher performance pay: Experimental evidence from india. *Journal of Political Economy*, 119(1):pp. 39–77.

OECD (2013). Education at a glance.

Prendergast, C. (1999). The provision of incentives in firms. *Journal of Economic Literature*, 37(1):7–63.

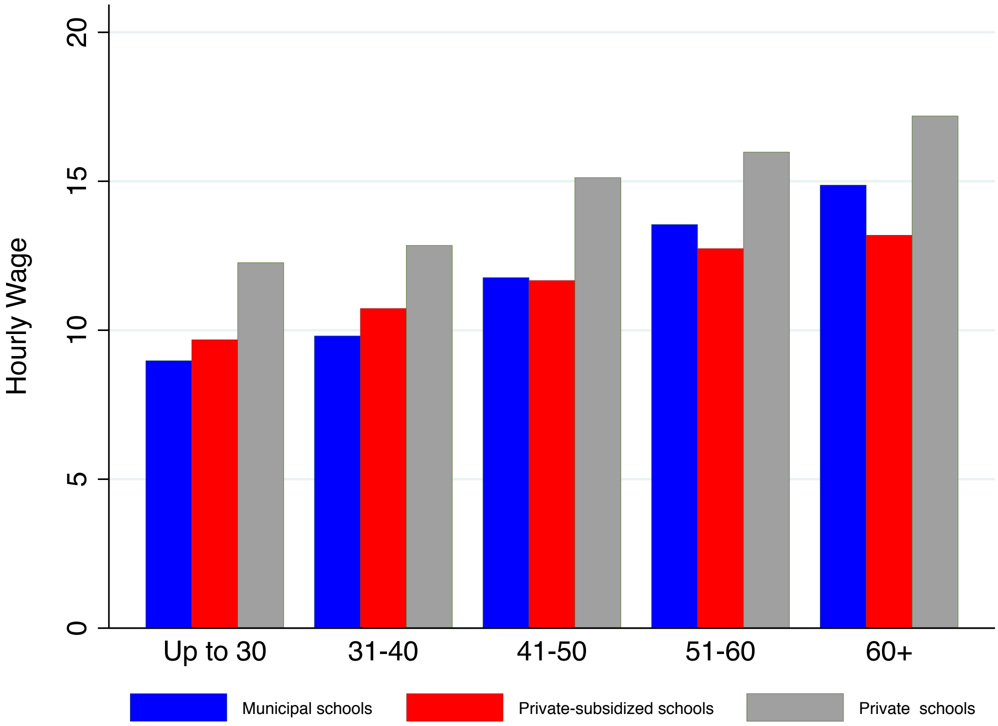
Ransom, M. and Sims, D. (2010). Estimating the firms labor supply curve in a "new monopsony" framework: Schoolteachers in missouri. *Journal of Labor Economics*, 28(2):331–355.

Rodriguez, B., Manzi, J., Peirano, C., Gonzalez, R., and Bravo, D., editors (2015). *Reconocimiento al merito docente AEP 2002-2014*. Centro UC Medicion - MIDE.

Wiswall, M. (2007). Licensing and occupational sorting in the market for teachers. *New York University, Department of Economics*. manuscript.

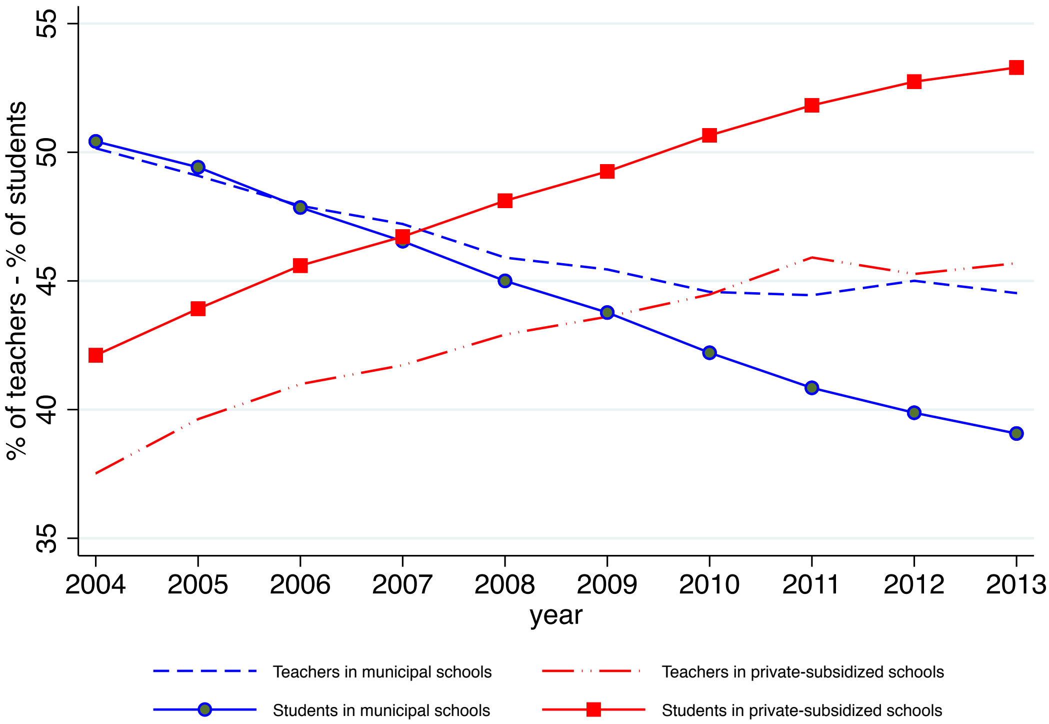
Figures

Figure 1: Average hourly wage by age group and type of school in 2005.



Source: *Encuesta Longitudinal Docente 2005: Análisis y Principales Resultados.*
Notes: Wages in USD of 2005

Figure 2: Student enrollment and teachers employed in municipal and private-subsidized schools



Source: Own calculations based on data from the Ministry of Education (Chile)

Figure 3: Timeline

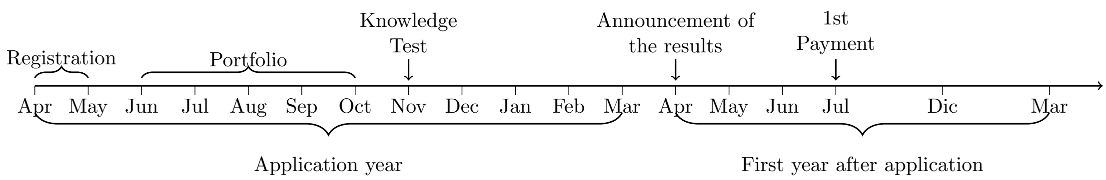


Figure 4: Flowchart for AEP sample

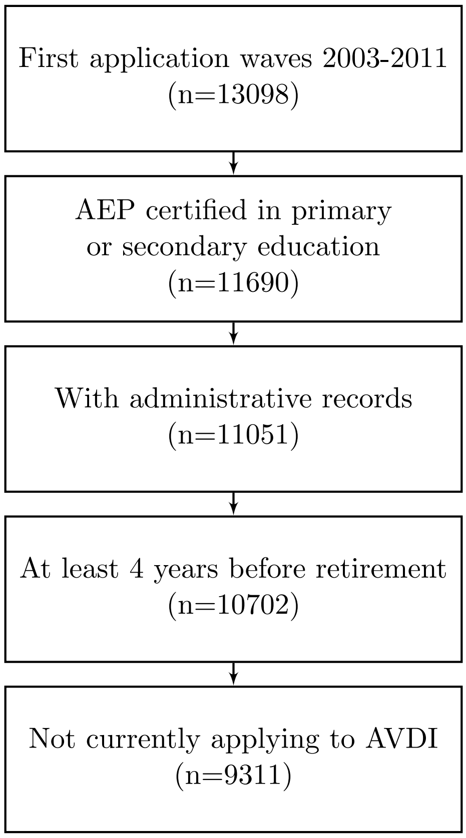
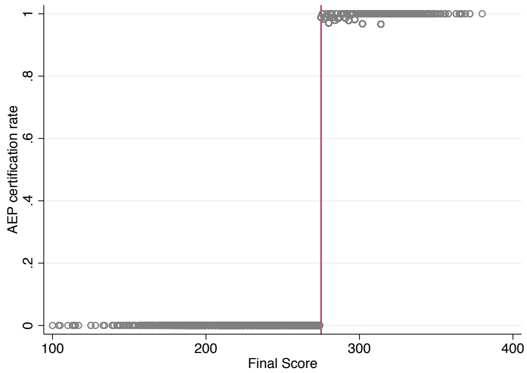
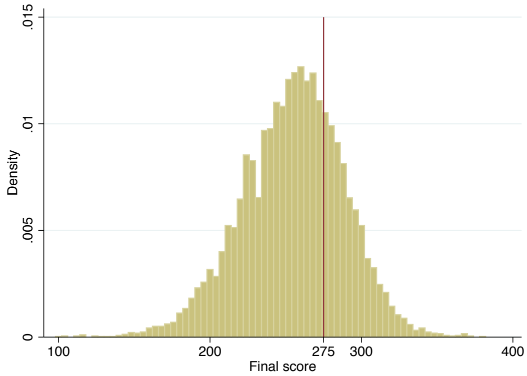


Figure 5: AEP Assignment Rule



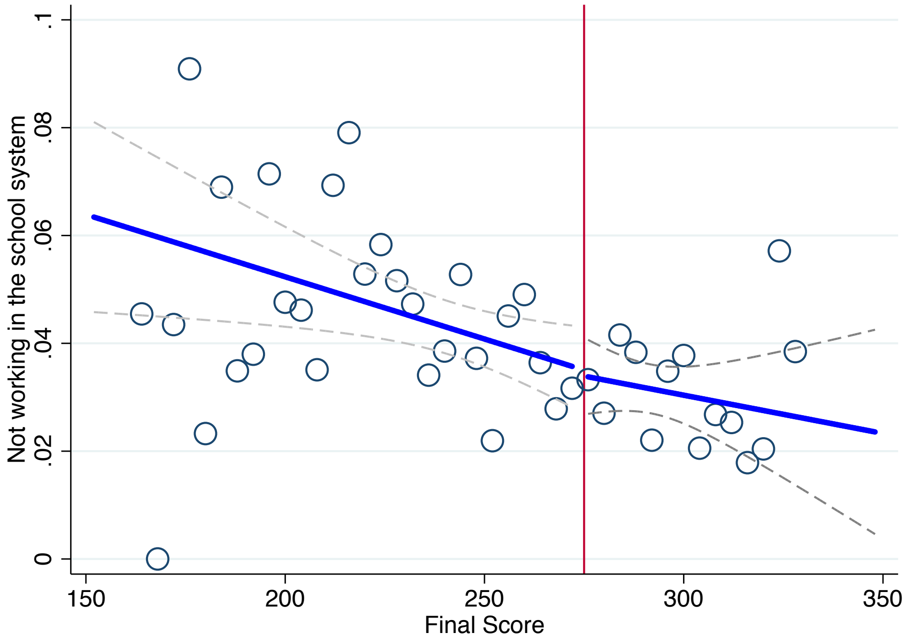
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Circles represent the proportion of applicants passing the exam within each final score cell.

Figure 6: Distribution of the AEP Final Score



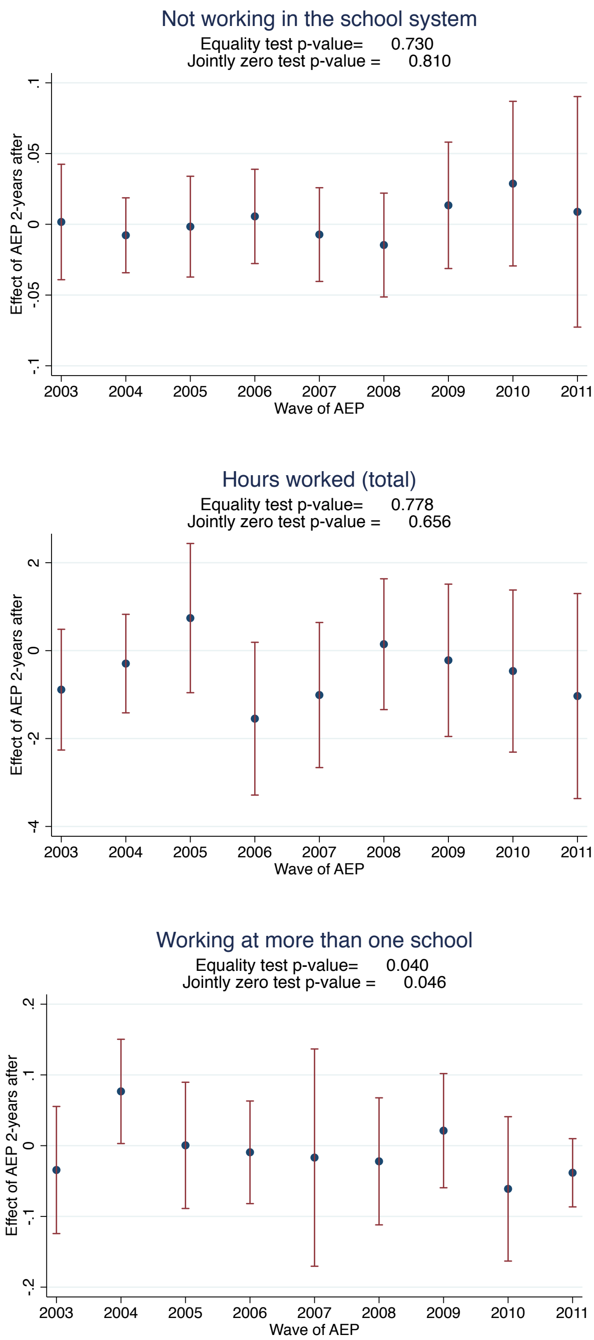
Source: Own calculations based on data from the Ministry of Education (Chile)

Figure 7: AEP effects on Retention and Labor Supply



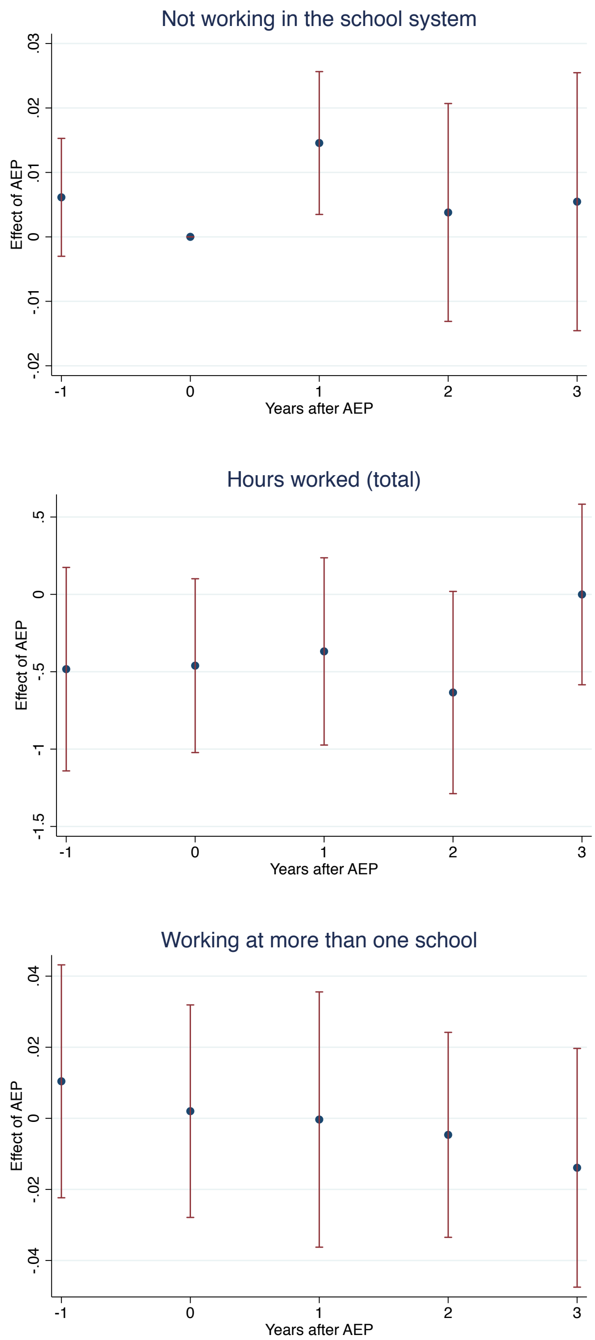
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: The circles represent mean of the outcome variable within bins of size 4 of the final score. Bins with less than 20 observations are excluded. The solid lines show fitted values of a piecewise linear polynomial of the score in the 150-350 window. Doted lines represent the confidence intervals, for errors clustered at the final score cell level.

Figure 8: AEP effects on Retention and Labor Supply by Application Wave



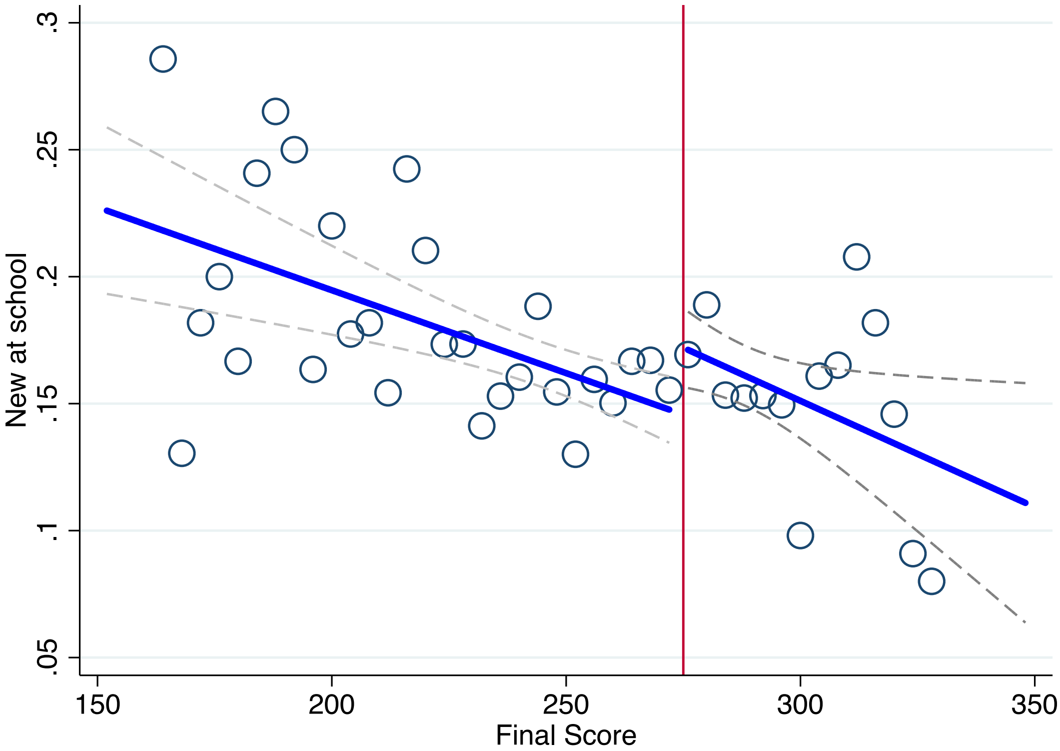
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Each point represent the estimates of equation (7) for each application wave separately, 2 years after application. The red lines represent the 95 confidence intervals. Robust standard errors, adjusted for clustering in final score cells.

Figure 9: AEP effects on Retention and Labor Supply over Time



Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Each point represent the estimates of equation (7), t years after the program. The red lines represent the 95 confidence intervals. Robust standard errors, adjusted for clustering in final score cells. Dependent variable at $t = -1$ for 2003 applicants coded as missing.

Figure 10: AEP effects on Between-School Mobility



Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: The circles represent mean of the outcome variable within bins of size 4 of the final score. Bins with less than 20 observations are excluded. The solid lines show fitted values of a piecewise linear polynomial of the score in the 150-350 window. Doted lines represent the confidence intervals, for errors clustered at the final score cell level.

Tables

Table 1: Turnover Rates

	No of teachers (2003)	Percentage of Teachers (2005)		
Experience	Baseline	Not teaching	Change of school	Change of commune
0-11 years	38,993	18	15	8
11-12 years	35,002	8	9	4
22+ years	66,647	12	6	2
All	140,642	12	9	4

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: 2003 baseline year. Measures two years after, 2005.

Table 2: Proportion of Applicants Receiving the AEP Award over Time

	All	2003	2004	2005	2006	2007	2008	2009	2010	2011
Panel A Final Sample										
AEP certification rate (%)	28	44	33	38	29	22	22	21	21	24
Compliance with allocation rule (%)	100	100	100	100	100	99	100	100	100	100
N	9,311	745	1,307	885	1,550	1,133	918	1,109	871	793
Panel B First time applicants										
AEP certification rate (%)	26	44	32	34	28	20	19	18	18	21
Compliance with the 275 allocation rule (%)	100	100	100	100	100	99	100	100	100	100
N	13,098	935	1,561	1,658	1,988	1,483	1,494	1,597	1,286	1,096

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Standard deviation in parenthesis. Data for teachers' applying to waves 2003-2011.

Table 3: Descriptive Statistics

	2003-2014		AEP applicants	
	Voucher System Teachers	AEP Applicants	At time of application	2-years after
Male	0.291	0.278	0.300	0.299
	(0.454)	(0.448)	(0.458)	(0.458)
Age	44.131	43.906	41.196	43.306
	(11.879)	(9.695)	(8.780)	(8.768)
Degree in education	0.947	0.981	0.970	0.986
	(0.224)	(0.136)	(0.171)	(0.116)
Years of experience	17.531	17.880	14.718	17.212
	(12.560)	(10.364)	(9.118)	(9.112)
Not working in the school system				0.040
				(0.196)
Hours worked (total)	34.727	36.186	35.918	36.581
	(8.770)	(7.256)	(7.031)	(7.224)
Main job: primary school teacher	0.754	0.721	0.596	0.564
	(0.431)	(0.448)	(0.491)	(0.496)
Working at more than one school	0.103	0.132	0.156	0.136
	(0.305)	(0.338)	(0.363)	(0.342)
In a managerial job	0.104	0.058	0.027	0.065
	(0.306)	(0.234)	(0.161)	(0.246)
AEP applicant (ever)	0.065			
	(0.246)			
Currently applying to AEP				0.021
				(0.143)
Receiving AEP	0.012	0.194		0.279
	(0.111)	(0.395)		(0.448)
AVDI applicant (ever)	0.169	0.418	0.303	0.303
	(0.374)	(0.493)	(0.460)	(0.460)
Currently applying to AVDI				0.058
				(0.233)
Receiving AVDI	0.026	0.097	0.047	0.057
	(0.160)	(0.295)	(0.212)	(0.231)
New at school	0.121	0.103		0.166
	(0.326)	(0.304)		(0.373)
Private-subsidized school	0.402	0.456	0.550	0.519
	(0.490)	(0.498)	(0.497)	(0.500)
Private school	0.117	0.019		0.012
	(0.322)	(0.138)		(0.107)
Working conditions (top-50 school)	0.404	0.417	0.426	0.432
	(0.491)	(0.493)	(0.495)	(0.495)
Student performance (top-50 school)	0.629	0.693	0.695	0.695
	(0.483)	(0.461)	(0.460)	(0.461)
SNED awarded school	0.325	0.376	0.369	0.404
	(0.468)	(0.484)	(0.483)	(0.491)
Change of municipality	0.067	0.056		0.101
	(0.251)	(0.230)		(0.301)
Rural school	0.143	0.131	0.115	0.113
	(0.350)	(0.337)	(0.319)	(0.316)
In municipality with zone allowance	0.419	0.461	0.453	0.455
	(0.493)	(0.498)	(0.498)	(0.498)
N	1,576,800	98,287	9,311	9,311

Source: Own calculations based on data from the Ministry of Education (Chile)

Notes: Standard deviation in parenthesis. For the 2003-2014 period, *New at school* stands for whether or not the teacher was teaching at that particular school in the previous year. For the AEP applicants 2 years after application, *New at school* is a dummy taking the value of 1 if the school is different from the school at time of application. Except *Not working in the school system*, the dependent variables for teachers not working in the school system 2 years after application are coded as missing. From the full set of observations in the 2003-2014 period, 16 percent are from teachers who applied to the at some time during the period. Yet, only 6 percent of the ever eligible candidates applied to the AEP.

Table 4: Test for Continuity of the Final Score

	All	2003	2004	2005	2006	2007	2008	2009	2010	2011
McCrary test p-value	0.864	0.412	0.081	0.651	0.973	0.692	0.973	0.993	0.388	0.337
Frandsen Discrete test p-value	0.363	0.339	0.251	0.250	0.892	0.870	0.397	0.880	0.277	0.856

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: McCrary (2008) test at the 275 cut-off, using a bandwidth of 30 and bin size 1.

Table 5: Balance at Baseline AEP

AEP Dependent Variable	Degree of polynomial (1)	 (2)
Male	0.009	0.023
	(0.017)	(0.021)
Age	-0.135	-0.316
	(0.282)	(0.420)
Degree in education	0.003	0.008
	(0.006)	(0.007)
Years of experience	-0.333	-0.733
	(0.319)	(0.476)
Hours worked (total)	-0.165	-0.461
	(0.226)	(0.285)
Working at more than one school	0.004	0.002
	(0.012)	(0.015)
In a managerial job	-0.003	-0.009
	(0.006)	(0.007)
Main job: primary school teacher	0.005	-0.012
	(0.014)	(0.018)
Receiving AVDI	0.008	-0.010
	(0.009)	(0.012)
Private-subsidized school	-0.027	-0.014
	(0.023)	(0.033)
Working conditions (top-50 school)	-0.037**	-0.005
	(0.018)	(0.026)
Student performance (top-50 school)	-0.009	0.012
	(0.019)	(0.026)
SNED awarded school	0.009	0.017
	(0.017)	(0.022)
Rural school	0.020*	0.019
	(0.012)	(0.015)
In municipality with zone allowance	-0.011	-0.013
	(0.019)	(0.023)
Wald test p-value	0.5089	0.1734

Source: Own calculations based on data from the Ministry of Education (Chile)

Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AEP data for teachers' applying to AEP waves 2003-2011, at the time of application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Robust standard errors,adjusted for clustering in final score cells, in parenthesis. Column numbers indicate the order of the polynomial on the score centered around 275.
* Indicates statistical significance at 10%

Table 6: AEP effects on Retention and Labor Supply

	All Teachers		0-11 years		12-21 years		22 +years	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Not working in the school system	0.0038	0.0036	-0.0018	0.0063	0.0078	0.0083	-0.0061	-0.0014
	(0.0086)	(0.0096)	(0.0167)	(0.0175)	(0.0179)	(0.0188)	(0.0098)	(0.0098)
N	9,311	9,311	3,756	3,756	2,872	2,872	2,683	2,683
Clusters	230	230	187	187	198	198	206	206
Hours worked (total)	-0.6344*	-0.5327*	-0.3629	-0.3012	-0.2493	-0.4344	-1.5792**	-1.1180*
	(0.3317)	(0.3218)	(0.5235)	(0.5758)	(0.5375)	(0.4566)	(0.6775)	(0.6235)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Clusters	229	229	187	187	197	197	205	205
Working at more than one school	-0.0047	-0.0032	-0.0041	-0.0054	-0.0048	-0.0010	0.0159	0.0200
	(0.0146)	(0.0141)	(0.0224)	(0.0223)	(0.0260)	(0.0247)	(0.0278)	(0.0291)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Clusters	229	229	187	187	197	197	205	205

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AEP data for teachers' applying to AEP waves 2003-2011, 2 years after application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Odd-columns present the estimates of equation (7). Even columns present the estimates of equation (7) and add controls interacted with wave fixed effects. Controls include gender, age, degree in education, years of experience, teaching at a single school, hours worked, receiving AVDI, rural school, private-subsidized school, working conditions (top-50 school), student performance (top-50 school), SNED awarding school and education level of the main job: primary; all at time of application and excluding the outcome variable at time of application. Robust standard errors, adjusted for clustering in final score cells, in parenthesis.
* Indicates statistical significance at 10%
** Indicates statistical significance at 5%
*** Indicates statistical significance at 1%.

Table 7: AEP effects on Between-School Mobility

	All Teachers		0-11 years		12-21 years		22 +years	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New at school	0.0447***	0.0434**	0.0470	0.0530	0.0296	0.0338	0.0394	0.0346
	(0.0168)	(0.0179)	(0.0314)	(0.0343)	(0.0342)	(0.0341)	(0.0266)	(0.0293)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Clusters	229	229	187	187	197	197	205	205
Private-subsidized school	-0.0350	-0.0424*	-0.0799*	-0.0803**	0.0438	0.0321	-0.0848**	-0.0738*
	(0.0329)	(0.0227)	(0.0453)	(0.0362)	(0.0402)	(0.0305)	(0.0428)	(0.0398)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Clusters	229	229	187	187	197	197	205	205
Private school	0.0006	0.0005	0.0197	0.0184	-0.0242***	-0.0268***	-0.0034	-0.0037
	(0.0061)	(0.0059)	(0.0131)	(0.0139)	(0.0069)	(0.0077)	(0.0030)	(0.0030)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Clusters	229	229	187	187	197	197	205	205
In municipality with zone allowance	-0.0153	-0.0092	-0.0110	-0.0016	0.0488	0.0492	-0.1000**	-0.0753*
	(0.0239)	(0.0252)	(0.0364)	(0.0378)	(0.0482)	(0.0487)	(0.0431)	(0.0452)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Clusters	229	229	187	187	197	197	205	205
Rural school	0.0245*	0.0219*	0.0292	0.0275	0.0301	0.0319	0.0222	0.0124
	(0.0138)	(0.0130)	(0.0217)	(0.0217)	(0.0254)	(0.0274)	(0.0254)	(0.0242)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Clusters	229	229	187	187	197	197	205	205
Working conditions (top-50 school)	-0.0180	-0.0245	-0.0197	-0.0254	0.0179	-0.0029	-0.0522	-0.0397
	(0.0271)	(0.0248)	(0.0386)	(0.0403)	(0.0422)	(0.0425)	(0.0387)	(0.0366)
N	8,831	8,831	3,469	3,469	2,741	2,741	2,621	2,621
Clusters	229	229	185	185	197	197	205	205
Student performance (top-50 school)	0.0032	-0.0047	0.0084	-0.0019	0.0764*	0.0605	-0.0954*	-0.0749
	(0.0287)	(0.0279)	(0.0350)	(0.0352)	(0.0409)	(0.0406)	(0.0552)	(0.0481)
N	8,831	8,831	3,469	3,469	2,741	2,741	2,621	2,621
Clusters	229	229	185	185	197	197	205	205

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AEP data for teachers' applying to AEP waves 2003-2011, 2 years after application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Odd-columns present the estimates of equation (7). Even columns present the estimates of equation (7) and add controls interacted with wave fixed effects. Controls include gender, age, degree in education, years of experience, teaching at a single school, hours worked, receiving AVDI, rural school, private-subsidized school, working conditions (top-50 school), student performance (top-50 school), SNED awarding school and education level of the main job: primary; all at time of application and excluding the outcome variable at time of application. Robust standard errors, adjusted for clustering in final score cells, in parenthesis.
* Indicates statistical significance at 10%
** Indicates statistical significance at 5%
*** Indicates statistical significance at 1%.

Table 8: AEP Heterogenous Effect on Between-School Mobility

	All Teachers	0-11 years	12-21 years	22 +years
By Working Conditions				
At good school when applying	-0.0009	0.0067	-0.0312	-0.0010
	(0.0349)	(0.0476)	(0.0588)	(0.0391)
At bad school when applying	0.0753***	0.0617	0.0927**	0.0655
	(0.0208)	(0.0488)	(0.0436)	(0.0402)
By Student Performance				
At good school when applying	0.0256	0.0468	-0.0240	0.0496
	(0.0211)	(0.0421)	(0.0269)	(0.0334)
At bad school when applying	0.0966**	0.1078	0.2010**	0.0341
	(0.0421)	(0.0801)	(0.0952)	(0.0525)

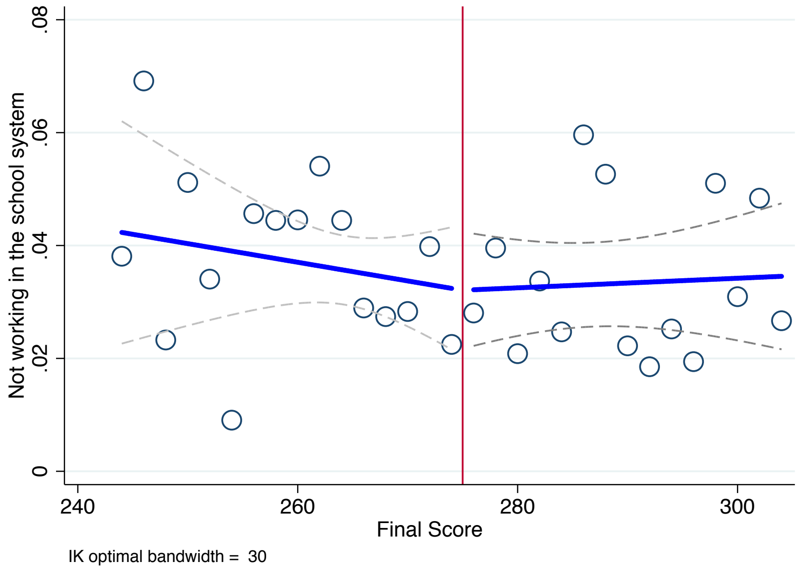
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AEP data for teachers' applying to AEP waves 2003-2011, 2 years after application. A school is coded as good if its characteristic listed in the corresponding Panel is above the median. A school is coded as bad if its characteristic listed in the corresponding Panel is below the median. Separate equations estimated for each good and bad schools. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score.
* Indicates statistical significance at 10%
** Indicates statistical significance at 5%
*** Indicates statistical significance at 1%.

Appendices

A AEP

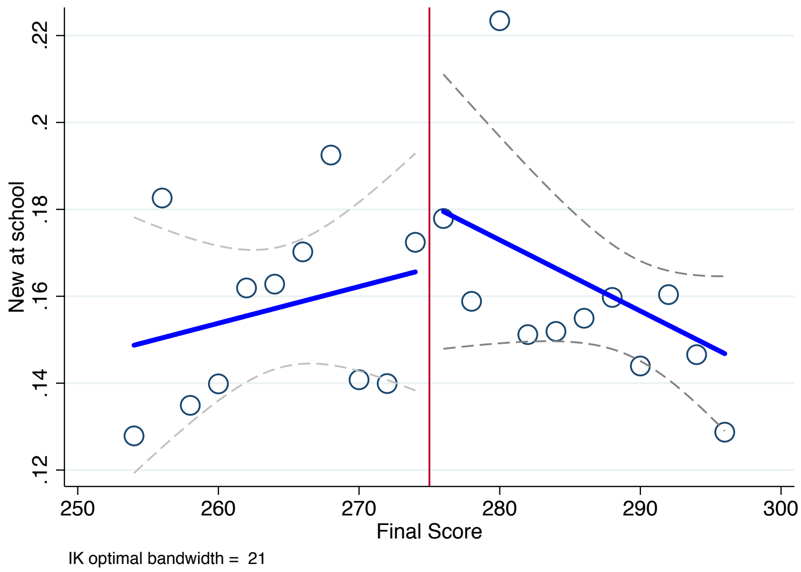
A.1 Figures

Figure A1: AEP effects on Retention and Labor Supply



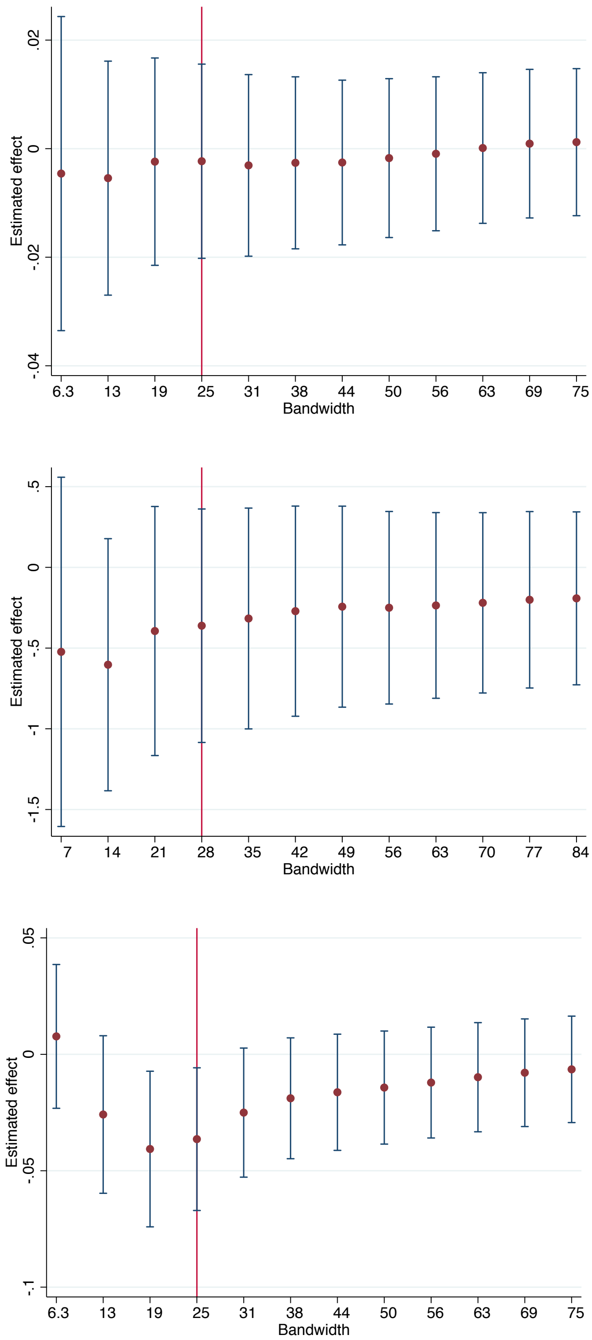
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: The circles represent mean of the outcome variable within bins of size 4 of the final score. Solid lines show fitted values of a piecewise linear polynomial. Doted lines represent the confidence intervals, for errors clustered at the final score cell level. Imbens and Kalyanaraman (2011)'s optimal bandwidth.

Figure A2: AEP effects on Between School-Mobility



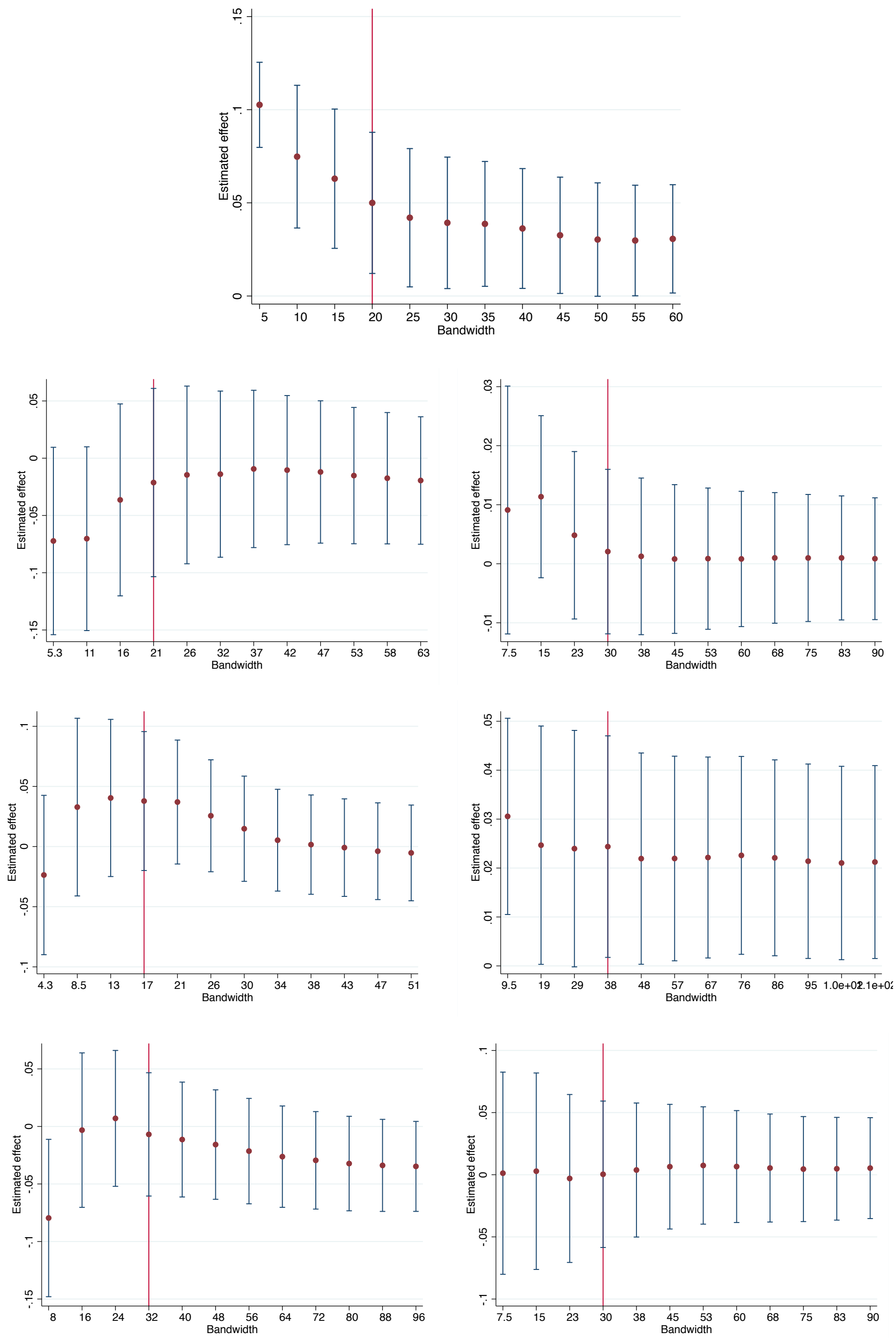
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: The circles represent mean of the outcome variable within bins of size 4 of the final score. Solid lines show fitted values of a piecewise linear polynomial. Doted lines represent the confidence intervals, for errors clustered at the final score cell level. Imbens and Kalyanaraman (2011)'s optimal bandwidth.

Figure A3: AEP effects on Turnover and Labor Supply by Application Wave



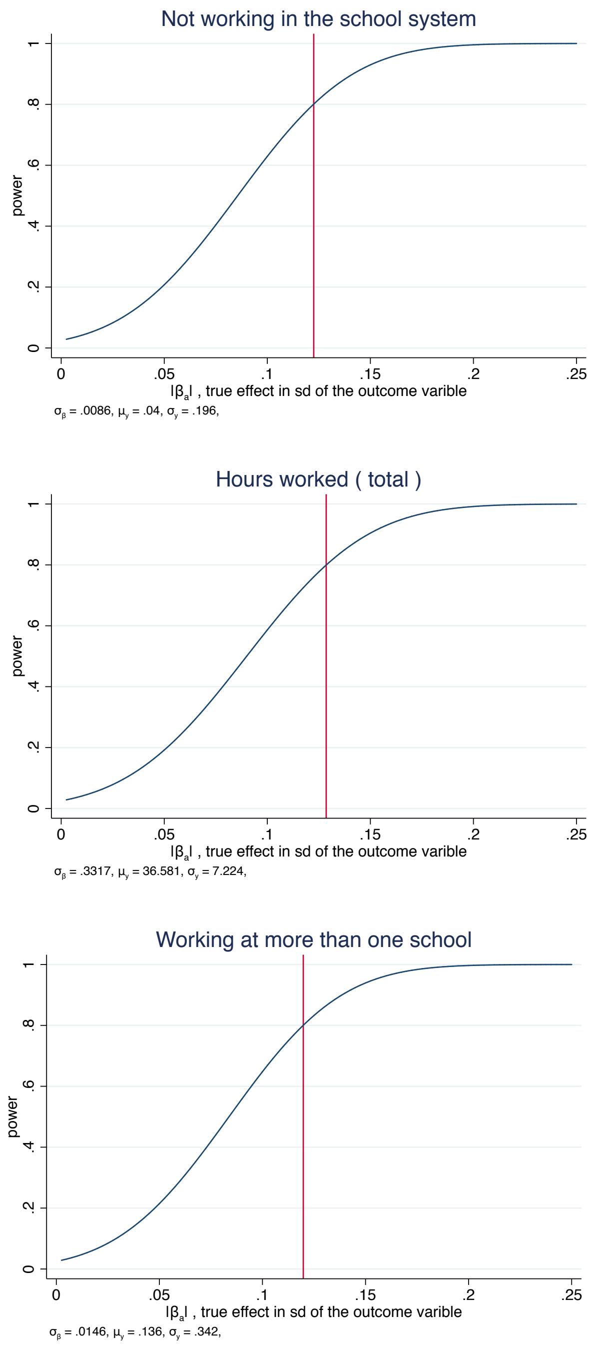
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Each point represent the point estimate of a fully non-parametric specification for each application bandwidth separately, 2 years after application. The blue lines represent the 95 confidence intervals. The red line indicates the optimal bandwidth following Imbens and Kalyanaraman (2011).

Figure A4: AEP effects on Between School Mobility by Application Wave



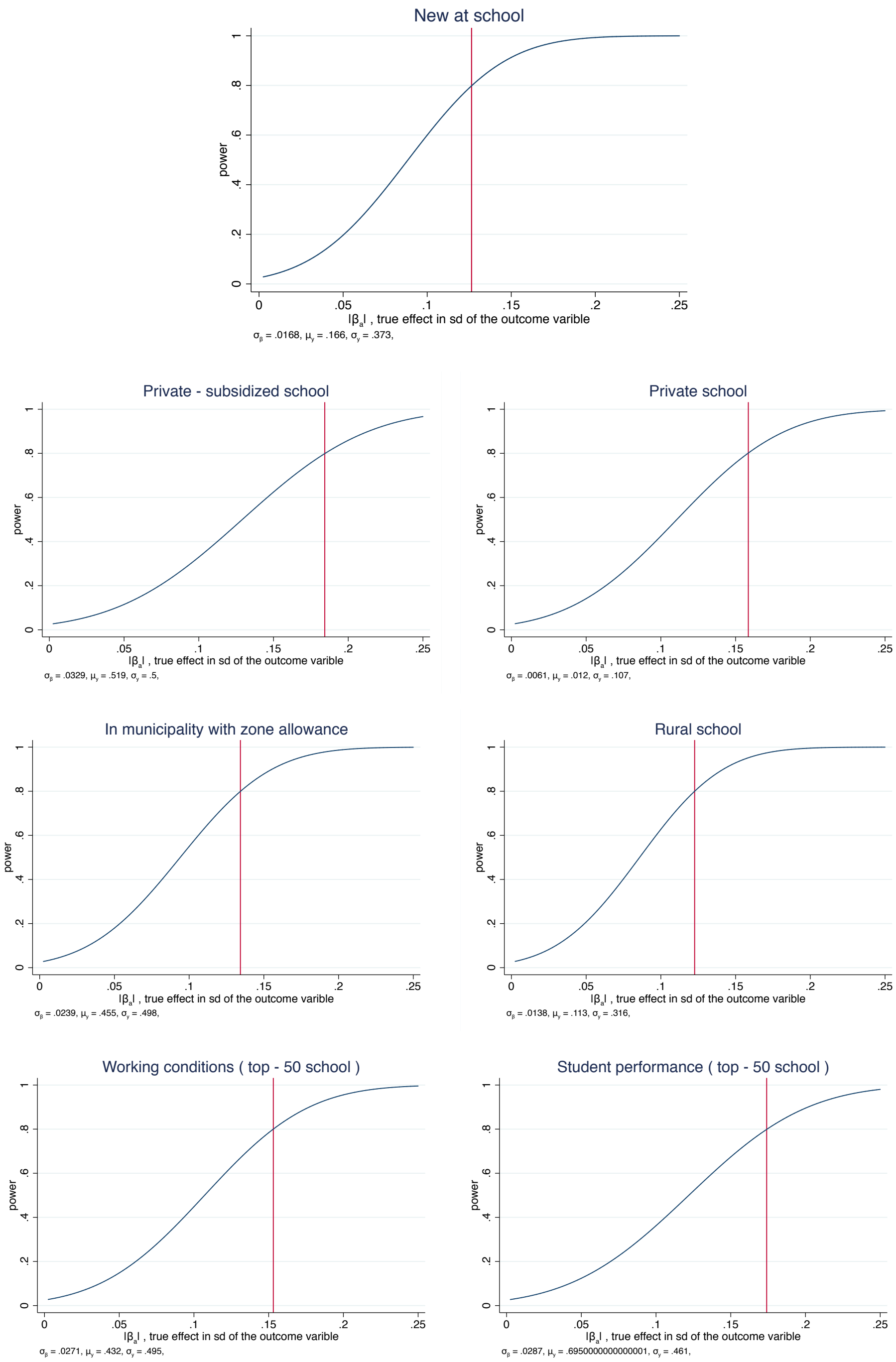
Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Each point represent the point estimate of a fully non-parametric specification for each application bandwidth separately, 2 years after application. The blue lines represent the 95 confidence intervals. The red line indicates the optimal bandwidt following Imbens and Kalyanaraman (2011).

Figure A5: AEP effects on Turnover and Labor Supply by Application Wave



Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Power of a two-sided test with β_a as the absolute value of the true effect, expressed in standard deviations of the outcome variable 2 years after application. The red line represents the minimum detectable effect for a two-sided test with 80% power and 5% statistical significance, using the variance the variance of the β coefficients of the specifications in Table 6

Figure A6: AEP effects on Between School Mobility by Application Wave



Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Power of a two-sided test with β_a as the absolute value of the true effect, expressed in standard deviations of the outcome variable 2 years after application. The red line represents the minimum detectable effect for a two-sided test with 80% power and 5% statistical significance,, using the variance the variance of the β coefficients of the specifications in Table 7.

A.2 Tables

Table A1: Minimum Detectable Effects

AEP	All Teachers	Years of experience		
Dependent variable		0-11	11-21	21+
Panel A Labor Supply				
Not working in the school system	0.024	0.047	0.050	0.027
Hours worked (total)	0.929	1.466	1.505	1.897
Working at more than one school	0.041	0.063	0.073	0.078
Panel B Between-School Mobility				
New at school	0.047	0.088	0.096	0.074
Private-subsidized school	0.092	0.127	0.113	0.120
Private school	0.017	0.037	0.019	0.008
In municipality with zone allowance	0.067	0.102	0.135	0.121
Rural school	0.039	0.061	0.071	0.071
Working conditions (top-50 school)	0.076	0.108	0.118	0.108
Student performance (top-50 school)	0.080	0.098	0.115	0.154

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Absolute value minimum detectable effect for a two-sided test with 80% power and 5% statistical significance, using the variance the variance of the β coefficients of the specifications in Table 6 and Table 7.

Table A2: Two-way clustering: AEP effects on Retention and Labor Supply

	All Teachers		0-11 years		12-21 years		22 +years	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Not working in the school system	0.0038	0.0036	-0.0018	0.0063	0.0078	0.0083	-0.0061	-0.0014
	(0.0085)	(0.0098)	(0.0166)	(0.0179)	(0.0178)	(0.0201)	(0.0098)	(0.0101)
N	9,311	9,311	3,756	3,756	2,872	2,872	2,683	2,683
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
Hours worked (total)	-0.6344*	-0.5327	-0.3629	-0.3012	-0.2493	-0.4344	-1.5792**	-1.1180*
	(0.3315)	(0.3243)	(0.5303)	(0.5983)	(0.5391)	(0.4852)	(0.6828)	(0.6530)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
Working at more than one school	-0.0047	-0.0032	-0.0041	-0.0054	-0.0048	-0.0010	0.0159	0.0200
	(0.0146)	(0.0141)	(0.0222)	(0.0229)	(0.0259)	(0.0256)	(0.0294)	(0.0315)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AEP data for teachers' applying to AEP waves 2003-2011, 2 years after application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Odd-columns present the estimates of equation (7). Even columns present the estimates of equation (7) and add controls interacted with wave fixed effects. Controls include gender, age, degree in education, years of experience, teaching at a single school, hours worked, receiving AVDI, rural school, private-subsidized school, working conditions (top-50 school), student performance (top-50 school), SNED awarding school and education level of the main job: primary; all at time of application and excluding the outcome variable at time of application. Robust standard errors, adjusted for clustering in final score cells and school level following Cameron et al. (2011)Cameron et al. (2011), in parenthesis.
* Indicates statistical significance at 10%
** Indicates statistical significance at 5%
*** Indicates statistical significance at 1%.

Table A3: Two-way clustering: AEP effects on Between-School Mobility

	All Teachers		0-11 years		12-21 years		22 +years	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New at school	0.0447***	0.0434**	0.0470	0.0530	0.0296	0.0338	0.0394	0.0346
	(0.0172)	(0.0185)	(0.0318)	(0.0364)	(0.0344)	(0.0353)	(0.0262)	(0.0296)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
Private-subsidized school	-0.0350	-0.0424*	-0.0799*	-0.0803**	0.0438	0.0321	-0.0848*	-0.0738*
	(0.0330)	(0.0230)	(0.0455)	(0.0367)	(0.0400)	(0.0316)	(0.0435)	(0.0414)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
Private school	0.0006	0.0005	0.0197	0.0184	-0.0242***	-0.0268***	-0.0034	-0.0037
	(0.0063)	(0.0062)	(0.0135)	(0.0148)	(0.0069)	(0.0079)	(0.0030)	(0.0031)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
In municipality with zone allowance	-0.0153	-0.0092	-0.0110	-0.0016	0.0488	0.0492	-0.1000**	-0.0753
	(0.0243)	(0.0255)	(0.0377)	(0.0390)	(0.0482)	(0.0493)	(0.0445)	(0.0468)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
Rural school	0.0245*	0.0219	0.0292	0.0275	0.0301	0.0319	0.0222	0.0124
	(0.0145)	(0.0140)	(0.0217)	(0.0228)	(0.0263)	(0.0285)	(0.0255)	(0.0258)
N	8,937	8,937	3,543	3,543	2,768	2,768	2,626	2,626
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
Working conditions (top-50 school)	-0.0180	-0.0245	-0.0197	-0.0254	0.0179	-0.0029	-0.0522	-0.0397
	(0.0276)	(0.0254)	(0.0396)	(0.0418)	(0.0419)	(0.0426)	(0.0398)	(0.0370)
N	8,831	8,831	3,469	3,469	2,741	2,741	2,621	2,621
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725
Student performance (top-50 school)	0.0032	-0.0047	0.0084	-0.0019	0.0764*	0.0605	-0.0954*	-0.0749
	(0.0292)	(0.0285)	(0.0357)	(0.0364)	(0.0408)	(0.0412)	(0.0563)	(0.0497)
N	8,831	8,831	3,469	3,469	2,741	2,741	2,621	2,621
Score clusters	230	230	187	187	198	198	206	206
School clusters	3,894	3,894	2,235	2,235	1,859	1,859	1,725	1,725

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AEP data for teachers' applying to AEP waves 2003-2011, 2 years after application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Odd-columns present the estimates of equation (7). Even columns present the estimates of equation (7) and add controls interacted with wave fixed effects. Controls include gender, age, degree in education, years of experience, teaching at a single school, hours worked, receiving AVDI, rural school, private-subsidized school, working conditions (top-50 school), student performance (top-50 school), SNED awarding school and education level of the main job: primary; all at time of application and excluding the outcome variable at time of application. Robust standard errors, adjusted for clustering in final score cells and school level following Cameron et al. (2011), in parenthesis.
* Indicates statistical significance at 10%
** Indicates statistical significance at 5%
*** Indicates statistical significance at 1%.

Online Appendix

B AVDI

In 2004 the Ministry of Education implemented a compulsory examination for municipal school teachers. Every 4 years, teachers of municipal schools are assessed through a written examination (*Evaluación Docente* (EV)). Municipal school teachers with an outstanding evaluation (EV) can apply to a performance award: *Asignación Variable al Desempeño Individual* or AVDI (following its Spanish acronym). For this purpose, teachers must take the same knowledge test than for AEP (no portfolio is required). The results of these tests are combined and those who score above a threshold of 275 receive a monetary annual compensation that lasts between two to four years, depending on when they are required to re-take the EV. For the average teacher, the AVDI award would be equivalent to a 6 to 10 percent increase of her monthly pay.

We use the administrative we already described in Section 3. Figure B1 presents a sample flowchart. We start with the 31,237 teachers that applied for the first time for an AVDI award between 2004 and 2011. Further, we restrict to individuals who applied for the award in primary or secondary education. We match this data with administrative records and restrict our analysis to individuals that at the time of application are at least four years away from the retirement age (i.e., 56 for females and 61 for males). We focus on the sample of 23,868 not currently applying to AEP.

We start by showing that the assignment rule was strictly enforced. In Figure B2, we plot the mean of a variable that takes the value of 1 if an individual has an AVDI award and 0 otherwise, for each possible score cell (circles). There is clearly a sharp discontinuity. Those who obtained the award have an aggregate score of 275 or more. In Table B1, we present the awardee rates by year. We divide the data in two samples, Panel A has the 23,870 teachers from our benchmark sample and Panel B has the 31,237 first time applicants. The table confirms the information on the graph: compliance with the allocation rule is 100 percent, regardless of the application wave or sample. Focusing on Panel A, 31 percent of the teachers that apply for AVDI obtained it.

In the first column of Table B2, we present average information for all employed teachers in the Municipal School System during the 2004-2014 period. In the second column, we present the same information but only for those who have applied to AVDI during the 2004-2014 window. Beginning with basic demographic and qualification variables, we observe that over the 2004-2014 period, the average Chilean teacher in a municipal school is a 47 years old woman with a degree in education and 21 years of teaching experience, working 35 hours a week. Around 89 percent of the teachers work at a single school, 80 percent work as primary school teachers, and 11 percent hold a managerial position. Every year, 11 percent of the teachers change schools and 4 percent move to a different municipality. Around 49 percent of the teachers work in municipalities considered as isolated and are monetarily compensated with an allowance. Around 30 percent of the teachers work in schools ranked in the top 50 percentile in terms of working conditions and 47 percent in schools ranked in the top 50 percentile in terms of student performance.

In the third and fourth column of Table B2, we describe the sample at the first time of application to AVDI and two-years after. Two-years after applying to AVDI, 3 percent of the teachers are not employed in the school system, 0.2 percent work in a private school, 6 percent change from municipality, and 14 percent moved to a different school from the one they were at when applying.

We exploit the sharp discontinuity in the allocation of the award for teachers with 275 points or more in the aggregate evaluation score to estimate the causal impact of an AVDI award. Like in section 5 we implement the regression discontinuity design using equation 7.

In Figure B3, we plot the histogram of the final score for the pooled sample of applicants. In column one of Table B3, we present the results of testing for a discontinuity using the McCrary (2008) test and Frandsen (2014)'s approach for variables with discrete support. Table B3 also presents the McCrary (2008) and Frandsen (2014)'s p-values for each AVDI wave. Figure B3 shows a clear spike in the final score before the cut-off of 275. Not surprisingly, we reject the no discontinuity hypothesis in several years for both tests.

In Table B4 we provide evidence on the continuity of baseline characteristics around the threshold. We estimate equation (7) using as outcome variables the characteristics of the teachers and their schools, at time of application to AVDI. The number of the column in this table indicates the order of the piece-wise polynomial of the score used in each specification. Unlike the case of AEP, there are systematic differences in the baseline variables and we tend to reject the null hypothesis of continuity for the 14 variables using the joint (Wald) test.

We have no explanation of why there might be manipulation of the data at the left of the cut-off (i.e., this stops teachers from receiving the award). We use a second degree polynomial as the benchmark specification and we also control for baseline variables interacted with wave fixed effects. The latter results are preferred. However, the causal interpretation should be considered with the appropriate caveats.

First, we look at the effect of receiving an AVDI award on teacher retention. In Table B5, we present OLS estimates of equation 7 in the odd columns. In the even columns we add controls for demographics, qualifications, labor outcomes, and main school's characteristics at the time of application. We show estimates by three experience levels:

0-11 years, 12-21 years and 22 or more years of experience. The estimates show a small positive and statistically significant on total hours worked. Second, in B6 we look at the pattern of mobility between schools which could have been caused by the program. We find no systematic evidence that the receiving an AVDI award affected between school mobility.

Finally, we also explore the effect of the receiving to both AEP and AVDI award (results available upon request from the authors). On average, awardees both programs will receive a 12 percent increase in their salary, yet not even this wages increase seems to alter teachers' behavior at the extensive margin.

B.1 Figures

Figure B1: Flowchart for AVDI sample

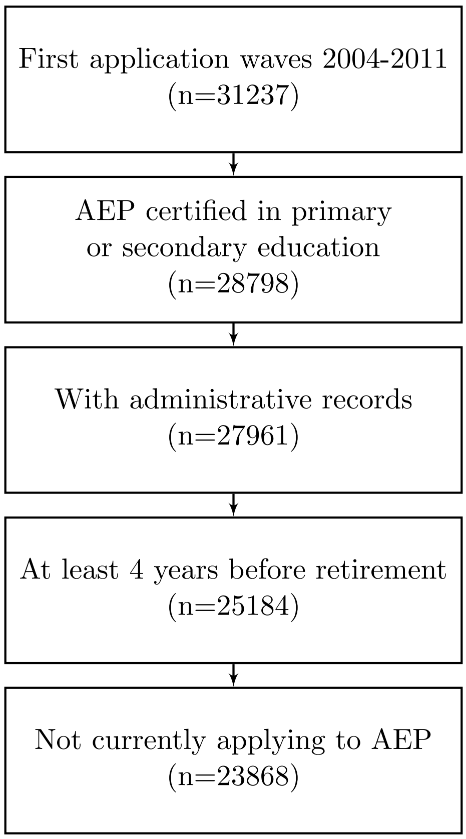
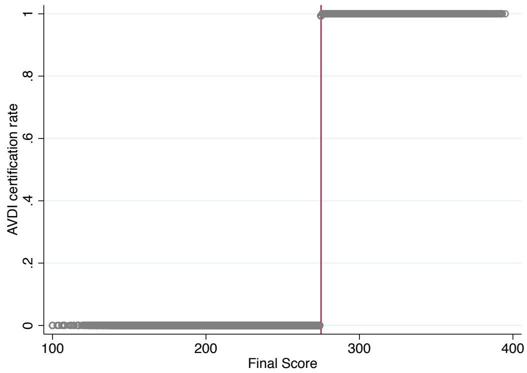
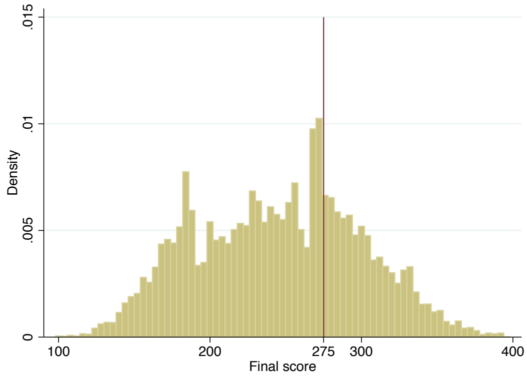


Figure B2: AVDI Assignment Rule



Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Circles represent the proportion of applicants passing the exam within each final score cell.

Figure B3: Distribution of the AVDI Final Score



Source: Own calculations based on data from the Ministry of Education (Chile)

B.2 Tables

Table B1: Proportions of Applicants Receiving the AVDI Award over Time

	All	2004	2005	2006	2007	2008	2009	2010	2011
Panel A Final Sample									
AVDI certification rate (%)	31	28	29	23	30	33	33	34	32
Compliance with allocation rule (%)	100	100	100	100	100	100	100	100	100
N	23,868	918	703	2,601	5,146	3,671	3,136	4,624	3,069
Panel B First time applicants									
AVDI certification rate (%)	30	27	28	22	29	32	30	33	31
Compliance with the 275 allocation rule (%)	100	100	100	100	100	100	100	100	100
N	31,237	1,191	859	3,240	6,486	4,348	5,375	6,153	3,585

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Notes: Standard deviation in parenthesis. Data for teachers' applying to waves 2004-2011.

Table B2: Descriptive Statistics

	2004-2014		AVDI applicants	
	Voucher System Teachers	AVDI Applicants	At time of application	2-years after
Male	0.300	0.270	0.288	0.286
	(0.458)	(0.444)	(0.453)	(0.452)
Age	47.526	47.148	44.531	46.665
	(11.302)	(9.625)	(9.373)	(9.318)
Degree in education	0.961	0.983	0.987	0.996
	(0.194)	(0.131)	(0.114)	(0.062)
Years of experience	21.146	21.272	18.243	20.769
	(12.750)	(11.126)	(10.634)	(10.505)
Not working in the school system				0.027
				(0.162)
Hours worked (total)	35.301	35.803	35.504	36.414
	(7.802)	(6.733)	(6.710)	(6.651)
Main job: primary school teacher	0.807	0.824	0.752	0.726
	(0.395)	(0.381)	(0.432)	(0.446)
Working at more than one school	0.114	0.117	0.124	0.108
	(0.318)	(0.321)	(0.329)	(0.310)
In a managerial job	0.112	0.055	0.041	0.072
	(0.316)	(0.228)	(0.197)	(0.259)
AVDI applicant (ever)	0.334			
	(0.472)			
Currently applying to AVDI				0.004
				(0.060)
Receiving AVDI	0.053	0.156		0.311
	(0.224)	(0.363)		(0.463)
AEP applicant (ever)	0.070	0.159	0.110	0.110
	(0.256)	(0.365)	(0.313)	(0.313)
Currently applying to AEP				0.011
				(0.107)
Receiving AEP	0.014	0.034	0.030	0.037
	(0.117)	(0.181)	(0.171)	(0.188)
New at school	0.112	0.084		0.147
	(0.315)	(0.278)		(0.354)
Private-subsidized school	0.000	0.039	0.014	0.027
	(0.000)	(0.194)	(0.119)	(0.163)
Private school	0.000	0.006		0.002
	(0.000)	(0.077)		(0.046)
Working conditions (top-50 school)	0.301	0.322	0.312	0.323
	(0.459)	(0.467)	(0.463)	(0.468)
Student performance (top-50 school)	0.466	0.526	0.499	0.517
	(0.499)	(0.499)	(0.500)	(0.500)
SNED awarded school	0.305	0.336	0.348	0.353
	(0.460)	(0.472)	(0.476)	(0.478)
Change of municipality	0.043	0.030		0.062
	(0.202)	(0.171)		(0.241)
Rural school	0.237	0.260	0.257	0.248
	(0.425)	(0.439)	(0.437)	(0.432)
In municipality with zone allowance	0.492	0.499	0.498	0.499
	(0.500)	(0.500)	(0.500)	(0.500)
N	757,831	259,434	23,868	23,868

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: Standard deviation in parenthesis. For the 2003-2014 period, *New at school* stands for whether or not the teacher was teaching at that particular school in the previous year. For the AEP applicants 2 years after application, *New at school* is a dummy taking the value of 1 if the school is different from the school at time of application. Except *Not working in the school system*, the dependent variables for teachers not working in the school system 2 years after application are coded as missing.

Table B3: Test for Continuity of the Final Score

	All	2004	2005	2006	2007	2008	2009	2010	2011
McCrary test p-value	0.000	0.796	0.823	0.789	0.587	0.630	0.000	0.000	0.000
Frandsen Discrete test p-value	0.559	0.307	0.286	0.135	0.017	0.111	0.587	0.688	0.034

Source: Own calculations based on data from the Ministry of Education (Chile)
Notes: McCrary (2008) test at the 275 cut-off, using a bandwidth of 30 and bin size 1.

Table B4: Balance at Baseline AVDI

AVDI	Degree of polynomial	
Dependent Variable	(1)	(2)
Male	0.021*	0.022*
	(0.012)	(0.013)
Age	-0.326	-0.157
	(0.255)	(0.354)
Degree in education	0.006**	0.005
	(0.003)	(0.003)
Years of experience	-0.144	-0.124
	(0.265)	(0.365)
Hours worked (total)	0.032	0.229
	(0.157)	(0.199)
Working at more than one school	-0.001	0.007
	(0.009)	(0.012)
In a managerial job	0.009**	0.002
	(0.005)	(0.007)
Main job: primary school teacher	0.045***	0.010
	(0.011)	(0.014)
Receiving AEP	0.012**	-0.004
	(0.005)	(0.006)
Working conditions (top-50 school)	0.016	0.028**
	(0.010)	(0.012)
Student performance (top-50 school)	-0.020*	-0.003
	(0.011)	(0.014)
SNED awarded school	-0.013	-0.007
	(0.014)	(0.020)
Rural school	0.029***	0.023
	(0.011)	(0.016)
In municipality with zone allowance	0.011	0.001
	(0.013)	(0.018)
Wald test p-value	0.0027	0.0366

Source: Own calculations based on data from the Ministry of Education (Chile)

Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AVDI data for teachers' applying to AVDI waves 2004-2011, at the time of application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Robust standard errors, adjusted for clustering in final score cells, in parenthesis. Column numbers indicate the order of the polynomial on the score centered around 275.

* Indicates statistical significance at 10%

** Indicates statistical significance at 5%

*** Indicates statistical significance at 1%.

Table B5: AVDI effects on Retention and Labor Supply

	All Teachers		0-11 years		12-21 years		22 +years	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Not working in the school system	0.0002	0.0011	0.0033	0.0066	-0.0134	-0.0130	0.0024	0.0037
	(0.0044)	(0.0043)	(0.0119)	(0.0115)	(0.0113)	(0.0109)	(0.0051)	(0.0053)
N	23,868	23,868	7,368	7,368	5,557	5,557	10,943	10,943
Clusters	288	288	272	272	272	272	283	283
Hours worked (total)	0.4070**	0.4356***	0.5958	0.5131	0.6114	0.5918	0.1911	0.2446
	(0.1706)	(0.1459)	(0.3711)	(0.3480)	(0.4236)	(0.3837)	(0.3106)	(0.2496)
N	23,228	23,228	6,994	6,994	5,423	5,423	10,811	10,811
Clusters	288	288	272	272	272	272	283	283
Working at more than one school	0.0013	0.0020	-0.0172	-0.0208	0.0056	0.0042	0.0133	0.0180
	(0.0098)	(0.0098)	(0.0171)	(0.0176)	(0.0199)	(0.0204)	(0.0162)	(0.0160)
N	23,228	23,228	6,994	6,994	5,423	5,423	10,811	10,811
Clusters	288	288	272	272	272	272	283	283

Source: Own calculations based on data from the Ministry of Education (Chile)

Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AVDI data for teachers' applying to AVDI waves 2004-2011, 2 years after application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Odd-columns present the estimates of equation (7). Even columns present the estimates of equation (7) and add controls interacted with wave fixed effects. Controls include gender, age, degree in education, years of experience, teaching at a single school, hours worked, receiving AEP, rural school, private-subsidized school, working conditions (top-50 school), student performance (top-50 school), SNED awarding school and education level of the main job: primary; all at time of application and excluding the outcome variable at time of application. Robust standard errors, adjusted for clustering in final score cells, in parenthesis.

* Indicates statistical significance at 10%

** Indicates statistical significance at 5%

*** Indicates statistical significance at 1%.

Table B6: AVDI effects on Between-School Mobility

	All Teachers		0-11 years		12-21 years		22 +years	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New at school	-0.0013	-0.0043	-0.0112	-0.0178	0.0155	0.0168	-0.0021	-0.0037
	(0.0111)	(0.0110)	(0.0214)	(0.0210)	(0.0282)	(0.0275)	(0.0131)	(0.0124)
N	23,228	23,228	6,994	6,994	5,423	5,423	10,811	10,811
Clusters	288	288	272	272	272	272	283	283
Private-subsidized school	-0.0065	-0.0068	-0.0169	-0.0206	0.0001	0.0002	-0.0018	-0.0016
	(0.0054)	(0.0054)	(0.0130)	(0.0134)	(0.0082)	(0.0089)	(0.0052)	(0.0051)
N	23,228	23,228	6,994	6,994	5,423	5,423	10,811	10,811
Clusters	288	288	272	272	272	272	283	283
Private school	0.0001	0.0002	-0.0016	-0.0015	0.0049	0.0051	-0.0011	-0.0011
	(0.0017)	(0.0018)	(0.0041)	(0.0042)	(0.0037)	(0.0037)	(0.0008)	(0.0008)
N	23,228	23,228	6,994	6,994	5,423	5,423	10,811	10,811
Clusters	288	288	272	272	272	272	283	283
In municipality with zone allowance	-0.0002	-0.0037	0.0190	0.0127	-0.0445	-0.0525	0.0000	0.0049
	(0.0181)	(0.0182)	(0.0300)	(0.0311)	(0.0322)	(0.0332)	(0.0253)	(0.0254)
N	23,224	23,224	6,994	6,994	5,422	5,422	10,808	10,808
Clusters	288	288	272	272	272	272	283	283
Rural school	0.0275**	0.0214*	0.0221	0.0219	0.0301	0.0224	0.0323	0.0159
	(0.0138)	(0.0129)	(0.0242)	(0.0248)	(0.0292)	(0.0268)	(0.0201)	(0.0186)
N	23,228	23,228	6,994	6,994	5,423	5,423	10,811	10,811
Clusters	288	288	272	272	272	272	283	283
Working conditions (top-50 school)	0.0079	0.0062	-0.0406*	-0.0343	0.0833***	0.0799***	0.0003	-0.0036
	(0.0108)	(0.0108)	(0.0229)	(0.0234)	(0.0283)	(0.0282)	(0.0198)	(0.0192)
N	23,151	23,151	6,943	6,943	5,406	5,406	10,802	10,802
Clusters	288	288	272	272	272	272	283	283
Student performance (top-50 school)	0.0098	0.0121	-0.0053	0.0276	0.0173	0.0162	0.0210	-0.0014
	(0.0139)	(0.0133)	(0.0238)	(0.0238)	(0.0310)	(0.0312)	(0.0210)	(0.0181)
N	23,151	23,151	6,943	6,943	5,406	5,406	10,802	10,802
Clusters	288	288	272	272	272	272	283	283

Source: Own calculations based on data from the Ministry of Education (Chile)

Notes: OLS regression. Dependent variable for teachers not working in the school system coded as missing. AVDI data for teachers' applying to AVDI waves 2004-2011, 2 years after application. Each cell reports the coefficient estimate of a dummy variable indicating if the final score was at least 275 points. All specifications include wave fixed effects interacted with the piece-wise polynomial of the final score. Odd-columns present the estimates of equation (7). Even columns present the estimates of equation (7) and add controls interacted with wave fixed effects. Controls include gender, age, degree in education, years of experience, teaching at a single school, hours worked, receiving AEP, rural school, private-subsidized school, working conditions (top-50 school), student performance (top-50 school), SNED awarding school and education level of the main job: primary; all at time of application and excluding the outcome variable at time of application. Robust standard errors, adjusted for clustering in final score cells, in parenthesis.

* Indicates statistical significance at 10%

** Indicates statistical significance at 5%

*** Indicates statistical significance at 1%.