# The Effect of a Homebuyer Subsidy on Children


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**Abstract**

Homeownership has been proposed as a key channel shaping intergenerational mobility. In this paper, we explore one potential mechanism for this effect: that homeownership and housing stability, more generally, could increase human capital formation in children. We study a large, novel housing policy – a homebuyer subsidy for low-income families in Santiago, Chile. We leverage an arbitrary discontinuity in subsidy assignment to estimate the causal impacts of homeownership on a wide array of primary, secondary, and tertiary education outcomes for children. We find that children in marginally eligible families significantly improve their attendance, grades, class ranks, and achievement test scores relative to children in families that narrowly miss the cutoff. The gains are larger for boys than girls, but do not substantially differ between students who are younger or older at the time of application. The gains are also more pronounced for children in larger families, suggesting that the alleviation of overcrowded living conditions may be an important mediator of the program's effects. These effects are not driven by sorting into different schools or changes in neighborhood quality. We find that, early in life, the subsidy increases children's preschool attendance, and later in life, children graduate high school and attend college at higher rates. Those who have left school also have higher employment rates. In all, we find that homebuyer subsidies are a promising tool for improving the economic fortunes of children from vulnerable families.



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# 1 Introduction

Housing is scarce and expensive in most of the world. Rapid urbanization in low- and middle-income countries has outpaced the availability of quality housing in city centers (UN-Habitat, 2022), while in high-income countries, affordable housing remains a persistent challenge. Given the potential for housing stability to positively influence various family outcomes, there is significant interest in housing policy as a tool to expand housing access and improve economic prospects for vulnerable populations. In the United States, approximately $67 billion, or 1% of total federal spending, is allocated to housing assistance each year, with most of it directed toward rental support.[1]

Recent empirical studies have questioned whether such programs can actually deliver on their promise. For example, wages and employment of adults appear unaffected - or even decline - after receiving housing assistance across a variety of contexts (Barnhardt et al., 2017; Belchior et al., 2023; Galiani et al., 2017; Jacob and Ludwig, 2012; Ludwig et al., 2013; Van Dijk, 2019). However, much less is known about the impact of housing policies on children. Early investment in children's health and education have been some of the most impactful public programs to date (Hendren and Sprung-Keyser, 2020), and the environment that children grow up in is critical to their schooling and later-life earnings (Chetty et al., 2016; Chyn, 2018; Kling et al., 2007; Pollakowski et al., 2022). Thus, it is conceivable that housing assistance delivered to families with children could have a large impact on children's long-run educational attainment and employment.

This paper provides new evidence on the causal effects of a unique housing policy—a homeownership subsidy for low-income families—on children's schooling and early-career employment outcomes. Our study is situated in Chile, a middle-income country and member of the OECD, where housing affordability issues persist despite substantial homeownership rates. We focus on families in Santiago, the capital of Chile—a rapidly growing metropolitan area comparable in size and economic significance to Madrid,[2] but with particularly strained housing affordability, making it an ideal setting for studying housing interventions.

[1] Source: Peter G. Peterson Foundation (2024)

[2] Santiago has a population of 6.5MM and Madrid 6.8MM. Their GDP per capita is estimated to be USD 29,507 and USD 36,911, respectively. However, Santiago's population density is almost twice as big (25.4 vs 15 residents per square mile). Source: World Bank and World Population Review.

In 2011, Chile introduced the *DS01* program, a major housing policy initiative that provides significant subsidies for low-income families to purchase homes in the private market. These subsidies cover up to about 85% of the purchase price of a home up to a maximum value of $40,000, representing a wealth transfer that is equivalent to about five times the average recipient's annual family income. Applicants need to pay the remaining portion of the home's value using their savings. From 2011 to 2020, there were over 155,900 applications for the program, with 31,873 families awarded subsidies. Housing purchases of the subsidy recipients accounted for more than half of all home purchases by the poorest 20% of households in Chile from 2012 to 2017.[3]

A key contribution of this study is our access to novel administrative data from the Chilean Housing Ministry on applicants to the subsidy and the status of their application (whether they were awarded a subsidy and if they used it). In addition, we have information on the children of the applicant families that can be linked to schooling data from the Ministry of Education and (formal) labor market outcomes from the Ministry of Labor. The education data includes enrollment data for public daycare facilities, preschools, primary, secondary, and tertiary educational systems,[4] as well as children's grades, class rankings, absenteeism, test scores, high school completion, preschool attendance, and post-secondary outcomes. Furthermore, it includes responses to questionnaires on topics like food consumption, drug use, educational expectations, and parental involvement, completed by parents and children during the standardized SIMCE tests. We further link employer-employee data to capture early labor market outcomes, creating a comprehensive life-cycle view of children's educational and economic trajectories following the subsidy.

We estimate the impact of the *DS01* policy on children's outcomes by leveraging a discontinuity in the assignment mechanism that determines which households are awarded the subsidy. Applicants are scored based on family characteristics, and subsidies are awarded to the most vulnerable applicants up to a cutoff that varies annually with the budget and is unknown ex-ante. Awardees need to use the voucher in the private market to purchase a house, and they can choose any home that meets minimum habitability standards and complies with price restrictions. The voucher must be used in the region of application within three years,[5] and applicants cannot sell or rent the house before five

[3]See Figure A2.

[4]This cross-level tracking is a unique advantage of the Chilean administrative data structure. In the U.S., educational data is often available only at the district level, making it difficult to follow children whose families relocate.

[5]This restriction is extendable.

years.

Among households just above the cutoff point, we find that 62% of awarded applicants use the voucher to purchase a housing unit. This take-up rate is slightly higher than some housing programs in the US (Chetty et al., 2016; Kling et al., 2005) or India (Barnhardt et al., 2017), but lower than the take-up rate for free housing measured in some programs in low-income countries (Agness and Getahun, 2024; Camacho et al., 2022). The high take-up rate can be explained by the monetary benefits of a homeownership subsidy in relation to temporary housing and the flexibility to choose the location of the unit. Imperfect compliance reflects the need to complement the voucher with savings or a mortgage in order to buy the house, as well as the limiting nature of the price cap on potential homes, which prevents applicants from selecting better neighborhoods in the city, and limits their housing choices. Empirically, we find that voucher users tend to relocate to neighborhoods that are comparable to their locations at the time of application but with slightly cheaper housing, higher population density, and lower average education levels. Moreover, over half of users relocate within one mile of their previous residence.

Our research design uses a standard fuzzy regression discontinuity framework that compares outcomes for families with a score just above the threshold to qualify for the subsidy and those with a score just below. Throughout, we report two sets of estimates: 1) an intention-to-treat (ITT) estimate based on the "reduced form" effect of scoring just above the threshold in a given round, and 2) an average treatment effect (ATE) estimate, which scales the reduced form effect by the fraction of marginal winners who buy a house, and captures the causal effect of actually using the subsidy to purchase a home on future children's outcomes. Consistent with the validity of our approach, we find no evidence that applicants can manipulate their scores around the cutoff, or that families look or behave differently on either side of the cutoff prior to application.

We find that receiving a homebuyer subsidy leads to significant improvements in primary and secondary educational outcomes, with gains in both cognitive and non-cognitive skills. Children in subsidy-winning households experience increases of 0.27 standard deviation units in grades, a 7.9 percentage point rise in school rank, and a 0.26 standard deviation improvement in math and verbal test scores. They are more likely to be enrolled at school, be in a grade appropriate for their age, and are less likely to be chronically absent. These results are consistent across alternative specifications and are robust to various bandwidth choices, suggesting that composition effects, pre-existing differences in household characteristics, or unobserved confounding factors do not drive the positive impacts of the subsidy. Interestingly, the gains arising from winning the subsidy and buying a home are stronger for boys, and we do not find important differences depending on the age at the time of application.

We examine several mechanisms that may underlie these positive impacts, including parental responses and family resources, school quality, neighborhood environment, and housing quality. We find no evidence that changes in school quality or neighborhood environment are important in our context. We believe this is due to several factors particular to our setting: most households do not relocate far from their original home, those who do move tend to settle in neighborhoods with similar characteristics, and public schools in Chile allow children to attend schools outside their municipality of residence. These factors likely limit the influence of neighborhood and school quality on the observed outcomes.

We also find that family resources do not improve for marginal subsidy winners. In fact, a secondary contribution of our work is a finding that parents' incomes and employment rates decline after winning the subsidy, consistent with results from earlier studies of other forms of housing assistance (Barnhardt et al., 2017; Kling et al., 2005; Van Dijk, 2019).[6] More generally, the characteristics of parents at the time of application seem to matter relatively little for the relative impacts of the subsidy. However, we find that gains in a child's academic performance are much stronger in larger families, suggesting that the subsidy may alleviate overcrowding and provide more favorable conditions for academic success.

We also examine the impacts of the housing subsidy on parents' and children's educational expectations using administrative data from questionnaires completed when children take standardized tests. We find no significant differences between families on either side of the subsidy cutoff in responses prior to subsidy allocation. However, after application, parents in winning households are 2.1 percentage points (3.2%) more likely to expect their child to earn a college degree and 3.3 percentage points (25.4%) more likely to believe their child will complete graduate studies, potentially leading to greater investment in their children's academic success and contributing to the observed improvements in educational outcomes. Children are also more likely to believe they will succeed in the future. These findings are consistent with Agness and Getahun (2024) and Kumar (2021), who show that

[6] There is a possibility that parents work less and spend more time in child-rearing and development. This is an important motivation for considering how children fare under a housing policy to be able to fully assess its efficacy.

children's own aspirations for education improve, and parents are more optimistic about their children's future after receiving housing assistance. To the extent that parents respond to these increased expectations by investing more in their children's schooling careers, this mechanism could be a mediator of the gains we observe.

Furthermore, we directly study parental responses regarding their engagement in their children's education, drawing on data from the SIMCE children's questionnaire. Our findings suggest that parents in awarded households become more engaged after receiving the subsidy. Despite not finding significant differences before application, Specifically, parents are 1.8 percentage points (3.5%) more likely to monitor their children's grades, 4.5 percentage points (5.5%) more likely to congratulate them for academic achievements, and 4.9 percentage points (10%) more likely to assist with study efforts. We observe no significant differences in engagement prior to the subsidy application, underscoring the subsidy's role in enhancing parental involvement. This enhanced engagement, alongside raised educational expectations, likely contributes to the observed improvements in children's academic outcomes, as parental time investment has been shown to significantly boost children's achievement (Guryan et al., 2008; Boneva and Rauh, 2018).

Finally, we consider how early and later investments in human capital formation are impacted by the homebuyer subsidy. We find that children of subsidy users are 9.4 pp more likely to attend preschool. We lack enough time to observe the full extent of college behavior for our entire sample of children. However, for older children (ages 7-18 at the time of their families' application for the early application cohorts), we find that end-of-high school performance outcomes - including high school graduation, their average grades and entrance exam scores for college - are significantly higher for children of marginally winning families relative to those from marginally losing families. Moreover, they attend college and receive professional degrees at higher rates. Conversely, they drop out of college at slightly elevated rates. For students who do not attend college, we look at early-career labor market outcomes and find suggestive evidence that the children of subsidy users are more likely to be employed, but we cannot yet detect increases in annual earnings.

This paper builds on a recent literature considering the effects of housing policies on individual-level outcomes. The effect of rent control (Diamond et al., 2019), eviction (Collinson et al., 2023), rental assistance (Jacob and Ludwig, 2012), and public housing (Van Dijk, 2019) on adult outcomes have all been studied. Less is known about how children are impacted by such policies. Studies of housing voucher programs have found mixed results on children's educational attainment and earnings: positive effects in Chetty et al. (2016) and Pollakowski et al. (2022); null effects in Jacob and Ludwig (2012)). Similarly, mixed findings have been found in work on forced moves from disadvantaged neighborhoods due to public housing demolitions (Chyn, 2018; Jacob, 2004) and slum-clearance programs (Rojas-Ampuero and Carrera, 2022). On the other hand, programs that provide free housing in the low-income country context have been found to significantly improve children's years of schooling (Agness and Getahun, 2024; Kumar, 2021; Camacho et al., 2022).

Our paper is the first to study a large-scale homebuyer subsidy, an initiative that promotes homeownership itself in contrast with rental assistance or public housing (Kling et al., 2007; Chetty et al., 2016; Chyn, 2018; Van Dijk, 2019; Schwartz et al., 2020; Pinto, 2022). Significantly, the subsidy provides recipients with a voucher to purchase a home in the private market. In contrast, "free" or other public housing programs often require tenants to relocate to neighborhoods with potentially very different characteristics and schools (Barnhardt et al., 2017; Kumar, 2021; Camacho et al., 2022; Belchior et al., 2023; Agness and Getahun, 2024).

Homebuyer subsidies offer a scalable alternative to free housing programs, particularly in developed countries, and have become part of current policy discussions in the 2024 U.S. presidential election. Vice President Kamala Harris recently proposed a $25,000 down-payment assistance program for first-time homebuyers.[7] The proposal has garnered public support with 57% of Americans in favor according to a recent poll.[8] To date, the only form of homeownership assistance in the U.S. has been a limited extension of the Housing Choice Voucher (HCV) program. While the broader HCV program provides $18 billion in rental assistance to 2.2 million families annually (Ellen, 2018), the HCV homeownership program has just 9,673 active participants since 2015.[9]

Our data enable us to follow children from daycare through high school and, for earlier cohorts, into college and the labor market. To our knowledge, this is the first study to examine the impacts of housing assistance across all levels of education: daycare, preschool,

[7] This subsidy would be available to individuals who have consistently paid their rent on time for the past two years, with larger amounts for those whose parents did not own a home (Campaign, 2024). At a campaign event, Harris stated: "I know what homeownership means. It's more than a financial transaction. It's so much more than that. It's more than a house ... It's financial security. It represents what you will be able to do for your children."

[8] Source: YouGov poll.

[9] Source: HCV Homeownership Dashboard. Figure current as of November 11, 2024.

primary, secondary, and post-secondary schooling. This comprehensive dataset provides a unique opportunity to analyze the long-term and multidimensional effects of housing stability on children's development. Furthermore, we capture both cognitive and non-cognitive outcomes[10]. Non-cognitive outcomes have often been overlooked in housing assistance research which typically centers on measures such as test scores and graduation rates.[11] However, non-cognitive skills have proven to be critical predictors of high school completion, post-secondary enrollment, and earnings (Becker et al., 2010; Jackson, 2018; Carlana et al., 2022; Card et al., 2024). Our research highlights the importance of examining both types of skills to fully understand the impact of housing assistance on educational and life outcomes.

We conclude that there are significant benefits to homebuyer subsidies and, more generally, homeownership for low-income families. Studying the impacts on parents alone would overlook the main source of social gains: improvements to human capital formation in children. A back-of-the-envelope calculation extrapolating the gains in educational attainment finds that the homeownership subsidy increases a child's present value of lifetime earnings by $22,403 USD, more than covering the costs of the program. Our findings underscore the potential for homeownership subsidies to yield long-term benefits in children's human capital development, positioning this policy as a promising tool for reducing intergenerational inequality.

The rest of the paper is organized as follows. Section 2 discusses the homebuyer subsidy and our Chilean context in more detail. Section 3 describes the sources of administrative data we combine for this project. Section 4 discusses our research design. Section 5 presents our main findings on K-12 educational outcomes. Section 6 discusses mechanisms. Section 7 presents evidence on early and later-life outcomes. Section 8 concludes.

[10]The Ministry of Education records grades and attendance as early as in first grade, providing a unique opportunity to track achievement across a child's entire school history

[11]Some of the few exceptions include Kling et al. (2007) (mental health), Jacob et al. (2015) (attendance), and Agness and Getahun (2024) (aspirations).

# 2 Housing, the *DS01* Subsidy and Education in Chile

## 2.1 Housing in Chile

Chile has a long tradition of subsidizing housing for disadvantaged families.[12] Until 2011, these policies primarily targeted the poorest 40% of the population by providing large subsidies to help them purchase homes. The introduction of the *DS01* homeownership program in 2011 marked a significant policy shift, expanding subsidies to include middle-income families and extending coverage to the poorest 60% of the population.

In 2017, 60.4% of households owned the house they were living in, while only 21.9% of households rented their unit. Panel A of Figure A3 illustrates homeownership rates by income quintile in Chile, showing a relatively stable ownership rate across the income distribution. The relatively equal distribution of homeownership in Chile may reflect the country's long-standing focus on housing subsidies for low-income families.[13] This pattern has been stable during the last decades. By contrast, homeownership rates in the U.S. are much more skewed by income. In 2019, only 40% of the bottom income quartile owned their homes, compared to nearly 90% in the top quartile.

Despite high homeownership rates, Chile faces a significant housing deficit in both the quantity and quality of available units. In 2017, more than 500,000 housing units were needed to solve the quantitative deficit.[14] This issue is particularly salient for the poorest 20%, who are 2.5 times more likely to face such a deficit than the richest 20% (Panel B of Figure A4). Concerning the qualitative deficit in housing units, Panel A of Figure A5 shows that 1,250,000 units were needed to address overcrowding, poor sanitation, and substandard construction. Again, this issue is particularly pressing for the lower end of the income distribution. More than 35% of households in the bottom income quintile live in

[12] Policies dating back to 1906 were introduced to improve housing conditions for the poorest households.
[13] Source: Survey of Consumer Finances 2019, Federal Reserve
[14] Quantitative deficit: 70,000 houses were severely damaged, 300,000 houses had more than one household living in the same house, and 180,000 had more than one family in the same house, with more than 2.5 individuals per bedroom (Panel A of Figure A4). Overcrowding is defined as having more than 2.5 people per bedroom in the housing unit and is an important challenge that many families in Chile face. In particular, more than 6% of households live in overcrowded houses. As seen in Figure A6, this is particularly important for the bottom quintile of the income distribution, as more than 12% of the households face this problem, compared to less than 3% in the top quintile. This situation differs markedly from the U.S., where overcrowding is defined less stringently as more than one person per room. Even by this more lenient measure, only 3.3% of U.S. households experienced overcrowding in 2019, compared to much higher rates of overcrowding among Chile's lower-income households (source: U.S. Census Bureau, American Community Survey, 2019).

these units, while less than 10% do so in the top quintile (Panel B of Figure A5).

During the period 2012-17, 23% of all sold housing units were bought only using the *DS01* subsidy, and 10% were purchased using a combination of subsidy and credit. As shown in Figure A2, there is a large amount of variation across the income distribution. More than 50% of the houses purchased by the bottom quintile were bought using either the subsidy or a combination of subsidy and credit. In contrast, only 18% of the households used this benefit in the top quintile. These figures highlight the critical role that housing subsidies play in enabling homeownership among Chile's lower-income families.

## 2.2 The *DS01* Policy

The *DS01* policy is a housing subsidy aimed at enabling homeownership for lower- to middle-income families in Chile. Through this subsidy, households apply for an up-front capital voucher to cover part of the cost of purchasing an existing housing unit in the private market. Applicants can select any house that meets the minimum habitability standards and complies with price restrictions. Applicants must specify one of Chile's 16 regions and select a preferred *comuna* (municipality) within it. However, this choice of *comuna* is not binding upon receipt of the subsidy.[15]

The subsidy is divided into three tiers, each targeting different income groups based on their vulnerability. The "high" subsidy tier is reserved for households within the poorest 60% of the population and requires minimum savings of $1,000. This subsidy provides winners with a $17,500 voucher for housing up to $35,000. The "medium" and "low" subsidies are targeted at the 80% and 90% most vulnerable and require savings of $1,400 and $2,800, respectively. They provide approximately $12,500 and $8,000 vouchers – though varying in the home purchase price – for housing up to $52,000 and $80,000, respectively. Panel A of Figure 1 shows the subsidy amount as a function of the house sale price separated by tier. The amount is fixed for the high subsidy as long as the price of the housing unit is greater than the subsidy amount, and it decreases in the value of the house for the medium and low subsidies, up to a minimum amount. In addition, the pricing cap for the high subsidy is more restrictive than the medium and low subsidies.

In Panel B of Figure 1, we show the distribution of the subsidy amount as a percentage

[15] Chile has 346 *comunas*, 52 of which are located in Santiago.

of the house's value for the different tiers of the subsidy. On average, the voucher covers 85% of the house price in the high subsidy tier, compared to 55% in the medium tier and 18% in the low tier.[16] Our analysis focuses on the high subsidy in Santiago, Chile's largest region, which houses nearly half of the country's population. We focus on the high subsidy tier because it aligns more closely with other studies on free or heavily subsidized housing, as it requires minimal upfront spending and no mortgage financing. It is also the most targeted program. We have a separate project that examines the effects of the medium and low subsidies, as well as the impact of the program across other regions of Chile. However, given the distinct nature of these subsidies and the differences in housing contexts outside Santiago, this paper concentrates on the high subsidy tier in Santiago.

After households submit their applications, a scoring system is used to determine eligibility. Each application receives a score based on various demographic factors, such as household size, single-parent status, presence of children or elderly members, and the household's savings. In Table A1, we show the components of the score and their impact on the overall score. Applications with the highest scores within each region and tier are selected to receive the voucher. The number of winning applications in each region depends on that year's budget, making the cutoff unknown ex-ante. The voucher must be used in the application region within three years (which is extendable), and the housing unit cannot be sold or rented before five years.

Figure A8 displays the cutoff scores by application call and tier. Changes in the pool of applicants drive variance in cutoff scores across application calls, as the budget allocation across regions and subsidy tiers remains relatively stable over time. For instance, the large drop in the cutoff score in the second call of 2019 for the low and medium subsidies is due to a reduced number in the pool of applicants.[17]

## 2.3 Education in Chile

Since our analysis focuses extensively on educational outcomes, we begin with an overview of the Chilean educational system. Preschool education in Chile consists of three levels: *Sala Cuna* (SC, up to two years old), *Nivel Medio* (NM, ages 2 to 4), and *Nivel Transición* (NT, ages 5 to 6). Starting in 2015, the upper level of Transition education (Kindergarten) became

[16] Figure A7 presents the distribution of the voucher amounts and the value of the houses purchased for the recipients by tier.

[17] Figure A13 shows the full evolution of applicants and winners over different application calls.

mandatory. All the other levels remain non-mandatory.[18] Primary education (*Educación Básica*) in Chile serves children ages 7 to 14 and covers grades 1 through 8.[19] As of 2020, primary education coverage was at 99.7% for children aged 7 to 14.

Secondary education (*Educación Media*), covering grades 9 through 12, is also mandatory. In 2020, secondary school attendance reached 87.7% for children aged 15 to 18.[20] A distinctive feature of the Chilean education system is that students are not required to attend a public school within their municipality. In our sample, over 30% of students attend a school outside their municipality. This contrasts with findings from other studies where location is a key determinant of school achievement due to factors like access to amenities, housing stability, and differential access to schools. (Chetty et al., 2016; Barnhardt et al., 2017; Camacho et al., 2022).

Tertiary education in Chile is divided into three types: universities, professional institutes (*Institutos Profesionales*), and technical training centers (*Centros de Formación Técnica*). Universities in Chile offer programs across a broad spectrum, including the humanities, social sciences, natural sciences, engineering, and medicine. Professional institutes provide shorter, career-oriented degrees in applied fields like business administration, accounting, and technical engineering. Technical training centers, on the other hand, offer short-cycle vocational programs, typically two years in length, to equip students with practical skills in areas like electronics, mechanics, healthcare, and computer technology.[21] Admission to traditional universities is primarily based on the PSU (*Prueba de Selección Universitaria*) entry exam.[22] In contrast, professional institutes and technical training centers generally do not require the PSU for admission, focusing primarily on secondary school completion.

[18]Preschool coverage is estimated at 33% for *Sala Cuna*, 49% for *Nivel Medio*, and 95% for *Nivel Transición*, with the higher coverage in the latter driven by the mandatory status of Kindergarten (Cite MINEDUC).

[19]Chilean schools are classified into three types based on funding: public, voucher, and private institutions. Public institutions are fundamentally funded by the government and are usually managed by local municipalities. Voucher schools are primarily privately financed by a combination of government funds and tuition paid by the student's families. Private institutions are financed exclusively through the tuition paid by students' families. Among students, 40% attended public institutions, 53% were enrolled in voucher schools, and 7% attended private schools.

[20]Of these students, 37% attended public institutions, 51% were in voucher schools, and 8% were enrolled in private schools.

[21]In 2020, 52% of tertiary students were enrolled in universities, 29% in professional institutes, and 19% in technical training centers.

[22]Traditional universities, which include both public and private institutions under the Council of Rectors (CRUCH), evaluate applicants based on PSU scores, secondary school grades, and class rank. More competitive programs, such as engineering, medicine, and law, often require higher PSU scores. Some private universities also require the PSU, though many place less emphasis on the score and offer alternative admission pathways.

# 3 Data and Summary Statistics

Our analysis is based on four primary data sources: subsidy records, labor market data for applicant families, educational records for applicants' children, and neighborhood characteristics. These data were accessed through agreements with the Chilean Ministries of Housing, Labor, and Education. We linked records across ministries using personal identifiers for both applicants and household members.

## 3.1 Subsidy Data

The subsidy dataset, provided by the Ministry of Housing, includes details on the application region, year, and specific program call. This information, combined with the vulnerability score, allows us to completely replicate the subsidy assignment process. This dataset also includes detailed applicant information, including address of origin, age, gender, nationality, disability status, marital status, and household composition (number of children, elderly members, and other adults). Additionally, the dataset contains financial information, such as savings, loans, and self-reported earnings. For households that utilize the subsidy, additional data include the date the subsidy was used, voucher amount, house value, and address of the purchased housing unit. [23]

The subsidy dataset provides information on household structure at the time of application, including unique identifiers for each household member, enabling us to link these records to education and labor market data. The data also contains some basic demographic information like the family member's age, gender, and relationship to the primary applicant. Since household composition is recorded at the time of application, information on new household members is only available for applicants who reapply. To ensure comparability, we exclude household members born after the application date, as this information is generally unavailable for most awarded households.

[23] Our main sample focuses on regular subsidy calls, excluding instances where all applicants were awarded the subsidy or where subsidies targeted households affected by natural disasters. If applicants appealed their initial score, we retained the higher score, as this score ultimately determined subsidy receipt.

## 3.2 Education Data

Our educational data, provided by the Ministry of Education[24], covers the period from 2008 to 2023. This dataset is linked to all household members from the subsidy data, offering a comprehensive view of educational outcomes alongside household characteristics. The dataset includes information on daycare and preschool enrollment, primary and secondary school enrollment, grades, attendance, standardized test scores (SIMCE), as well as tertiary education entry test scores, enrollment, and graduation status. In addition, it has information on the school or college they are enrolled in, including whether it is a private, public, or voucher school and its location.

Our key academic performance measures include grades, dropout and repetition indicators, class rank percentiles, and average test scores, including math and verbal subject tests. In addition, we construct an indicator of whether they were in the grade they were supposed to be in according to their date of birth and an indicator of whether they were enrolled at school. We also have information on absenteeism, measured as the percentage of class days missed during the academic year. Additionally, we construct an indicator for chronic absenteeism, defined as missing more than 10% of class days.

Other outcomes include a school quality indicator based on the school's national ranking (via SIMCE scores), as well as indicators for attending a public or private school, priority student classification, and changes in school or comuna of residence. Priority student status is largely based on belonging to the most vulnerable 80% of households, as determined by the *Registro Social de Hogares*. Public schools receive additional government funding for each priority student they enroll.

During the SIMCE test, both students and their parents complete questionnaires addressing topics such as food consumption, drug use, educational expectations, and parental involvement. These questionnaires specifically ask about expectations for educational attainment, with options ranging from 1) not completing high school to 5) completing graduate studies. Using these responses, we measure changes in both children's and parents' expectations for the child's highest educational attainment, categorizing outcomes as high school, college degree, or graduate degree. We also analyze children's responses to assess whether they hold improved expectations regarding their grades and future goals.

[24] MINEDUC: Agencia de Calidad de la Educación (2024).

Additionally, we use the children's questionnaire to track changes in food consumption (breakfast, lunch, and fruit) and drug use (cigarettes, alcohol, and marijuana). Lastly, we explore parental engagement by examining responses on their likelihood of knowing their child's grades, helping them study, and celebrating their academic achievements.

To analyze high school completion and post-secondary outcomes, we collapse the data to a single observation per student, restricting the sample to those who were in school at the time of application. Then, we generate indicators for whether they graduated high school, took the college entry exam, attended, dropped out, or graduated college. In addition, we present the average grades in high school for the graduates and the standardized scores in math, verbal, history, and science for the ones taking the entry exam.

For college dropouts and graduates, we limit the sample to students who enrolled in a post-secondary program. For tertiary attendance, we restrict the sample to students who graduated high school. However, our results do not change if we use the full sample. Finally, for students who enroll in post-secondary programs, we calculate the number of years attended and create indicators for institutional quality.[25]

## 3.3 Labor Market Data

We obtained an employer-employee dataset from the Ministry of Labor that provides detailed wage information and payment dates for each applicant with unemployment insurance coverage from January 2002 to December 2023, covering all formal employment in Chile. The dataset includes information on monthly earnings received from each employer, contract type (permanent or temporary), work location, and workers' educational attainment.Using these data, we construct yearly variables to measure employment status, total months worked, and annual earnings. We further disaggregate earnings and months worked by contract type, allowing us to differentiate between permanent and temporary employment.

Because the dataset is sourced from unemployment insurance records, it excludes self-employed individuals, independent contractors, civil servants, and informal sector workers. However, approximately 90% of applicants in our sample appear in the dataset at least once, indicating that most have engaged in the formal labor sector at some point.

[25] We consider whether the student attended a university (versus a technical institution) and the number of years the institution was accredited by the Ministry of Education.

In our main analysis, we include working-age individuals, defined as individuals between 18 and 65 years old, and impute zero earnings for any year in which earnings are not reported. We then restrict the sample to the working-age population, defined as individuals between 18 and 65 years old. Our results are robust to different sample selections, including: (1) excluding individuals under 25 until their first appearance in the dataset, (2) excluding each person until their initial entry in the dataset, and (3) excluding each person from both their first appearance and after their last appearance in the dataset. We further analyze the subsidy's effects conditional on employment, examining both earnings and months worked. To handle years with no employment, we use Poisson regressions for annual earnings and months worked. A limitation of the dataset is the absence of hours worked, restricting our analysis of the intensive margin to the number of months in which earnings are reported.

## 3.4 Neighborhood Data

To examine the significance of location in our analysis, we gather neighborhood information from three primary sources to understand applicants' origins and destinations. First, the 2017 Census data provides essential indices such as education levels, overcrowding, housing material quality, housing deficits, population density, and socioeconomic characteristics. Second, data from *Espacio Público* (2017), [26] offers information on neighborhood amenities, including green spaces, educational facilities, supermarkets, public transit stops, and healthcare centers. Third, data from the *Servicio de Impuestos Internos* (Chilean IRS) provides information on housing unit and square foot valuations and land sizes.

After extensive data cleaning, we geolocated both the origin and final addresses of applicants, successfully matching 98.5% of origin addresses and 93.2% of final addresses.[27] We then linked each address to its corresponding census tract. In Chile, there are 46,087 census tracts across 346 municipalities, with Santiago containing 3,426 tracts within 52 municipalities.[28]

[26]Espacio Público employs a geographic division called *Unidad Vecinal*, which slightly differs from census tracts. We linked our locations to these units to maintain consistency.

[27]The difference in geolocation success rates is primarily due to data quality; origin addresses were consistently structured by region, *comuna*, street, and number, whereas final addresses were often combined into a single cell with varied formats across applications.

[28]To enhance matching accuracy, we created a crosswalk to correctly align neighborhoods with addresses that referenced specific buildings, villas, or condominiums.

### 3.5 Summary Statistics

For our main sample, we keep applications that we are able to link to at least one household member in the education data. This matching process yields 131,251 applications for the high subsidy in Santiago, representing 84.2% of the full sample. Restricting to applicants with children under 18 at the time of application reduces the sample to 90,362 applications. The first four columns of Table A4 present summary statistics for all applicants, winners, subsidy users, and non-users, respectively. Column (5) shows the differences in demographic characteristics between users and non-users, calculated by taking the difference between columns (3) and (4). As shown in column (1), most applicants linked to the education data are female and in their mid-to-late thirties, with about two-thirds being single parents. The average household comprises four members, including 1.5 children attending school. They have applied 1.2 times before, on average, and the average number of years of schooling in their neighborhood of residence is ten.

Column (2) shows that winners' demographic characteristics are largely similar to the rest of the sample, with notable differences in household size, number of school-aged children, and normalized score. This is not surprising considering that the number of household members, and especially the number of children in the household, is a crucial component of the score. Column (5) indicates that among winners, subsidy users are, on average, two years younger and have fewer children in school. They also have lower scores and have applied fewer times on average. Finally, they report a lower income and tend to live in slightly worse neighborhoods than non-users in terms of average years of schooling. Simple comparisons between winning and losing households—or between users and non-users—would be biased by these demographic differences. Our research design relies on comparisons between winning and losing applicants at the cutoff, where the two groups are statistically indistinguishable on a host of measures.

Column (1) of Table 7 provides summary statistics on the labor participation of the children's parents. On average, 46% of parents are employed in a given year. Including non-working parents as having zero employment, the average number of months worked is 4, with 2.7 months under permanent contracts and 1.3 months under temporary contracts. In terms of earnings, parents average 63.2 UF per year, or approximately $3,384 USD, again with non-working parents counted as zero earners. Around 75% of these earnings are from permanent contracts, while the remaining 25% come from temporary contracts.

# 4 Design

Our research design relies on comparing the children of applicants who barely lost the subsidy to those of applicants who barely won. We focus on two key parameters: first, a reduced-form estimate of the effect of winning the subsidy (ITT); and second, an adjusted estimate that accounts for the likelihood of subsidy usage among winners compared to those who barely missed receiving it. We also detail our approach to reapplications, describe our estimation strategy, and present evidence on the validity of our regression discontinuity (RD) design.

## 4.1 ITT Estimates

We first estimate the effect of winning the subsidy on a child's human capital formation without accounting for whether the family ultimately used the subsidy. To capture this intent-to-treat (ITT) effect, we model the outcome using the following specification in Equation 1:

$$y_{itc} = \alpha_0 + \alpha_1 f(Score_{ic}) + \beta_{ITT} D_{ic} + \alpha_2 D_{ic} \cdot f(Score_{ic}) + \Pi X_{ict} + \varepsilon_{itc} \tag{1}$$

The $y_{itc}$ is the outcome of interest of the applicant $i$, at time $t$ and call $c$. The $Score_{ic}$ represents the applicant score in call $c$. The $X_{ict}$ controls flexibly for a set of application characteristics, including gender by age of the applicant and year fixed effects. The $D_{ic}$ is a dummy variable that takes the value of 1 if the applicant's score is greater than 0, indicating that they won the subsidy. The $\alpha_1 f(\cdot) + \alpha_2 D_{ic} f(\cdot)$ is a flexible function capturing the relationship between the application score and the outcome. We allow for different parameters on either side of the cutoff. T Our coefficient of interest, $\beta_{ITT}$, estimates the effect of winning the subsidy on the outcome for applicants at the cutoff score.

To implement our estimation, we need to take a stand on the functional form of $f(\cdot)$, the weights applied to data near and far from the cutoff, as well as the bandwidth to use. In our main results, $f(\cdot)$ is modeled using a linear polynomial with a triangular kernel. We also explore alternative functional forms and weights in robustness checks. We select the optimal distance from the cutoff using the bandwidth selection procedure proposed by Calonico et al. (2014) for each outcome at the time of the application. Throughout the analysis, we cluster standard errors at the applicant level.

## 4.2 LATE Estimates

Given the application process, many unsuccessful applicants reapply in subsequent years, particularly those near the cutoff. In particular, approximately 70% of applicants just below the cutoff reapply, and around 60% of these eventually win the subsidy (Figure A14). Therefore, comparisons between winners and losers around the cutoff may include losing applicants who later win, potentially benefiting from the subsidy as their children experience improved housing. This dynamic likely causes the ITT estimate to understate the subsidy's effect on children's educational attainment.

To address this, we model whether an application ultimately uses the subsidy around the cutoff. We rely on variation in subsidy-using rates driven by the discontinuous jump in the probability of winning the subsidy at the cutoff. This first step is captured in Equation 2. We then use predictions from that model to capture how educational outcomes of interest vary with how likely the family is to use the subsidy around the cutoff in Equation 3.

$$Used_{itc} = \gamma_0 + \gamma_1 f(Score_{ic}) + \beta D_{ic} + \gamma_2 D_{ic} \cdot f(Score_{ic}) + \Gamma X_{ict} + u_{itc} \tag{2}$$

$$y_{itc} = \delta_0 + \delta_1 f(Score_{ic}) + \beta_{LATE} \hat{Used}_{itc} + \delta_2 D_{ic} \cdot f(Score_{ic}) + \Delta X_{ict} + v_{itc} \tag{3}$$

Here, $Used_{itc}$ is a binary variable indicating whether applicant $i$ in call $c$ used the subsidy to purchase a house by time $t$. The remaining terms are defined as in the previous section. In Equation 3, $\beta_{LATE}$ captures the Local Average Treatment Effect (LATE), representing the causal effect of using the subsidy on the outcome for applicants at the cutoff. In practice, we estimate this set of equations through a two-stage least squares (2SLS) regression. The distance from the cutoff we impose to limit our estimation sample is computed using the optimal bandwidth proposed by Calonico et al. (2014). Standard errors are clustered at the applicant level.

Identification of $\beta_{LATE}$ relies on the discontinuous jump in the winning probability at the cutoff. This increased probability drives higher subsidy usage rates among applicants who barely win compared to those who barely lose. A causal interpretation of $\beta_{LATE}$ requires that all other factors influencing children's educational outcomes remain continuous around the cutoff (Lee and Lemieux, 2010; Cattaneo et al., 2020b). As the score is used exclusively for the *DS01* subsidy, no other policy changes occur at the discontinuity. Moreover, since the cutoff depends on the application call demand and is unknown before application, it is impossible for an applicant to manipulate their scores to cross the threshold. In the following section, we provide evidence that scores were in fact not manipulated, and that other characteristics and pre-application outcomes remain smooth around the cutoff.

Households receive a bonus score each time they apply unsuccessfully in the past. In Section 4.3, we show that while this bonus increases applicants' scores when reapplying, there is no discontinuity in the number of past applications at the threshold. In other words, winners and losers near the cutoff do not statistically differ in the number of prior applications. Further, in Section 5.2, we demonstrate that our main estimates remain robust when controlling for the number of previous applications.

Panel A of Figure 2 reports the first stage for the high subsidy in Santiago, using Equation 2 and pooling across application calls. We find that around 62% of winning applicants eventually use the voucher to purchase a home, compared to 38% of losing applicants, resulting in a 23 percentage point increase at the threshold. This jump indicates a sufficiently strong first stage for estimating the policy's effects. Moreover, this result suggests that the ITT estimates need to be rescaled by a factor of approximately 4 to 5 to calculate the LATE of using the voucher to purchase a home. In Panel B of Figure 2, we show how take-up rates for winning and losing applicants evolve over time. Take-up gradually increases for both groups, with a relatively stable 25 percentage point difference on average.

Take-up for the *DS01* subsidy is higher than in some housing programs (Chetty et al., 2016; Barnhardt et al., 2017; Kling et al., 2005) but lower than programs with nearly complete take-up (Agness and Getahun, 2024; Camacho et al., 2022). In our setting, monetary benefits and increased housing stability and quality are likely drivers of the take-up rates. However, requirements for savings and housing price caps, which limit neighborhood options, may deter some winning families from using the subsidy.

## 4.3 Design Validity

To assess the validity of our design, we test for potential manipulation of application scores around the cutoff. Specifically, we examine whether there is a discontinuity in the distribution of applicants' scores, which would indicate strategic behavior. Additionally, we assess the continuity of observable characteristics and prior outcomes for both applicants and their children near the cutoff, ensuring comparability between winners and losers.

Figure 3 presents the results of a score manipulation test for the high subsidy, using a local polynomial fit to the empirical distribution of the score on either side of the cutoff. This test evaluates whether there is a structural break in the score distribution at the cutoff (Cattaneo et al., 2020a). While maintaining the flavor of the McCrary test (Lee and Lemieux, 2010; McCrary, 2008), this approach does not require pre-binning the scores into a histogram. With a $p$-value of 0.966, we cannot reject that scores are not manipulated. This is unsurprising, given the varying nature of the cutoffs across application calls.

Another key assumption in the RD design is that observable characteristics (predetermined variables) should remain continuous across the cutoff, ensuring that observed outcome differences are attributable to subsidy receipt rather than preexisting differences between winners and losers. In Table 1, we apply our ITT specification from Equation 1 to demographic characteristics at the time of application and find no significant discontinuities in any demographic variables. Notably, there is no significant difference in the number of prior applications at the cutoff; both winners and losers averaged 1.2 previous applications. These findings are robust to different bandwidth selections.

Finally, we test for "pretrends," or differences in the outcomes of interest prior to application, by estimating models of the form in Equation 1 on outcomes in the year before the program call. Panel A of Table 2 shows that, while children in subsidy-winning households performed slightly better at the time of application, these differences are statistically insignificant and economically small relative to the control mean. Overall, our findings confirm that the design is valid and that subsequent results are not driven by prior differences in children's academic performance.

In addition to checking for differences at the time of application, Section 5 considers whether winning and losing applicants followed different trends prior to applying. To do this, we estimate versions of our main specification on outcomes at each time period prior to application and find no evidence for pretrends on our main education outcomes.

### 4.4 Children at the Cutoff

Since our RD design focuses on comparisons near the cutoff, our estimates of the homebuyer subsidy's effects are most relevant to children in this range. We briefly characterize the sample of children for this subgroup in Table 2. The average student grade is 5.7 out of 7, with an average class rank in the 49th percentile. Approximately 17% of students are not in the expected grade based on their birth date, indicating prior grade retention, with 4.4% retained in a given year. The annual dropout rate for the control group is 0.5%, and the cumulative dropout rate averages around 4.4%. Absenteeism is about 10% of school days, with chronic absenteeism—defined as missing more than 10% of days—reaching 36%.

Panel B shows that children of winning and losing applicants generally attend schools with comparable characteristics. About 34% attend public schools, while only 0.4% are enrolled in private institutions. The remaining 65% attend voucher schools. The average class size is 36 students, and average school quality, measured by percentile rank in test scores, is at the 44th percentile. Additionally, 62% of students are classified as priority students, enabling public and voucher schools to receive additional funding. Finally, around 12% of the sample switched schools in a given year, and 2.6% reported changing their municipality of residence.

## 5 Results

### 5.1 Main Results: Primary and Secondary Education Achievement

We begin by examining the effect of the homebuyer subsidy on K-12 academic performance. Panel A of Figure 4 presents regression discontinuity results for grades after the application, using a linear polynomial with triangular kernel weights and pooling across years and calls. Grades are negatively correlated with the vulnerability score on both sides of the threshold. However, we find a 0.035-point increase at the threshold, equivalent to an improvement of approximately 0.06 standard deviations.

In Panel B, we use the panel structure of our data to trace the evolution of grade differences before and after the application. Before the application, there are no significant grade differences between winners and losers. After the application, however, we observe a significant and sustained improvement in grades for children in winning households, starting in the year following the award. This grade increase shows no substantial dynamics over time, remaining relatively constant after being awarded the voucher.

Table 3 displays the regression discontinuity results for additional achievement outcomes, with both ITT and ATE coefficients estimated using equations 1 and 3, respectively. Each cell reports an individual RD estimate calculated using the optimal bandwidth proposed by Calonico et al. (2014) and fitting a linear polynomial on each side of the cutoff, with standard errors clustered at the applicant level. The results reveal significant positive effects across most outcomes. The ATE estimates suggest a 0.27 standard deviation increase in grades, a 0.08 percentage point rise in class rank percentile, and a 0.32 standard deviation improvement in test scores. Moreover, we observe a 2% increase in school attendance, a 9% increase in the probability of students being in the correct grade for their age, and reductions in both grade repetition and dropout rates. Although there is no significant effect on the overall percentage of school days missed, we find a 4.1 percentage point decrease in chronic absenteeism. Figure 5 provides graphical evidence of the discontinuities across some of these achievement outcomes.

These results are notably larger than those found in Jacob (2004), which investigates the educational impact of housing assistance following the Chicago public housing demolitions—one of the few studies to examine intermediate secondary school outcomes, particularly non-cognitive skills. The authors found no significant effects on GPA, standardized test scores, absenteeism, dropout rates, or age-grade mismatch. Similarly, our results are more pronounced than the effects on standardized test scores reported in Schwartz et al. (2020) for housing vouchers in New York City.

Most of the related literature assessing secondary education outcomes uses broader metrics, such as school enrollment, high school completion, years of schooling, and exit test scores. However, Jackson (2018) highlights that non-cognitive indicators like attendance, course grades, and grade repetition can differ from test score outcomes and have meaningful long-term impacts on student success. In Section 7.2, we benchmark our findings against this literature by presenting results for high school graduation, university entry scores, and post-secondary outcomes.

## 5.2 Robustness

Table 4 demonstrates that our results are robust across various model specifications. In Columns (3) and (4), we show that the estimates remain consistent regardless of whether we exclude controls or include controls for the outcome at the time of application. Column (5) confirms that the results are not sensitive to bandwidth selection, as using the average bandwidth yields similar estimates.

Further robustness checks in Columns (6) and (7) indicate that the results hold when excluding weights or using a second-degree polynomial instead of a linear polynomial. Finally, Column (8) shows that our estimates are, if anything, stronger when excluding the COVID-19 period (2020 onward) despite the sample size being reduced by half. In Table A5, we also demonstrate that our results remain consistent across a range of bandwidths from 30 to 100, in intervals of ten.

## 5.3 Heterogeneities

Table 5 shows that the impact of housing assistance is larger for boys than for girls across all main academic achievement outcomes. Specifically, boys from awarded households improve their grades by 0.34 standard deviations and increase their class rank by 10 percentage points, whereas girls experience smaller gains of 0.20 standard deviations in grades and 6 percentage points in class rank. Similarly, boys' test scores increase by 0.5 standard deviations, and they are 10.2 percentage points (12.5%) more likely to be in the correct grade for their age, while the effects on these outcomes for girls are not statistically significant.

These findings contrast with results from the Moving to Opportunity (MTO) experiment (Chetty et al., 2016; Kling et al., 2007) and other housing subsidy programs (Pollakowski et al., 2022), where girls experienced larger educational gains than boys. Prior studies suggest that girls adapt more readily to new neighborhood norms, engage in less risky behavior, and face fewer challenges with relocation compared to boys (Clampet-Lundquist et al., 2011). In our setting, however, most awarded households do not move far from their original location, and relocations rarely involve significant changes in neighborhood quality. Additionally, children are no more likely to switch schools after receiving the subsidy. Therefore, unlike in the MTO studies, our setting does not expose children to substantial changes in neighborhood or school characteristics. We provide further evidence of this in Section 6. Our findings regarding heterogeneity in gender align more closely with studies on housing relocation in Chicago and Australia (Deutscher, 2020; Jacob, 2004; Jacob et al., 2015).

The age of the child at the time of receiving housing assistance has also proven to be important in other settings. Longer exposure to improved neighborhood and school environments during critical developmental stages can be beneficial, while older children may face greater challenges adjusting socially and academically after relocation. However, as shown in Figure 6, age at application does not appear to be a significant source of heterogeneity in our setting. The ITT effect on grades remains stable across age groups, ranging between 0.03 and 0.05, corresponding to a 0.2–0.4 standard deviation increase. If anything, older children at application perform slightly better academically, though this difference is not significant. Results for other achievement measures are presented in Table A6.

Our findings differ from studies that report larger benefits for younger children receiving housing assistance (Agness and Getahun, 2024; Chetty et al., 2016; Gennetian et al., 2012; Jacob et al., 2015; Kling et al., 2007; Schwartz et al., 2020). However, most of these studies look at differences in high school completion or earnings in a particular year after the move, finding that the effects are driven by a larger dosage of childhood exposure to improved neighborhood environments. In our setting, families tend to remain close to their original location and experience little improvement in neighborhood conditions on average. Moreover, by tracking achievement outcomes yearly after the application, we capture intermediate cognitive and non-cognitive outcomes, adding insight into achievement dynamics over time.

Our results align with those of Deutscher (2020), who found that relocation effects are stronger during late childhood or teenage years. In Section 7.2, we present findings on high school graduation, which may be more comparable with other studies. Regardless, we believe that these differences can partially be explained by modest changes in neighborhood and school characteristics after the move.

Finally, we find no evidence of significant heterogeneity based on other applicant characteristics, including marital status, gender, and self-reported income, as shown in Figure A15.

# 6 Mechanisms

## 6.1 Neighborhood

Neighborhood quality plays a critical role in children's educational outcomes by shaping access to resources, ensuring safety, and influencing peer networks. Studies consistently demonstrate that exposure to neighborhoods with higher socioeconomic status can improve long-term outcomes by providing better access to schools, libraries, and safe recreational spaces that promote a positive learning environment (Chetty et al., 2016). Low-crime, socioeconomically stable neighborhoods also contribute to reduced stress and better mental well-being, which support children's academic focus and resilience (Cutler and Glaeser, 1997). Social exposure to peers from higher socioeconomic backgrounds within these neighborhoods can further elevate academic aspirations, setting higher educational benchmarks and expectations (Sacerdote, 2001). Together, these studies find that neighborhood quality can be an influential factor in improving educational opportunities and outcomes, particularly for children from disadvantaged backgrounds.

However, households that use the subsidy in our setting generally remain close to their original location and experience only modest changes in neighborhood quality. Furthermore, Section 6.2 demonstrates that children from awarded households typically do not switch schools after relocation. Thus, it is less likely that neighborhood quality will play a decisive role in shaping educational outcomes in our context.

Our data include initial locations for all applicants and final locations for households that received and used the voucher subsidy. Unfortunately, final location data are unavailable for non-awarded households.[29] Consequently, our neighborhood analysis focuses on heterogeneity by neighborhood quality at the time of application. We classify neighborhoods into terciles of quality (bad, medium, good) based on average years of education within each census tract.[30]

Table A2 displays neighborhood characteristics for subsidy users at the census tract level. Columns (1) and (2) show average neighborhood quality in the initial and final

[29] The Housing Ministry does not collect final location data for non-awarded applicants, and our other data sources do not provide location granularity sufficient to track neighborhood changes.

[30] When applying, applicants specify a preferred municipality (*comuna*), though this preference is non-binding when choosing a home. We explore differential effects at the *comuna* level, similar to Van Dijk (2019). However, too few households households apply to municipalities outside their residence.

locations, respectively. Column (3) reports the difference in neighborhood quality, and column (4) shows the number of applicants. Panel A shows that users tend to relocate to neighborhoods with slightly lower average education levels and higher population density. However, these areas also have less overcrowding, lower housing deficits, and better housing materials, indicating trade-offs in neighborhood quality. Panel B examines amenities per capita, revealing that users' new neighborhoods generally offer fewer amenities, including educational and healthcare facilities, supermarkets, bus stops, and drugstores. Panel C shows that, on average, they move to slightly cheaper neighborhoods.

Figure A10 displays the distribution of neighborhood quality based on residents' average years of education. Panel A shows that differences between initial and final neighborhoods are minimal. Although users generally move to slightly less educated areas, almost 50% experience no change in neighborhood quality, and most changes are close to zero, suggesting very small shifts in neighborhood quality. Additionally, Figure A11 displays the distribution of distances from users' initial and final addresses to the city center, as well as the distance between these two locations. Over half of users relocate within one mile of their previous residence, with new homes generally situated slightly farther from the city center. These findings suggest that applicants do not move far from their original neighborhoods, and when they do, they tend to relocate to areas with similar characteristics.

Figure A12 presents the distribution of census tracts for voucher-awarded applicants at the time of application (Panel A) and for voucher users (Panel B). It also shows the distribution of users' final locations (Panel C) and the average years of schooling by census tract (Panel D). These maps reveal two key insights: first, the geographic distribution of voucher winners closely resembles that of voucher users, indicating minimal selection differences between the groups. Second, while users' final locations tend to be more concentrated in some peripheral neighborhoods, these areas exhibit similar average years of schooling as their initial locations. This visual evidence aligns with previous findings, suggesting that users experience only minor changes in neighborhood quality upon moving.

In Figure 8, we present ITT estimates for grades by neighborhood of origin, revealing minimal variation in effects across neighborhood types. Children from higher-quality neighborhoods show slightly smaller gains, with effects no longer statistically significant at the upper end. Table A8 presents results for other outcomes, with the strongest effects observed among households originating from "medium" human capital neighborhoods. Results remain consistent across alternative measures of neighborhood quality, as shown in Figure A16.

Our findings diverge from the broader literature emphasizing the role of neighborhood quality in educational attainment (Chetty et al., 2016; Deutscher, 2020; Laliberté, 2021; Schwartz et al., 2020; Van Dijk, 2019). These studies often examine policies that facilitate moves to substantially better neighborhoods and schools. In our context, most households do not relocate to significantly improved neighborhoods or switch schools.[31] Our results align with those from Jacob et al. (2015) and Haltiwanger et al. (2020), which found limited educational impacts from neighborhood quality alone, and from Haltiwanger et al. (2020), which reported no significant effects for families moving to lower-quality neighborhoods.

## 6.2 School Quality

School quality is a key predictor of a child's human capital formation. Access to high-quality schools enhances teacher quality, curriculum rigor, available resources, and peer influences, all of which improve high school completion rates and college enrollment, especially for disadvantaged children. Consequently, school quality has proven to be an important mediator in studies of the MTO experiment and other housing mobility programs (Chetty et al., 2016; Barnhardt et al., 2017; Camacho et al., 2022). However, in our context, families tend to remain close to their original residences, and Chile's public school system does not require students to live in the same municipality as their school. Consequently, changes in school quality are less likely to be a relevant factor in our setting.

To assess this directly, we examine changes in school quality using school characteristics as outcomes in our main design. These results are presented in Table 6. We find no evidence that children from subsidy-winning households sort into different schools following relocation. Specifically, they are equally likely to attend public or private schools, with no significant changes in schools' average test scores or class sizes. Furthermore, we observe no increase in school switching rates among these students; if anything, they are slightly less likely to switch schools post-application, though this difference is not statistically sig-

[31] In related research, we examine how neighborhood quality influences outcomes for recipients of the medium and low subsidy tiers. Our findings in that context differ from those in this paper, as neighborhood quality appears to play a significant role. Specifically, the null overall effects we observe seem to be driven by positive outcomes for children moving from low-quality neighborhoods and negative outcomes for those moving from high-quality neighborhoods. This pattern likely reflects the greater mobility in neighborhood characteristics among medium and low subsidy users, which we attribute to less restrictive price caps, allowing for more varied relocation choices and potentially explaining the contrasting findings.

nificant.[32]

We attribute these findings to the limited relocation distance in our setting and the flexibility of Chile's public school system, which allows students to attend schools outside their municipality of residence. This feature may also explain the absence of differential effects by neighborhood type. Our results align with studies that allow for more flexibility in housing location choices, where changes in neighborhood or school quality may be less pronounced (Agness and Getahun, 2024; Kumar, 2021).

## 6.3 Housing Conditions

Given the limited effects of neighborhood and school quality, housing conditions emerge as a potential mechanism influencing children's educational outcomes. Poor housing quality—characterized by overcrowding, limited space, and inadequate facilities—can increase stress, reduce focus, and lead to higher rates of illness, all of which negatively impact school performance. Overcrowded conditions, in particular, restrict access to quiet, private spaces necessary for studying and rest. Research shows that children in improved housing environments experience academic benefits due to reduced stress and better sleep quality (Goux and Maurin, 2005; Lavy et al., 2012).

To investigate housing conditions as a potential mechanism, especially overcrowding, we analyze the effect of the homebuyer subsidy on standardized grades by household size at the time of application. These results are reported in Figure 7. The findings indicate that the effect of the voucher increases with household size, with children from larger households benefiting more significantly. Specifically, children in households with three or fewer members show a modest, statistically insignificant improvement of 0.034 standard deviations. In contrast, children from households with more than four members experience a gain of over 0.08 standard deviations, more than doubling the effect seen in smaller households. For larger households, the ATE reaches 0.32 standard deviations. Table A7 confirms that these patterns hold across our other main achievement outcomes.

We interpret household size at application as an effective proxy for overcrowding. Approximately 9% of households in the lowest 40% of the income distribution live in overcrowded conditions, defined as more than 2.5 people per bedroom (Figure A6). These find-

[32]Approximately 12% of children in our sample switch schools annually, excluding transitions between elementary, middle, and high school.

ings indicate that improved housing conditions—particularly increased living space—are likely a key mechanism driving the positive impact of housing assistance on children's educational outcomes. Our results align with studies in developing countries where housing renovations are associated with substantial gains in children's academic performance (Cattaneo et al., 2009; Galiani et al., 2017; Kumar, 2021).

## 6.4 Parental Responses

When families receive housing assistance, parents may adjust their labor market behavior due to changes in household stability, income, and time allocation. Economic theory suggests that increased stability from housing assistance may reduce the need for immediate work if the subsidy alleviates financial pressures (Moffitt, 1992). This effect could lead parents to reduce their working hours or exit the labor market, reallocating time to leisure, child-rearing, or other household activities. Alternatively, housing assistance might act as a stabilizing factor, enabling parents to pursue better employment opportunities or skill development as stable housing alleviates stress and allows focus on long-term goals (Jacob and Ludwig, 2012). Empirically, recent studies find that parents' income and employment rates often decline after receiving housing assistance (Barnhardt et al., 2017; Kling et al., 2005; Van Dijk, 2019).

We present our results on labor market outcomes using a Poisson regression in Table 7. The Poisson regression allows us to interpret our findings in percentage terms, while better handling of zeros through periods of unemployment. We find that after receiving the subsidy, parents reduce formal labor participation by 0.9% and report earnings in fewer months by a similar margin. This decrease is primarily driven by a reduction in work in permanent positions. Similarly, we find a reduction in their yearly earnings of 1.5% on average, which is mostly coming from jobs with permanent contracts. These findings align with literature suggesting a modest reduction in labor participation following housing assistance. Reduced work engagement could serve as a mechanism for enhancing children's academic outcomes: by working fewer hours, parents may have more time to support their children's education (Kalil and Ziol-Guest, 2008).

In Figure 9, we present ITT estimates from the RD analysis on parental expectations for their children's educational attainment using responses from the parents' SIMCE questionnaire. We focus on high school completion (Panel A), college completion (Panel B), and graduate studies (Panel C), both pre-and post-subsidy application. Before applying, expectations were similar across groups, with parents in awarded households slightly less likely to expect college or graduate completion. However, post-application, parents in winning households are 2.1 percentage points (3.2%) more likely to expect their child to complete college and 3.3 percentage points (25.4%) more likely to expect graduate studies.

In Figure A20, we show that children also report higher academic expectations following the subsidy award. Specifically, there is weak evidence that they are more likely to anticipate attending post-secondary education and believe in their ability to achieve good grades. Furthermore, children in awarded households are 3.2% more likely to express confidence in reaching their future goals as adults (Panel C).

These findings align with previous research showing that housing assistance can enhance parental optimism and children's educational aspirations (Agness and Getahun, 2024; Kumar, 2021). In our context, increased parental expectations may also encourage greater investment in their children's education, potentially explaining improvements in educational outcomes.

Figure 10 further explores parental engagement, using responses from the SIMCE children's questionnaire to assess how subsidy receipt impacts parental involvement in education. Consistent with having more availability to support their children's education, parents in awarded households increase their engagement after winning the subsidy. Specifically, parents are 1.8 percentage points (3.5%) more likely to keep track of their children's grades, 4.5 percentage points (5.5%) more likely to congratulate them for academic achievements, and 4.9 percentage points (10%) more likely to help them study. Importantly, we observe no significant differences in parental engagement prior to the application.

In summary, our findings indicate that parental responses play a crucial role in mediating the positive effects of the subsidy on children's academic performance. Parents from subsidy-receiving households reduce their formal labor market participation and increase their involvement in their children's education by tracking grades, celebrating achievements, and providing study support. This enhanced engagement, alongside raised educational expectations, likely contributes to the observed improvements in children's academic outcomes, as parental time investment has been shown to significantly boost children's achievement (Guryan et al., 2008; Boneva and Rauh, 2018).

# 7 Early and Long-run Outcomes

## 7.1 Pre-school and Daycare

Preschool education is widely recognized as a critical foundation for children's academic and social development, equipping them with essential cognitive and social skills that shape future educational outcomes. Research consistently associates preschool attendance with improved test scores, higher high school graduation rates, and increased college enrollment (Heckman and Raut, 2016; Deming, 2009; Gray-Lobe et al., 2022). For disadvantaged children, preschool is particularly beneficial, as it provides structured learning environments that might otherwise be inaccessible, helping to bridge early achievement gaps and promote educational equity.

In Table 8, we present the impact of winning the subsidy (ITT) and using it to purchase a home (ATE) on daycare and preschool attendance. We analyze all levels collectively and then by specific categories: *Sala Cuna* (ages 0–2), *Nivel Medio* (ages 2–4), pre-kindergarten (age 5), and kindergarten (age 6). The results indicate that winning a voucher is associated with a 2.2 percentage point increase in preschool attendance among children ages 0–5, reflecting a 4.5% rise relative to the control mean. This effect is primarily driven by increased enrollment in early preschool, while we observe no significant differences in daycare attendance or for children over age 5.

To our knowledge, this study is the first to explore the impact of housing assistance on daycare and preschool attendance. Previous studies on housing programs have typically focused on later educational outcomes, such as high school or college achievements. By examining preschool attendance, particularly across detailed age groups, our analysis offers new insights into how housing stability may affect young children during formative years.

Although we observe an increase in preschool attendance, we do not find that primary and secondary school outcomes are stronger for children who were preschool-aged at the time of application. This may suggest that housing stability alone is insufficient to yield significant advantages in subsequent schooling for younger children or that the benefits may require a longer time to materialize. Given our study's current time frame, we lack sufficient data to explore the potential long-term impacts of preschool attendance on high school completion or college outcomes for these children.

## 7.2 Post-secondary Education

Improvements in secondary academic performance, coupled with elevated parental expectations, can lay the groundwork for increased post-secondary attainment. Research shows that students are more likely to complete college when their parents hold high educational aspirations (Kumar, 2021; Zhang et al., 2011). Given the positive effects we observe in primary and secondary education, these academic gains may extend into post-secondary outcomes (Heckman et al., 2006; Chetty et al., 2014; Oreopoulos and Salvanes, 2011; Jackson, 2018). We explore this directly by analyzing the impact of homebuyer subsidies on various post-secondary outcomes.

Table 9 presents our findings for high school completion, college entry exam scores, and college enrollment. We find that winning the subsidy increases high school graduation rates by 1.4 percentage points (1.6%), corresponding to a 6.8% increase in completion rates among subsidy users. Children from awarded households also see an average improvement in high school grades of 0.038 points. While these students are equally likely to take the college entry exam as their non-awarded counterparts, those who do take the exam score 0.054 standard deviations higher in math and verbal, with similar improvements in history and science exams. This corresponds to a 0.25 standard deviation improvement for families that use the subsidy to buy a home.

Additionally, students in awarded households are 1.8 percentage points (3%) more likely to attend college, which corresponds to a 14% increase relative to the control mean for subsidy users. Those attending college extend their studies by approximately 1.5 months (a 7% increase with respect to the control mean). For families using the subsidy, this impact is closer to 6.5 months. They are also more likely to enroll in a university rather than a technical institution. However, conditional on attending college, they are slightly more likely to drop out, although this difference is not statistically significant. Lastly, we find no indication that they attend institutions with significantly longer accreditation periods by the Ministry of Education.

Our findings on high school completion and post-secondary enrollment are in line with results from other housing policies when considering the ITT estimates (Chetty et al., 2016; Jacob et al., 2015; Camacho et al., 2022; Kumar, 2021; Laliberté, 2021). When examining subsidy users, our ATE estimates are among the higher impacts observed in the literature, though slightly below those of Agness and Getahun (2024). Our results also compare in magnitude to conditional cash transfers, tax credit programs (Dahl and Lochner, 2012; Behrman et al., 2005), and early childhood interventions (Deming, 2009; Heckman et al., 2010), indicating that stable housing support can yield lasting educational benefits on par with financial and early childhood investments.

Following the approach of Chetty et al. (2016), Table A9 presents results by age at application. We find that effects on test scores and high school completion are primarily driven by children already in high school at the time of application. This contrasts with prior studies that generally observe higher benefits from longer policy exposure (Chetty et al., 2016; Chyn and Katz, 2021; Agness and Getahun, 2024). However, consistent with the broader literature, we observe that effects on college attendance are strongest for children under age 13, supporting the view that early exposure to housing stability has a lasting impact on post-secondary outcomes.

In Figure A17, we present results for high school completion and college enrollment, examining heterogeneity across demographic and neighborhood characteristics. Echoing our findings in primary and secondary education, applicants' individual characteristics do not significantly alter outcomes. However, the effects remain stronger for larger households and those from low- and medium-quality neighborhoods. Interestingly, age at application shows no significant variation for students still in school at application. We also find no effect for students who were 18 or older at the time, implying minimal preexisting differences in educational outcomes before receiving the subsidy.

## 7.3 Labor Market

Educational attainment and performance in primary, secondary, and post-secondary schooling are powerful predictors of labor market outcomes, including employment stability, earnings potential, and career progression. Research has demonstrated that academic skills acquired in early education foster both cognitive and non-cognitive abilities, which are crucial for workplace productivity and adaptability (Card, 1999; Heckman et al., 2006; Heckman and Kautz, 2012). Skills developed through early academic achievement—such as critical thinking, perseverance, and social adaptability—are particularly influential for long-term professional success. The positive educational outcomes observed in our early cohorts likely pave the way for improved labor market prospects, as the cumulative benefits of academic success reinforce career progression and earnings over time.

Table 10 presents the results of a Poisson regression on labor market outcomes for children not enrolled in post-secondary education. We find that children from subsidy-winning households are 1.2% more likely to be employed and work, on average, 3% more months per year. This increase, which equates to roughly 0.15 additional months of employment annually, is observed across both permanent and temporary positions. Although we observe a slight increase in yearly earnings for this group, the effect is not statistically significant. Given our study's time frame, these young adults represent children who were older at the time of application or part of the policy's earliest cohorts. Additional longitudinal data will be necessary to capture the full impact on labor market outcomes for those who were younger at the time of application.

Our findings align with the broader literature on housing assistance and labor market outcomes, albeit with modest effects compared to other policy contexts (Jacob and Ludwig, 2012).[33] However, While studies like the MTO experiment documented limited labor market improvements for adults (Chetty et al., 2016), our results suggest that even small increases in stability and employment during formative years can yield incremental but positive labor market outcomes for young adults.

In terms of magnitude, our effects are smaller than the substantial gains in labor market outcomes seen in studies like Dahl and Lochner (2012), which analyzed income support policies and found significant increases in earnings and employment. This may reflect differences in how direct income transfers, such as tax credits, versus housing-based support influence labor market behavior. Nonetheless, our results suggest that housing stability provides a modest, yet meaningful, boost to employment consistency among young adults, especially those from lower-income backgrounds. These incremental gains may amplify over time, indicating that housing assistance programs could play a valuable role within a larger strategy to enhance long-term labor market outcomes for children from disadvantaged households.

### 7.4 Net benefits calculation

The *DS01* subsidy increased educational attainment at every point in a child's school career. However, we currently lack enough data to observe earnings increases for those who attend

[33] Our estimates for months worked are similar to findings from the Welfare-to-Work Voucher Program, which noted temporary reductions in labor supply immediately following assistance but longer-term improvements in employment stability (Mills et al., 2006).

college. To calculate the net benefits of the program, we perform a simple back-of-the-envelope calculation that extrapolates increases in college attendance to lifetime earnings through the returns to college education in Chile. Following Chetty et al. (2016), we use 2022 average earnings of $23,005 USD for the entire Chilean population as our benchmark.[34] We use our estimate of a 10% increase in college attendance due to the subsidy with a 62% return to college degrees in Chile (González-Velosa et al., 2015).[35]

Taken together, we estimate the total present value of lifetime benefits to children from the homebuyer subsidy is equal to $22,403 USD. For the average winning household with 1.7 children, this estimate is $38,085 USD. Subsidy-winning households see their incomes decline 1.5% from a baseline of $3,389 USD.[36] The remaining present value of lifetime benefits to household income from the homeowner subsidy is equal to -$704 USD.[37] At an average subsidy cost of $20,000 USD, net benefits to the average family are $17,381 USD, and the marginal value of public funds is 1.84. This is comparable to programs that subsidize college education, like CUNY's Pell Grant program and Tennessee's Hope Scholarship (Hendren and Sprung-Keyser, 2020).

# 8 Conclusion

The UN estimates that 1.6 billion people globally live in inadequate housing (UN-Habitat, 2022), ranging from slums to overcrowded or otherwise poor-quality homes. Relatedly, housing tenure and homeownership are often recognized as pivotal mechanisms for breaking cycles of poverty, as stable housing plays a fundamental role in wealth accumulation and intergenerational mobility (Chetty et al., 2014; Chetty and Hendren, 2018). However, few housing policies have directly aimed to expand private homeownership among low-income families, despite its potential to drive long-term economic mobility.

This paper examines the causal effects of a generous and large-scale homebuyer subsidy

[34] Average earnings number from *Instituto Nacional de Estadísticas (INE)*. At a 5% interest rate, this gives a PDV lifetime (30-year) earnings estimate of $361,345 USD.

[35] While not all college attendees will graduate, we think this is still a conservative estimate. Our estimates of college attendance do not contain all of the students with higher grades and performance in K-12, so that estimate is likely to increase over time as more data becomes available. Moreover, even some college attendance is likely to improve earnings, and we see improved labor market outcomes for those who do not attend college.

[36] To contextualize this number, many parents are not employed in the formal sector in our sample.

[37] Because the average winning applicant is 37 years old, we assume there are 23 more years they could work.

in Santiago, Chile. We find that, like other housing policies before it, parents slightly reduce their employment and earnings in response. However, the focus of this paper - and perhaps where the focus of the impact of most housing policies should be - is on the children of subsidy recipients. This has been cited as a primary motivation for recent proposals of homebuyer subsidies in the U.S. context.[38]

Our findings reveal substantial academic gains among children of subsidy recipients, evidenced by improved grades, class rankings, and achievement test scores, as well as reductions in chronic absenteeism. Boys exhibit larger educational gains than girls, while applicant characteristics and children's age at the time of application show limited differential impacts. Additionally, we observe that these educational benefits are more pronounced in larger families, suggesting that alleviating overcrowded living conditions may be a key pathway through which the subsidy impacts child development. Increased preschool attendance rates also highlight the policy's early positive influence on school readiness and early learning.

The evidence suggests that these effects are not driven by relocation to higher-quality schools or neighborhoods, underscoring the importance of housing stability in fostering human capital independently of external environmental changes. As children transition to adulthood, we find that those from subsidy-recipient families are more likely to complete high school, attend college, and secure employment if they enter the labor market directly compared to their peers from non-subsidy households.

The program's benefits appear substantial relative to its costs. A preliminary calculation indicates that the policy yields an estimated $38,000 USD increase in the present value of lifetime earnings for children against a program cost of approximately $20,000 USD per household. These findings suggest that well-designed, targeted homebuyer subsidies can be a powerful policy tool for improving children's educational attainment and, ultimately, enhancing intergenerational mobility, making a strong case for integrating such initiatives within broader social welfare and housing policies.

[38]U.S. Vice President Kamala Harris said the following in a recent campaign speech proposing a homebuyer subsidy: "Together, we will build what I call an 'opportunity economy' ... an economy where everyone can compete and have a real chance to succeed; everyone, regardless of who they are or where they start, has an opportunity to build wealth for themselves and their children." Source: whitehouse.gov.

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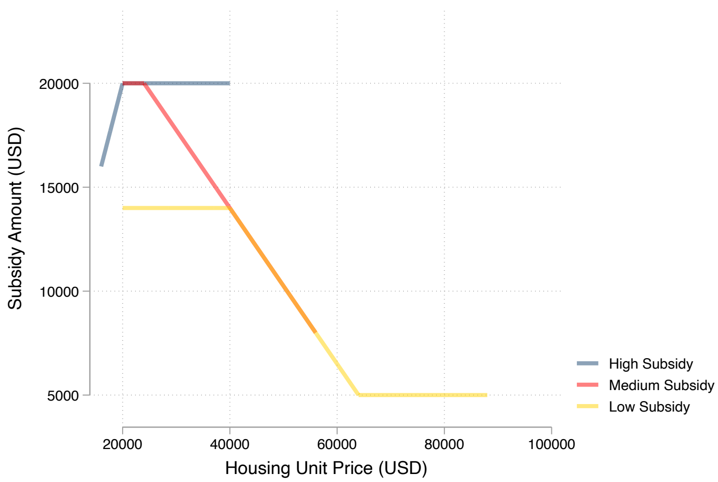
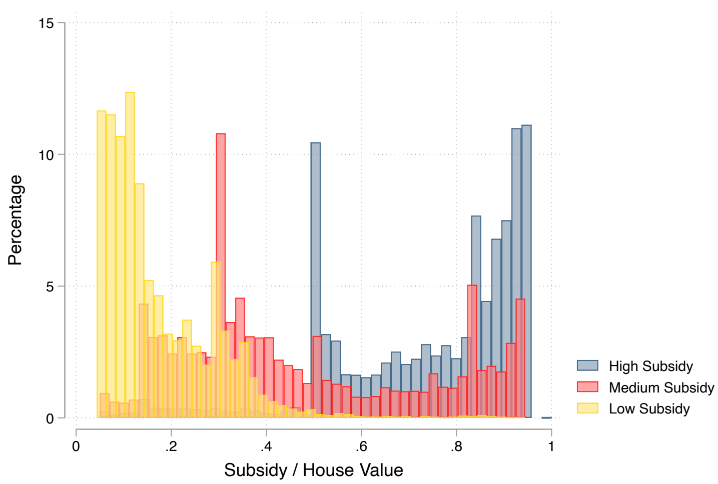
# Figures

**Figure 1:** Voucher Subsidy Amount and House Prices



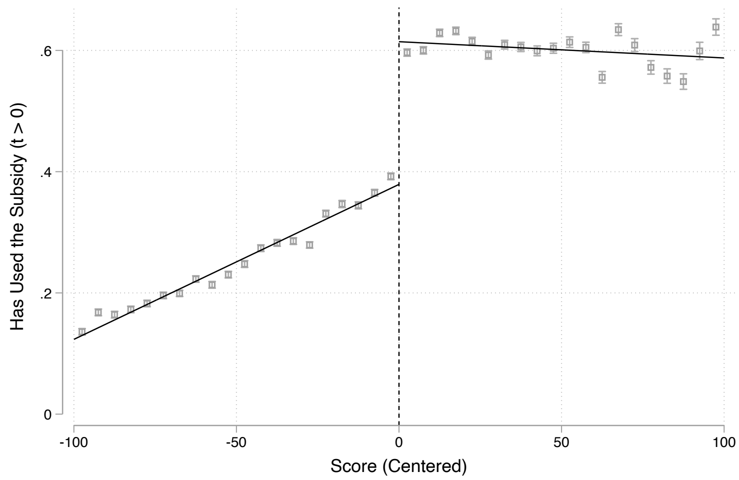

Panel A: Subsidy Amount vs Unit Price



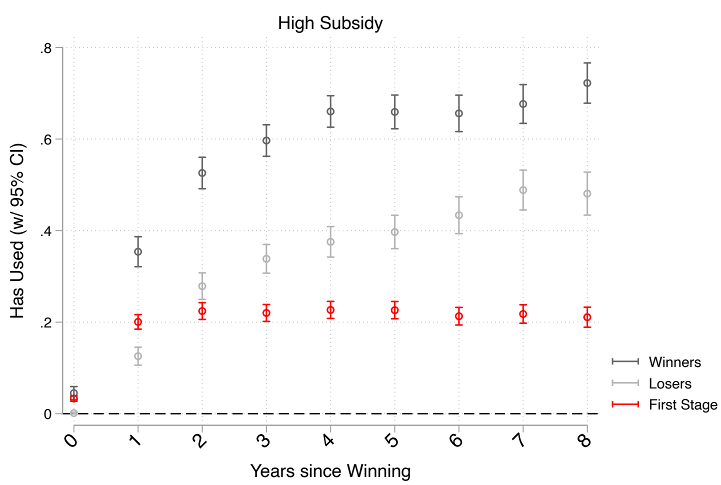

Panel B: House Price Covered by the Voucher

*Notes*: Panel A displays the voucher subsidy amount as a function of the housing unit price in USD by subsidy tier. The amount is fixed for the high subsidy as long as the house price exceeds the subsidy amount, while it decreases with house value for medium and low subsidies, reaching a minimum. The pricing cap for the high subsidy is more restrictive than for the medium and low subsidies. Panel B shows the distribution of the voucher amount relative to the house value by subsidy tier, covering 85% of the house price on average for the high subsidy, and 55% and 18% for the medium and low subsidies, respectively.

## **Figure 2:** First Stage



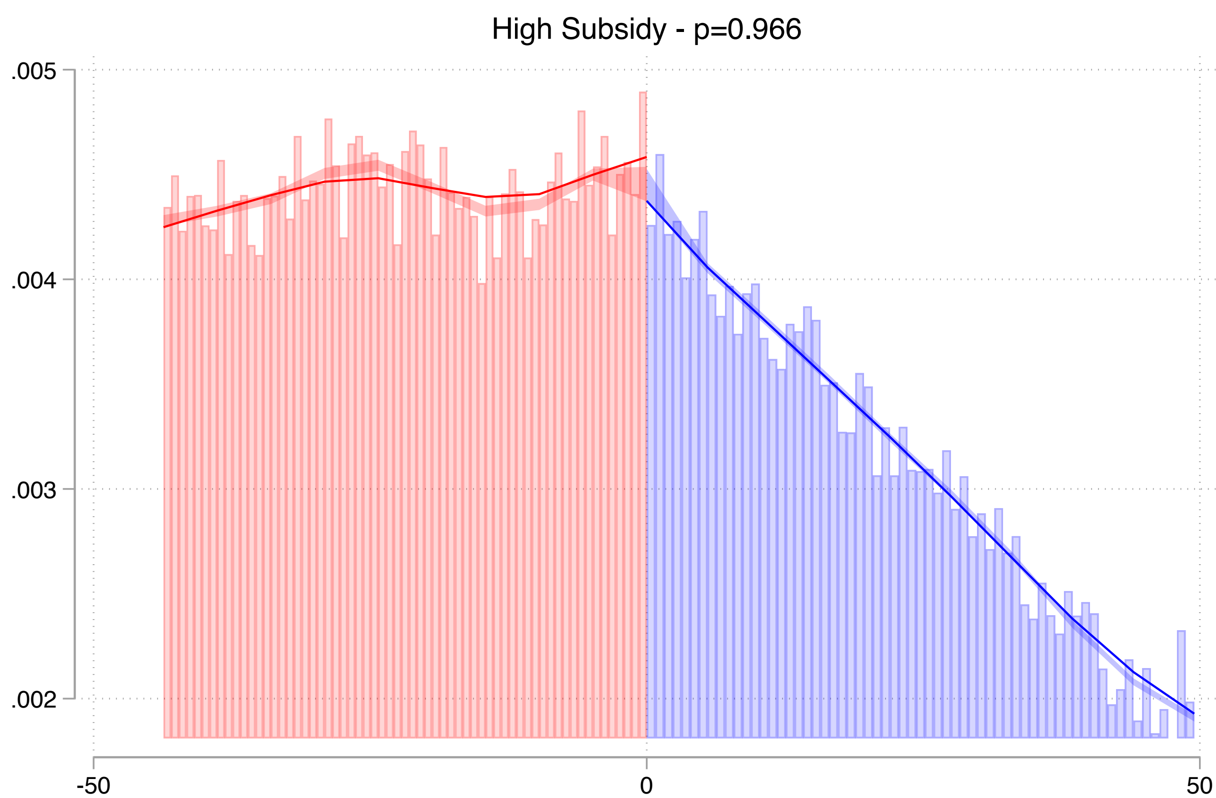

Panel A: Pooled First Stage




Panel B: Evolution of First Stage over time

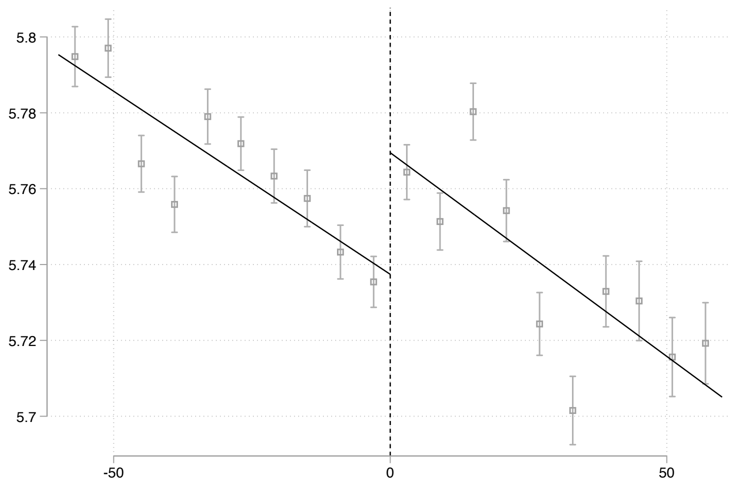
*Notes*: Panel A displays the first stage of the regression discontinuity, running Equation 2 on having used the subsidy after application and pooling across application calls and years. We find a 0.25 percentage point jump around the threshold, suggesting we will need to rescale the ITT estimates by approximately four to find the LATE of buying a house using the voucher. Panel B shows the evolution of the cumulative fraction of applicants that use the subsidy in each period after the application for both awarded and non-awarded applicants, pooling application calls and controlling for the score using a polynomial degree 1. The first stage in each period is given by the difference between the fraction for winners and losers, and it is stable at 0.22 percentage points over time.

**Figure 3:** McCrary test after application

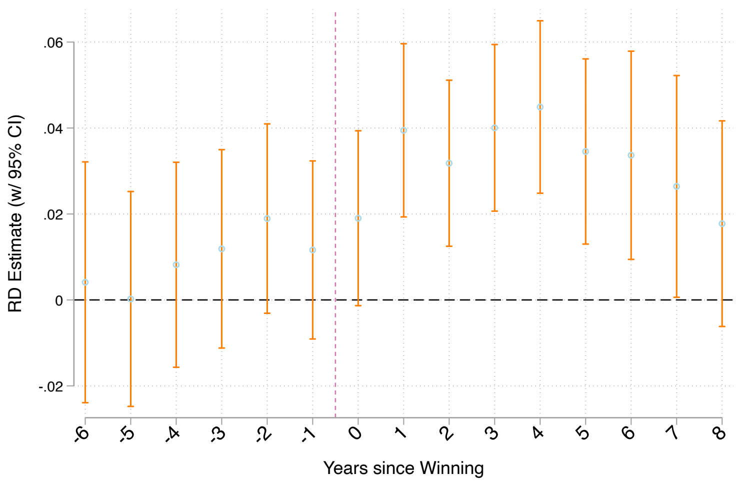



*Notes:* This figure shows the result of the McCrary test for manipulation of the scores pooling across application calls. We find a p-value of 0.966, suggesting we cannot reject the no-manipulation of the scores, providing evidence of the validity of the regression discontinuity design. This is not surprising, given the varying nature of the cutoff scores across application scores.

**Figure 4:** Regression Discontinuity and Event Study: Grades



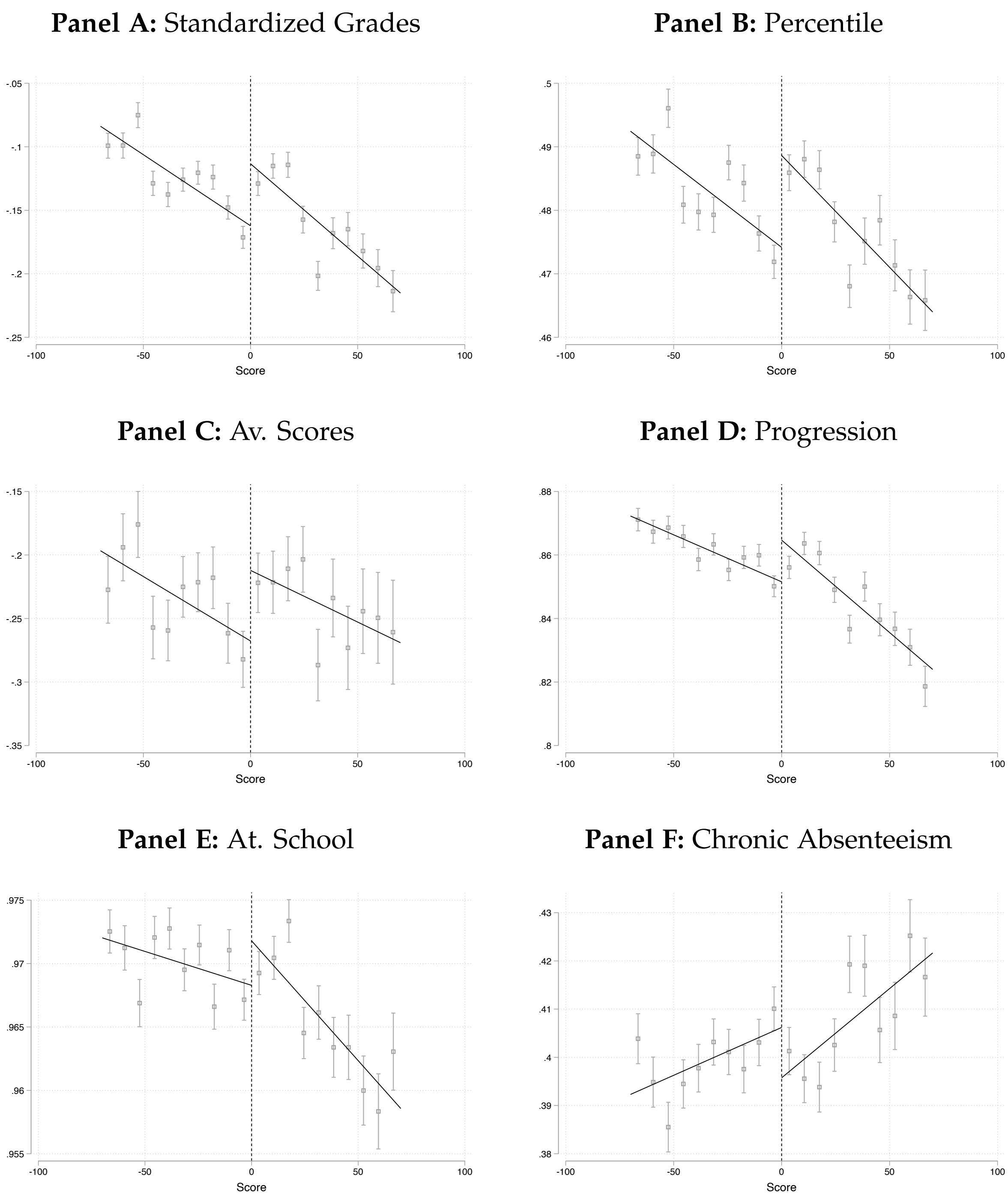

Panel A: Regression Discontinuity




Panel B: Event Study

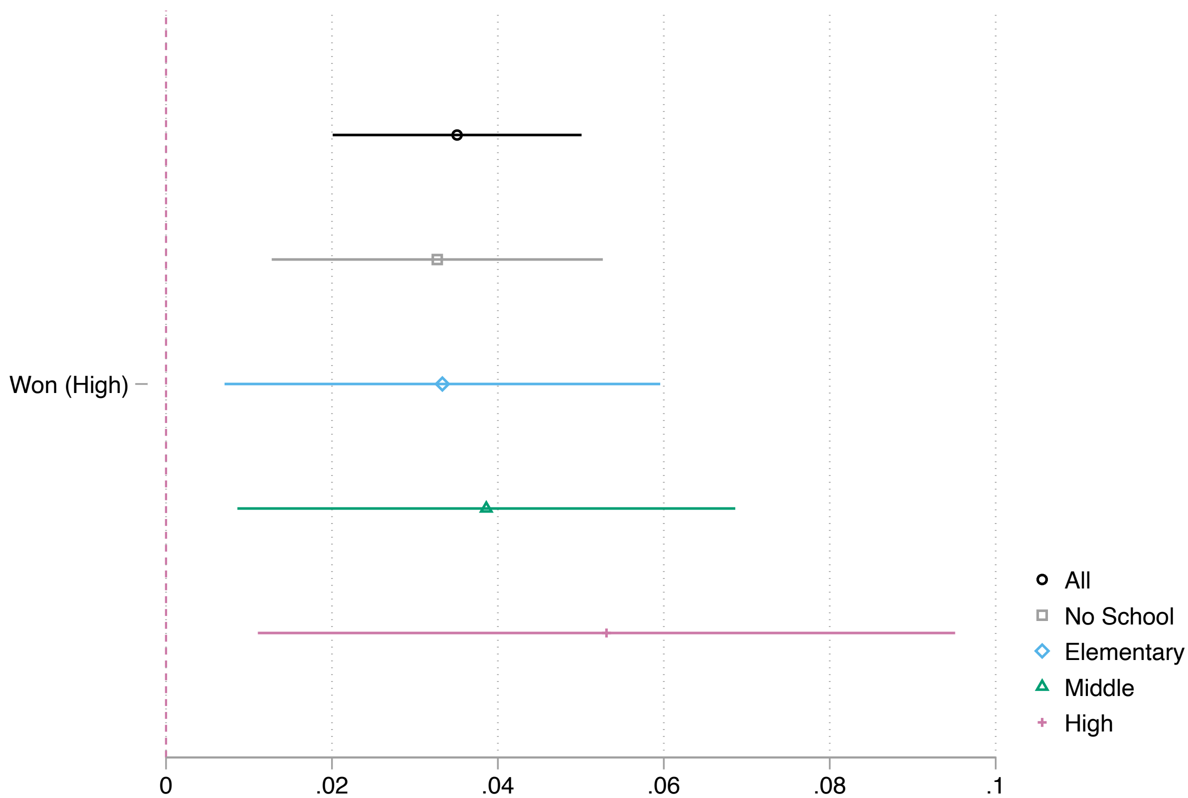
*Notes*: Panel A displays the coefficient of Equation 1 on grades for the high subsidy, shown in Table 3. Panel B displays the evolution of grades over time in relation to application, pooling across calls. Standard errors are clustered at the applicant level and consider scores using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects.

**Figure 5:** RD plot for main achievement outcomes



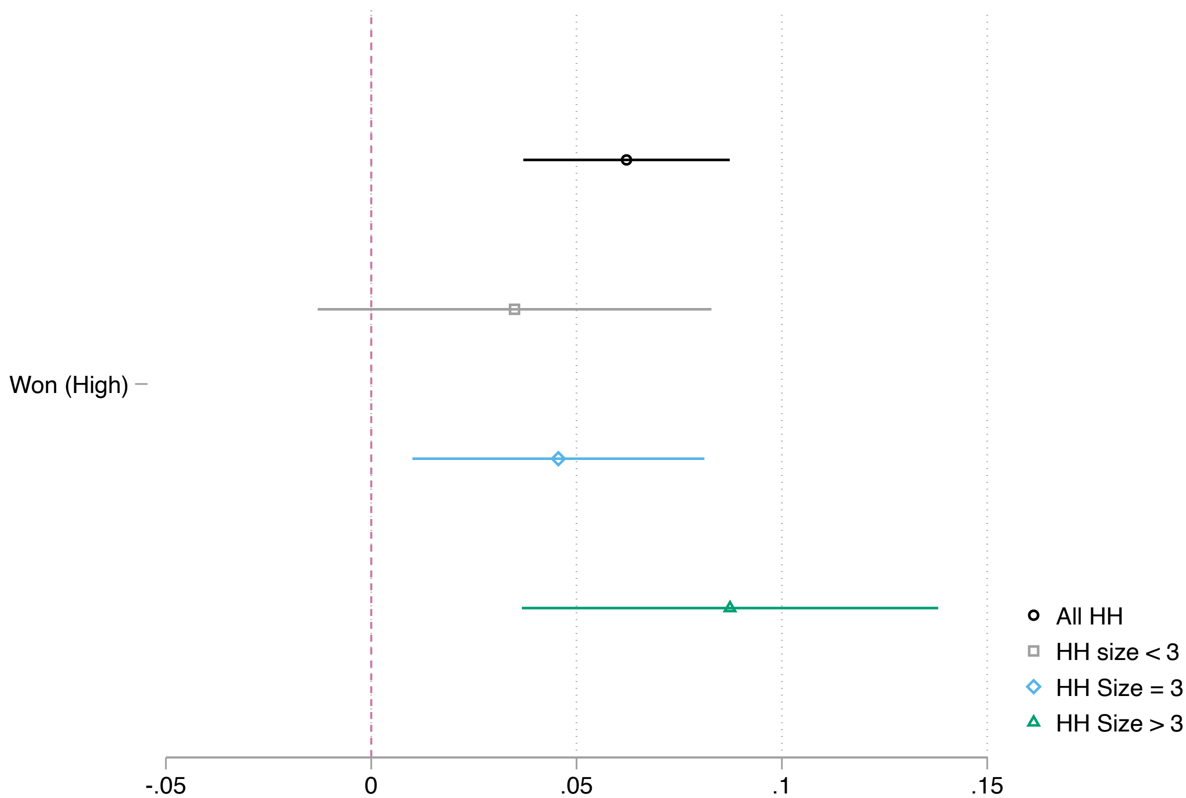

*Notes*: This figure shows the result of the estimate of the ITT estimate from the regression discontinuity for some of the achievement outcomes, pooling years after the application. Outcomes include standardized grades (A), class rank percentile (B), average test scores (C), probability of not being retained (D), indicator of not having dropped out of school (E), and chronic absenteeism (F). Standard errors are clustered at the applicant level, and regression considers scores using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects. ***, **, * indicates significance at 1, 5, and 10%.

**Figure 6:** Heterogeity by Age at Application: Grades



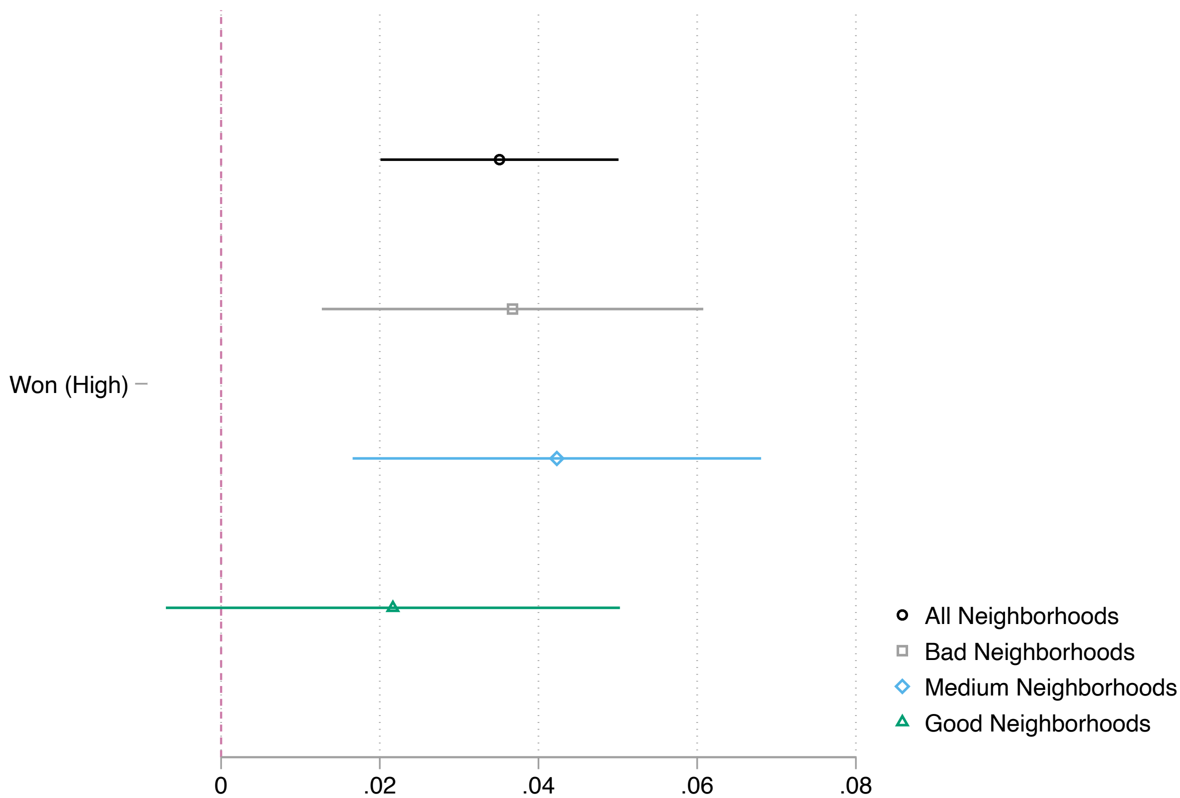

*Notes:* This figure displays the heterogeneous effects depending on age at application for the ITT estimates on grades. Each horizontal bar reports the coefficient of the jump at the cutoff and the confidence interval of the estimate at the 10% significance level, using Equation 1 and fitting a linear polynomial at each side of the cutoff. All estimates include year and gender by age fixed effects and consider scores the IMSE-optimal bandwidth. Standard errors are clustered at the applicant level.

**Figure 7:** Heterogeity by Household Size: Grades




*Notes:* This figure displays the heterogeneous effects depending on household size at application for the ITT estimates on grades. Each horizontal bar reports the coefficient of the jump at the cutoff and the confidence interval of the estimate at the 10% significance level, using Equation 1 and fitting a linear polynomial at each side of the cutoff. All estimates include year and gender by age fixed effects and consider scores the IMSE-optimal bandwidth. Standard errors are clustered at the applicant level.

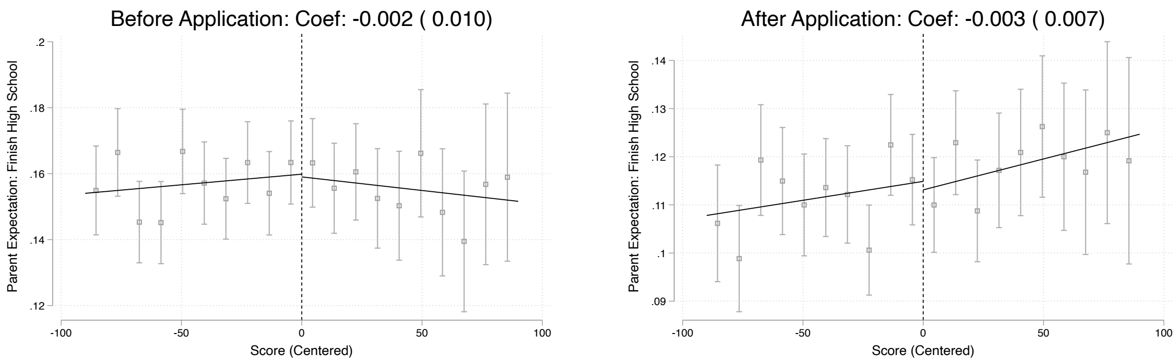
**Figure 8:** Heterogeity by Neighborhood of Origin: Grades



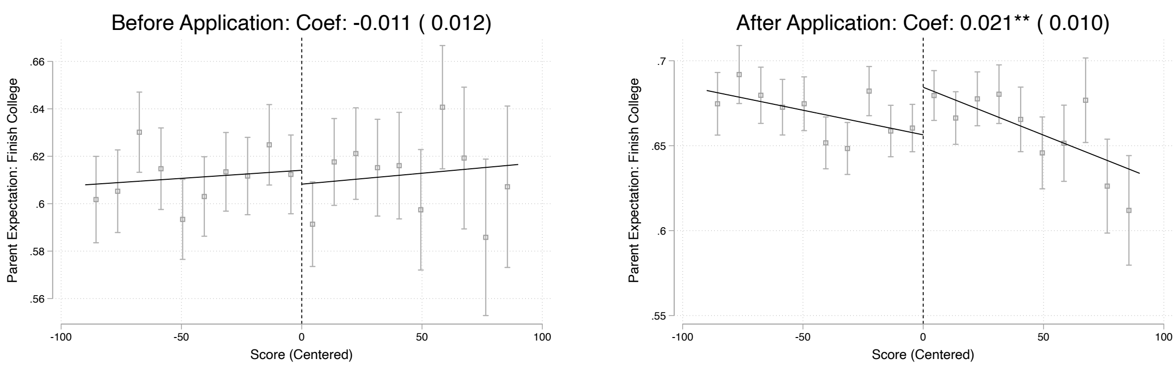

*Notes:* This figure displays the heterogeneous effects depending on neighborhood quality of origin for the ITT estimates on grades, using average years of schooling at the census tract level. Each horizontal bar reports the coefficient of the jump at the cutoff and the confidence interval of the estimate at the 10% significance level, using Equation 1 and fitting a linear polynomial at each side of the cutoff. All estimates include year and gender by age fixed effects and consider scores the IMSE-optimal bandwidth. Standard errors are clustered at the applicant level.

**Figure 9:** RD of parents' expectations about children's education

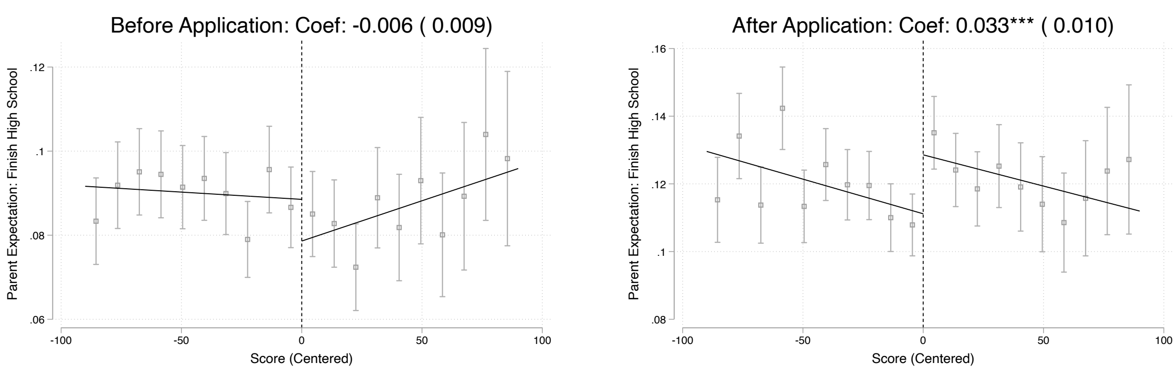
**Panel A:** High School completion




**Panel B**: College completion



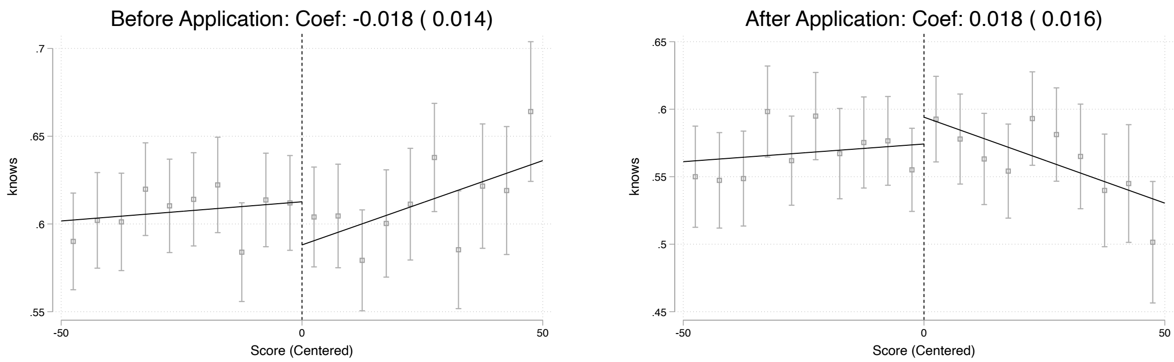

**Panel C:** Graduate studies completion



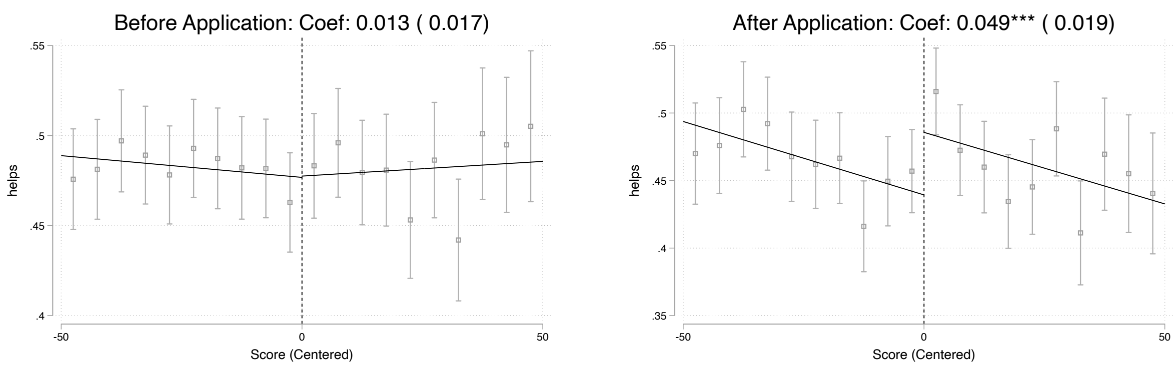

*Notes*: This figure shows the result of the ITT estimate of the regression discontinuity regarding the parents' expectations regarding the maximum education level reached by their child before and after the application. In Panel A, the outcome variable indicates that parents think their children will finish high school. In Panels B and C, the outcome variable indicates that parents think their child will complete a college and a graduate degree, respectively. Standard errors are clustered at the applicant level, and scores are considered using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects. ***, **, * indicates significance at 1, 5, and 10%.

**Figure 10:** RD of parents' behavior

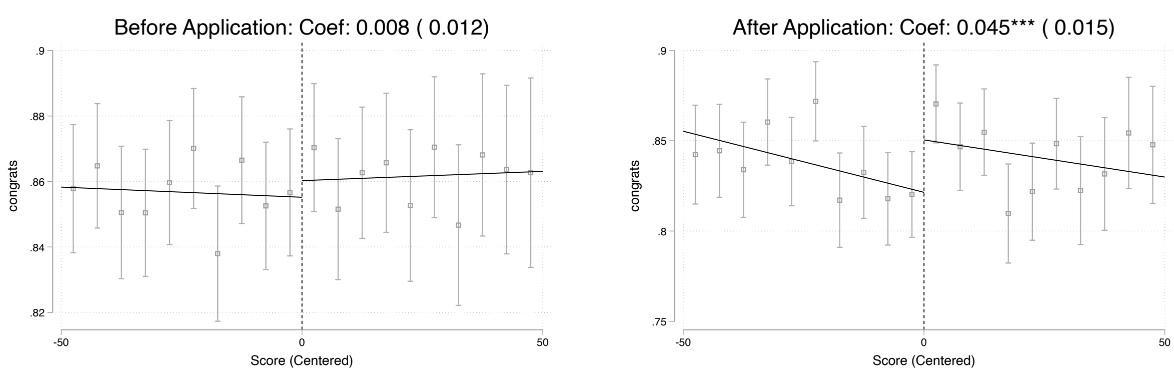
**Panel A:** Parents know children's grades




**Panel B**: Parents helps children study




**Panel C:** Parents congratulate children's good grades




*Notes*: This figure shows the result of the ITT estimate of the regression discontinuity regarding parental responses in relation to their children's studies. In Panel A, the outcome variable indicates whether the parent knows their children's grades. Panel B indicates whether the parent helps their children study, and Panel C whether they congratulate their children when they get good grades. Standard errors are clustered at the applicant level, and scores are considered using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects. ***, **, * indicates significance at 1, 5, and 10%.

# Tables

**Table 1:** Differences in Demographics at application

| Dep. Variable | Control Mean | ITT | Observations | Bandwidth |
|---|---|---|---|---|
| **Panel A: Application Characteristics (Applicant)** | | | | |
| Applicant's Age | 36.363 | 0.205 | 38,859 | 55.373 |
| | | ( 0.184) | | |
| Applicant's Gender | 0.930 | -0.001 | 41,725 | 60.751 |
| | | ( 0.006) | | |
| Married = 1 (Applicant) | 0.305 | 0.012 | 38,642 | 54.984 |
| | | ( 0.012) | | |
| Single-Parent | 0.621 | -0.013 | 34,601 | 47.990 |
| | | ( 0.014) | | |
| Household Size | 1.005 | 0.007 | 38,162 | 54.121 |
| | | ( 0.018) | | |
| Children at School | 1.426 | -0.002 | 41,479 | 60.290 |
| | | ( 0.020) | | |
| Former Applications | 1.177 | 0.035 | 42,930 | 63.128 |
| | | ( 0.042) | | |
| Self-reported Income | 11.401 | 0.157 | 35,528 | 49.570 |
| | | ( 0.135) | | |
| NH quality (ed) | 9.930 | 0.028 | 48,056 | 73.660 |
| | | ( 0.032) | | |
| **Panel B: Chlidren Characteristics** | | | | |
| Age | 11.895 | 0.041 | 53,886 | 86.933 |
| | | ( 0.056) | | |
| Ind. Female | 0.495 | -0.008 | 50,031 | 78.023 |
| | | ( 0.009) | | |
| Grade | 5.979 | 0.024 | 56,781 | 94.746 |
| | | ( 0.053) | | |

*Notes*: This table shows the differences in demographic characteristics at the time of application. Panel A presents the characteristics of the application, while Panel B shows the characteristics of the children. Columns (1), (3), and (4) display the mean of the variable for non-awarded households, the number of applicants, and the optimal IMSE-bandwidth to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Standard errors are clustered at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 2:** Differences in Outcomes at application

| Dep. Variable | Control Mean | ITT | Observations | Bandwidth |
|---|---|---|---|---|
| **Panel A: Achievement Outcomes** | | | | |
| Grades | 5.685 | 0.009 | 34,762 | 55.138 |
| | | ( 0.013) | | |
| Grades (sd) | -0.151 | 0.017 | 35,337 | 56.325 |
| | | ( 0.022) | | |
| Percentile | 0.485 | 0.005 | 36,729 | 59.245 |
| | | ( 0.006) | | |
| Ind. Percentile $> 0.5$ | 0.473 | 0.009 | 35,904 | 57.543 |
| | | ( 0.011) | | |
| Score Verbal | -0.205 | 0.012 | 11,682 | 60.264 |
| | | ( 0.036) | | |
| Score Math | -0.246 | 0.022 | 10,042 | 71.152 |
| | | ( 0.038) | | |
| Av. Score | -0.241 | 0.018 | 11,791 | 58.728 |
| | | ( 0.035) | | |
| Ind. Progression | 0.830 | 0.007 | 41,759 | 65.298 |
| | | ( 0.008) | | |
| Ind. at School | 0.956 | 0.003 | 47,089 | 77.336 |
| | | ( 0.004) | | |
| Ind. Dropout ($> 14$) | 0.005 | 0.003 | 15,008 | 82.984 |
| | | ( 0.002) | | |
| Ind. Repeated | 0.044 | -0.002 | 49,180 | 81.940 |
| | | ( 0.004) | | |
| Absenteeism | 0.100 | -0.002 | 44,032 | 75.813 |
| | | ( 0.002) | | |
| Chronic Absenteeism | 0.362 | -0.001 | 47,707 | 82.954 |
| | | ( 0.009) | | |
| **Panel B: Other Outcomes** | | | | |
| Ind. Public School | 0.341 | -0.001 | 53,294 | 93.040 |
| | | ( 0.009) | | |
| Ind. Private | 0.004 | 0.001 | 38,537 | 58.744 |
| | | ( 0.001) | | |
| School Quality | 0.444 | 0.005 | 44,569 | 75.500 |
| | | ( 0.005) | | |
| Class Size | 36.012 | 0.028 | 43,983 | 74.000 |
| | | ( 0.162) | | |
| Ind. Change School | 0.119 | -0.000 | 43,169 | 72.071 |
| | | ( 0.007) | | |
| Ind. Change Comuna | 0.026 | -0.000 | 41,025 | 74.975 |
| | | ( 0.002) | | |
| Ind. Priority Student | 0.612 | -0.001 | 32,879 | 50.385 |
| | | ( 0.012) | | |

*Notes*: This table shows the differences in the main primary and secondary school outcomes at the time of application. Panel A presents the main achievement outcomes, while Panel B shows additional variables related to school quality. Columns (1), (3), and (4) display the mean of the variable for non-awarded households, the number of applicants, and the optimal IMSE-bandwidth to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Standard errors are clustered at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 3:** Achievement outcomes

| | Control Mean | ITT | ATE | Observations | Bandwidth |
|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) |
| Grades | 5.685 | 0.035*** | 0.163*** | 374,813 | 55.075 |
| | | ( 0.009) | ( 0.044) | | |
| Grades (sd) | -0.151 | 0.059*** | 0.273*** | 381,350 | 56.270 |
| | | ( 0.014) | ( 0.070) | | |
| Percentile | 0.485 | 0.017*** | 0.079*** | 396,337 | 59.219 |
| | | ( 0.004) | ( 0.020) | | |
| Ind. Percentile $> 0.5$ | 0.473 | 0.026*** | 0.122*** | 387,852 | 57.537 |
| | | ( 0.007) | ( 0.032) | | |
| Av. Score | -0.240 | 0.058*** | 0.321*** | 56,408 | 58.371 |
| | | ( 0.021) | ( 0.121) | | |
| Score Math | -0.247 | 0.052*** | 0.272** | 55,622 | 70.234 |
| | | ( 0.019) | ( 0.107) | | |
| Score Verbal | -0.205 | 0.046** | 0.264** | 55,269 | 60.003 |
| | | ( 0.021) | ( 0.122) | | |
| Ind. Progression | 0.865 | 0.012** | 0.059** | 394,492 | 58.882 |
| | | ( 0.005) | ( 0.025) | | |
| Ind. at School | 0.956 | 0.004** | 0.019** | 501,755 | 77.336 |
| | | ( 0.002) | ( 0.009) | | |
| Ind. Dropout | 0.003 | -0.000 | -0.000 | 513,710 | 85.808 |
| | | ( 0.000) | ( 0.001) | | |
| Ind. Repeated | 0.033 | -0.002* | -0.009* | 465,443 | 73.655 |
| | | ( 0.001) | ( 0.005) | | |
| Absenteeism | 0.100 | -0.001 | -0.004 | 473,524 | 75.553 |
| | | ( 0.001) | ( 0.005) | | |
| Chronic Absenteeism | 0.366 | -0.009* | -0.041* | 506,994 | 84.025 |
| | | ( 0.005) | ( 0.022) | | |
| Controls | - | Yes | Yes | - | - |

*Notes*: This table shows the differences in the main primary and secondary school achievement outcomes after application. Columns (1), (4), and (5) display the mean of the variable for non-awarded households, the number of applicants, and the optimal IMSE-bandwidth to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Column (3) presents the LATE estimates, rescaling the ITT estimates by the first stage in Equation 2 and presenting the effects of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 4:** Achievement outcomes: Robustness

| | Mean | Preferred | No Control | Cont t-1 | Av. BW | No Weight | Poly 2 | No COVID |
|---|---|---|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Grades | 5.685 | 0.035*** | 0.035*** | 0.027*** | 0.035*** | 0.032*** | 0.039*** | 0.044*** |
| | | ( 0.009) | ( 0.009) | ( 0.010) | ( 0.009) | ( 0.008) | ( 0.013) | ( 0.010) |
| Grades (sd) | -0.151 | 0.059*** | 0.059*** | 0.040*** | 0.058*** | 0.056*** | 0.065*** | 0.075*** |
| | | ( 0.014) | ( 0.014) | ( 0.014) | ( 0.014) | ( 0.013) | ( 0.021) | ( 0.017) |
| Percentile | 0.485 | 0.017*** | 0.017*** | 0.007* | 0.017*** | 0.016*** | 0.020*** | 0.020*** |
| | | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.006) | ( 0.005) |
| Ind. Percentile $> 0.5$ | 0.473 | 0.026*** | 0.026*** | 0.012* | 0.026*** | 0.023*** | 0.034*** | 0.031*** |
| | | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.006) | ( 0.006) | ( 0.010) | ( 0.008) |
| Av. Score | -0.241 | 0.057*** | 0.057*** | 0.055** | 0.057*** | 0.057*** | 0.065** | 0.075*** |
| | | ( 0.021) | ( 0.021) | ( 0.022) | ( 0.021) | ( 0.019) | ( 0.031) | ( 0.022) |
| Score Math | -0.246 | 0.050*** | 0.050*** | 0.050** | 0.051** | 0.051*** | 0.052* | 0.067*** |
| | | ( 0.019) | ( 0.019) | ( 0.021) | ( 0.021) | ( 0.017) | ( 0.029) | ( 0.020) |
| Score Verbal | -0.205 | 0.046** | 0.046** | 0.039* | 0.045** | 0.050*** | 0.051 | 0.060*** |
| | | ( 0.021) | ( 0.021) | ( 0.023) | ( 0.021) | ( 0.019) | ( 0.031) | ( 0.022) |
| Ind. Progression | 0.830 | 0.015*** | 0.015*** | 0.007 | 0.015*** | 0.015*** | 0.015* | 0.019*** |
| | | ( 0.005) | ( 0.005) | ( 0.006) | ( 0.006) | ( 0.005) | ( 0.008) | ( 0.006) |
| Ind. at School | 0.956 | 0.004** | 0.004** | 0.005* | 0.004* | 0.003* | 0.004 | 0.005** |
| | | ( 0.002) | ( 0.002) | ( 0.003) | ( 0.002) | ( 0.002) | ( 0.003) | ( 0.002) |
| Ind. Dropout | 0.010 | -0.000 | -0.000 | -0.001 | -0.000 | -0.000 | -0.000 | -0.001 |
| | | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) |
| Ind. Repeated | 0.044 | -0.003** | -0.003** | -0.003* | -0.003** | -0.002** | -0.003* | -0.006*** |
| | | ( 0.001) | ( 0.001) | ( 0.002) | ( 0.001) | ( 0.001) | ( 0.002) | ( 0.002) |
| Absenteeism | 10.020 | -0.105 | -0.105 | -0.009 | -0.143 | -0.059 | -0.204 | -0.329*** |
| | | ( 0.112) | ( 0.112) | ( 0.129) | ( 0.126) | ( 0.099) | ( 0.168) | ( 0.121) |
| Chronic Absenteeism | 0.362 | -0.009* | -0.009* | -0.006 | -0.011** | -0.005 | -0.012* | -0.012** |
| | | ( 0.005) | ( 0.005) | ( 0.005) | ( 0.006) | ( 0.004) | ( 0.007) | ( 0.006) |
| Observations | - | 375,205 | 375,205 | 183,857 | 399,831 | 375,205 | 375,205 | 201,675 |
| Children | - | 62,636 | 62,636 | 31,315 | 66,793 | 62,636 | 62,636 | 32,555 |
| Controls | - | Yes | No | Yes | Yes | Yes | Yes | Yes |

*Notes*: Each cell reports the coefficient of the jump at the cutoff, using Equation 1.In column (1), we present our preferred specification, controlling for age by gender and using the IMSE-optimal bandwidth. Column (3) uses no controls, and column (4) controls for the outcome at application. Column (5) uses the average optimal bandwidth across outcomes, and column (6) uses no weights. Column (7) presents the results using a polynomial degree 2, and column (8) restricts the sample to the years before COVID (before 2020). Standard errors clustered at the applicant level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 5:** Achievement outcomes by Gender

| | Male | | Female | |
|---|---|---|---|---|
| | ITT | ATE | ITT | ATE |
| Dep. Variable | (1) | (2) | (3) | (4) |
| Grades (sd) | 0.071*** | 0.344*** | 0.046** | 0.200** |
| | ( 0.019) | ( 0.095) | ( 0.019) | ( 0.090) |
| Percentile | 0.020*** | 0.099*** | 0.014** | 0.058** |
| | ( 0.006) | ( 0.027) | ( 0.006) | ( 0.027) |
| Av. Score | 0.085*** | 0.511*** | 0.029 | 0.134 |
| | ( 0.029) | ( 0.177) | ( 0.029) | ( 0.155) |
| Ind. Progression | 0.021*** | 0.102*** | 0.009 | 0.039 |
| | ( 0.008) | ( 0.038) | ( 0.007) | ( 0.032) |
| Absenteeism | -0.226 | -1.026 | 0.018 | 0.164 |
| | ( 0.148) | ( 0.696) | ( 0.144) | ( 0.671) |
| Mean Grades (sd) | -0.284 | | -0.028 | |
| Mean Percentile | 0.450 | | 0.518 | |
| Mean Av. Score | -0.268 | | -0.209 | |
| Mean Ind. Progression | 0.797 | | 0.856 | |
| Mean Absenteeism | 10.173 | | 10.023 | |
| Bandwidth | Optimal | | Optimal | |
| Observations | 190,315 | | 184,890 | |
| Children | 62,576 | | 62,576 | |
| Controls | Yes | | Yes | |

*Notes*: This table shows the effects on our main achievement outcomes, split by gender. Columns (1) and (3) display the ITT estimates of winning the subsidy, while (2) and (4) show the LATE estimates of using the voucher to buy a house. All estimates include year and age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 6:** School Quality Outcomes

| | Control Mean | ITT | ATE | Observations | Bandwidth |
|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) |
| Ind. Public School | 0.352 | -0.000 | 0.002 | 523,481 | 88.615 |
| | | ( 0.007) | ( 0.030) | | |
| Ind. Private | 0.004 | -0.002* | -0.007 | 392,599 | 58.501 |
| | | ( 0.001) | ( 0.005) | | |
| School Quality | 0.445 | 0.004 | 0.015 | 471,465 | 75.319 |
| | | ( 0.004) | ( 0.017) | | |
| Class Size | 36.024 | 0.111 | 0.462 | 459,242 | 72.242 |
| | | ( 0.097) | ( 0.457) | | |
| Ind. Change Comuna | 0.025 | -0.001 | -0.005 | 447,901 | 76.160 |
| | | ( 0.001) | ( 0.004) | | |
| Ind. Change School | 0.117 | -0.004 | -0.019 | 452,356 | 70.710 |
| | | ( 0.003) | ( 0.012) | | |
| Controls | - | Yes | Yes | - | - |

*Notes*: This table shows the effects on our other primary and secondary education outcomes after application, focusing on school characteristics. Columns (1), (4), and (5) display the mean of the variable for non-awarded households, the number of applicants, and the optimal IMSE-bandwidth to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Column (3) presents the LATE estimates, rescaling the ITT estimates by the first stage in Equation 2 and presenting the effects of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 7:** Labor Market outcomes for parents

| Dep. Variable | Mean Control | ITT | ATE | Observations | Bandwidth |
|---|---|---|---|---|---|
| Employed | 0.462 | -0.009* | -0.034* | 309,416 | 60 |
| | | ( 0.005) | ( 0.019) | | |
| Months Worked | 3.967 | -0.009* | -0.039* | 309,416 | 60 |
| | | ( 0.005) | ( 0.022) | | |
| Months Worked - Permanent | 2.664 | -0.017** | -0.060** | 309,416 | 60 |
| | | ( 0.007) | ( 0.025) | | |
| Months Worked - Temporary | 1.399 | 0.005 | 0.018 | 309,416 | 60 |
| | | ( 0.010) | ( 0.036) | | |
| Yearly Earnings | 63.200 | -0.015** | -0.061** | 309,416 | 60 |
| | | ( 0.007) | ( 0.031) | | |
| Yearly Earnings - Permanent | 45.770 | -0.022** | -0.080** | 309,416 | 60 |
| | | ( 0.009) | ( 0.036) | | |
| Yearly Earnings - Temporary | 17.430 | -0.010 | -0.045 | 309,416 | 60 |
| | | ( 0.016) | ( 0.064) | | |
| Controls | | Yes | Yes | | |

*Notes*: This table shows the differences in labor market outcomes for parents after application. It includes the applicant of the household and their partner, and we restrict the sample to households that have children in their schooling years. Columns (1), (4), and (5) display the mean of the variable for non-awarded households, the number of applicants, and the bandwidth selected to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Column (3) presents the LATE estimates, rescaling the ITT estimates by the first stage in Equation 2 and presenting the effects of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 8:** Day-care and Preschool Attendance

| | Control Mean | ITT | ATE | Observations | Bandwidth |
|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) |
| In School (0/1) | 0.484 | 0.022*** | 0.094** | 92,711 | 89.177 |
| | | ( 0.008) | ( 0.045) | | |
| In School SC (*Sala Cuna*) | 0.235 | 0.012 | 0.099 | 17,538 | 99.983 |
| | | ( 0.013) | ( 0.128) | | |
| In School NM- (*Nivel Medio Inferior*) | 0.404 | 0.046*** | 0.213** | 15,558 | 68.317 |
| | | ( 0.015) | ( 0.087) | | |
| In School NM+ (*Nivel Medio Superior*) | 0.428 | 0.024** | 0.086 | 23,205 | 76.791 |
| | | ( 0.012) | ( 0.062) | | |
| In School PK (*Pre-Kinder*) | 0.698 | 0.014 | 0.056 | 29,580 | 78.024 |
| | | ( 0.010) | ( 0.050) | | |
| In School KN (*Kindergarten*) | 0.824 | -0.000 | -0.001 | 37,897 | 91.673 |
| | | ( 0.007) | ( 0.033) | | |
| Controls | - | Yes | Yes | - | - |

*Notes*: This table shows the differences in daycare and preschool attendance after application. Columns (1), (4), and (5) display the mean of the variable for non-awarded households, the number of applicants, and the optimal IMSE-bandwidth to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Column (3) presents the LATE estimates, rescaling the ITT estimates by the first stage in Equation 2 and presenting the effects of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%. SC (-+) corresponds to *Sala Cuna* (children aged 0-2), while NM- (*Nivel Medio Inferior*) and NM+ (*Nivel Medio superior*) are for children aged 3 and 4, respectively. PK (*Pre-Kinder*) and KN (*Kindergarten*) include children aged 5 and 6, respectively. In School (0/1) combines all children aged 1-5, only excluding Kindergarten enrollment, which is currently mandatory in Chile.

**Table 9:** High School and Post-Secondary outcomes

| | Control Mean | ITT | ATE | Observations | Bandwidth |
|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) |
| Ind. graduated HS | 0.853 | 0.014** | 0.058* | 32,046 | 71.881 |
| | | ( 0.006) | ( 0.030) | | |
| Grades HS | 5.614 | 0.038*** | 0.169** | 21,157 | 60.681 |
| | | ( 0.014) | ( 0.070) | | |
| Ind. PSU | 0.829 | 0.007 | 0.029 | 25,790 | 66.421 |
| | | ( 0.010) | ( 0.045) | | |
| Av. Score | -0.316 | 0.054** | 0.254** | 17,057 | 59.040 |
| | | ( 0.022) | ( 0.109) | | |
| Score Math | -0.283 | 0.043** | 0.191* | 17,536 | 63.629 |
| | | ( 0.021) | ( 0.099) | | |
| Score Verbal | -0.311 | 0.058** | 0.290** | 16,316 | 56.086 |
| | | ( 0.023) | ( 0.114) | | |
| Score History | -0.302 | 0.054* | 0.224* | 13,420 | 82.606 |
| | | ( 0.030) | ( 0.127) | | |
| Score Science | -0.301 | 0.062* | 0.335* | 9,736 | 59.801 |
| | | ( 0.036) | ( 0.197) | | |
| Ind. college | 0.592 | 0.018** | 0.083** | 27,579 | 73.233 |
| | | ( 0.009) | ( 0.040) | | |
| Years of college | 1.727 | 0.119*** | 0.530** | 27,136 | 71.422 |
| | | ( 0.044) | ( 0.211) | | |
| Ind. dropout | 0.354 | 0.019 | 0.091 | 17,125 | 77.025 |
| | | ( 0.014) | ( 0.063) | | |
| Ind. graduated | 0.444 | -0.006 | -0.018 | 7,008 | 61.470 |
| | | ( 0.024) | ( 0.109) | | |
| Ind. University | 0.398 | 0.031** | 0.143** | 17,729 | 82.961 |
| | | ( 0.014) | ( 0.068) | | |
| Years Accredited | 5.600 | -0.062 | -0.287 | 15,413 | 75.440 |
| | | ( 0.042) | ( 0.201) | | |

*Notes*: This table shows the differences in high school completion and post-secondary outcomes after application. Columns (1), (4), and (5) display the mean of the variable for non-awarded households, the number of applicants, and the optimal IMSE-bandwidth to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Column (3) presents the LATE estimates, rescaling the ITT estimates by the first stage in Equation 2 and presenting the effects of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table 10:** Labor Market outcomes for children not in College

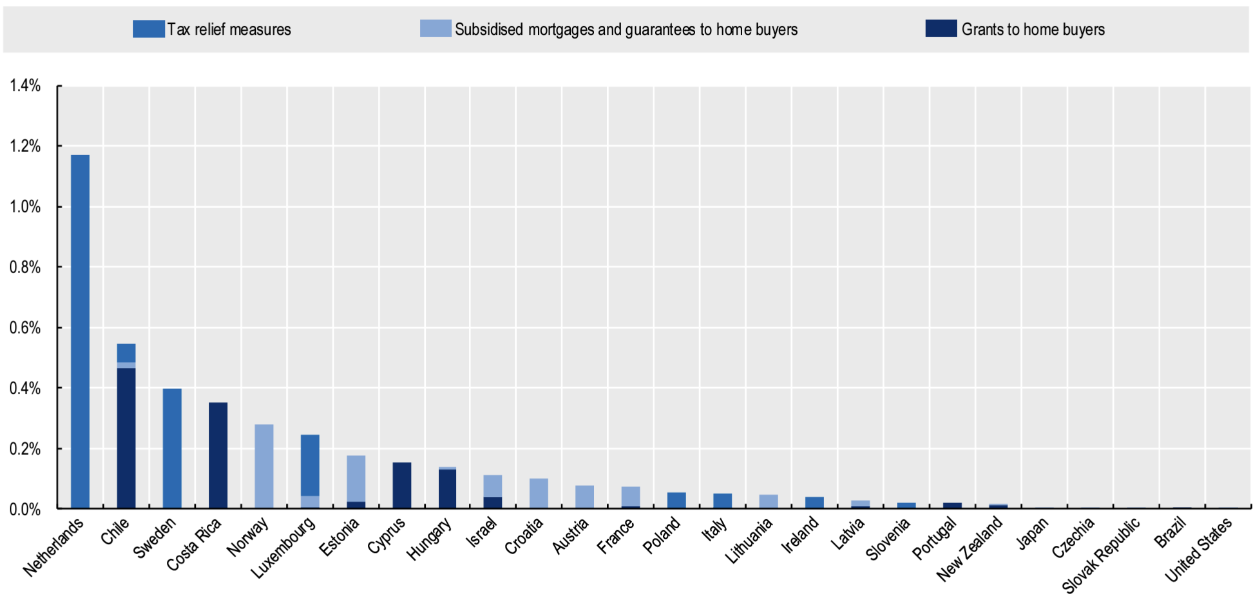
| Dep. Variable | Mean Control | ITT | ATE | Observations | Bandwidth |
|---|---|---|---|---|---|
| Employed | 0.536 | 0.012** | 0.049* | 32,251 | 60 |
| | | ( 0.006) | ( 0.024) | | |
| Months Worked | 4.696 | 0.029* | 0.121* | 32,251 | 60 |
| | | ( 0.018) | ( 0.069) | | |
| Months Worked - Permanent | 3.248 | 0.033 | 0.135 | 32,251 | 60 |
| | | ( 0.037) | ( 0.151) | | |
| Months Worked - Temporary | 1.449 | 0.026* | 0.110* | 32,251 | 60 |
| | | ( 0.013) | ( 0.054) | | |
| Yearly Earnings | 44.888 | 0.028 | 0.121 | 32,251 | 60 |
| | | ( 0.027) | ( 0.114) | | |
| Yearly Earnings - Permanent | 33.482 | 0.031 | 0.113 | 32,251 | 60 |
| | | ( 0.050) | ( 0.210) | | |
| Yearly Earnings - Temporary | 10.832 | 0.012 | 0.052 | 32,251 | 60 |
| | | ( 0.019) | ( 0.092) | | |
| Controls | | Yes | Yes | | |

*Notes*: This table shows the differences in labor market outcomes for children who were not currently enrolled in post-secondary education. Columns (1), (4), and (5) display the mean of the variable for non-awarded households, the number of applicants, and the bandwidth selected to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Column (3) presents the LATE estimates, rescaling the ITT estimates by the first stage in Equation 2 and presenting the effects of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

# Appendix

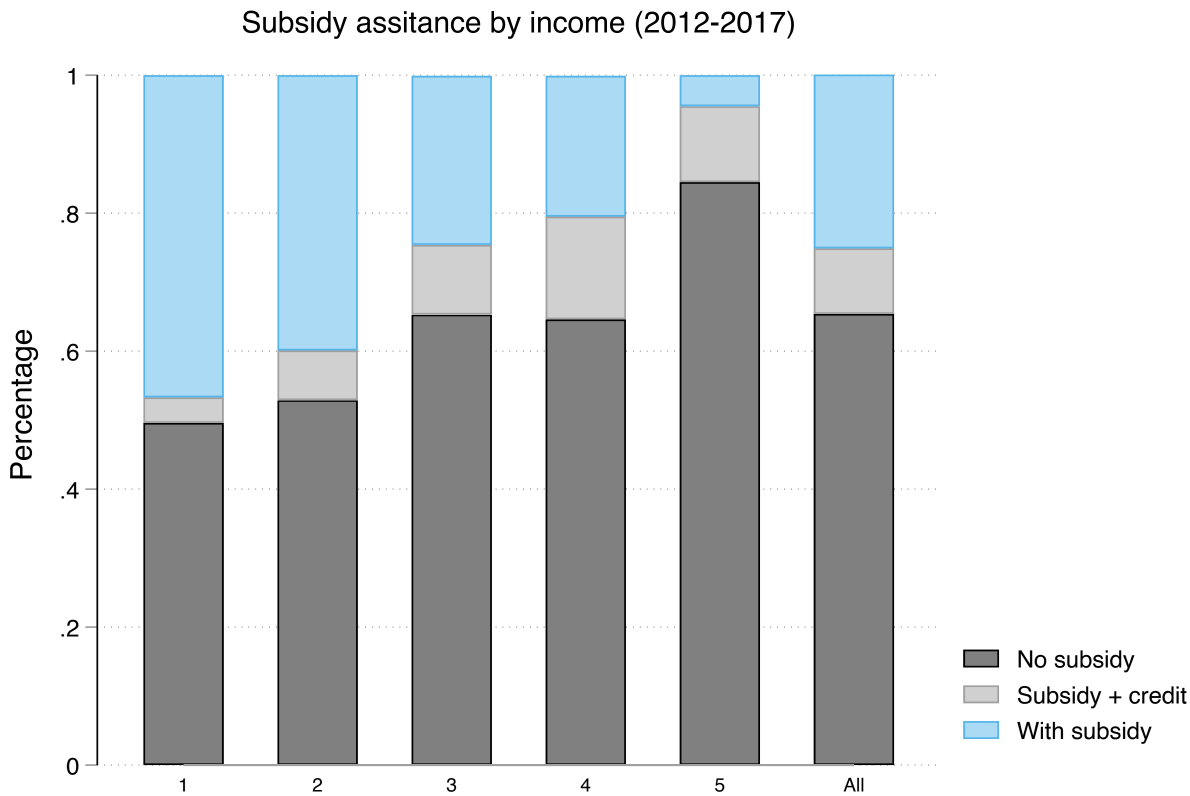
## A Appendix Figures

**Figure A1:** Public spending financial support and tax relief for homebuyers




*Notes:* Figure displays the amount of public spending financial support and tax relief for homebuyers. Amounts are shown as % of GDP, 2022 or the latest available year. Chile is the country that spends the most on grants to homebuyers. *Source*: OECD Questionnaire on Affordable and Social Housing (QuASH).

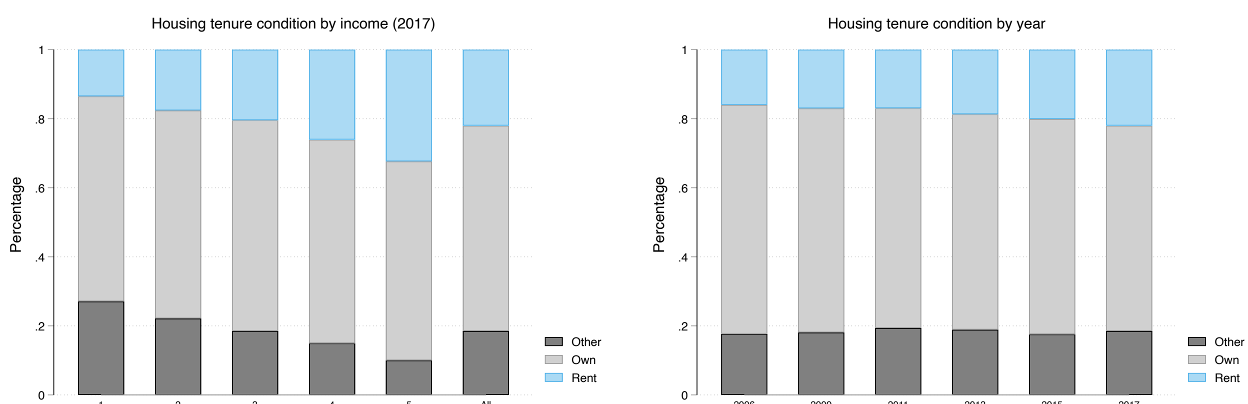
**Figure A2:** Subsidy Assistance by Income level




*Notes:* This figure shows the distribution of the percentage of houses sold using 1) Only the subsidy; 2) Combination of subsidy and credit; and 3) No subsidy, by income quintile. It considers all of the housing units sold between 2012 and 2017. More than half of the units sold to the lowest quintile were bought only using the subsidy.

**Figure A3:** Housing Tenure

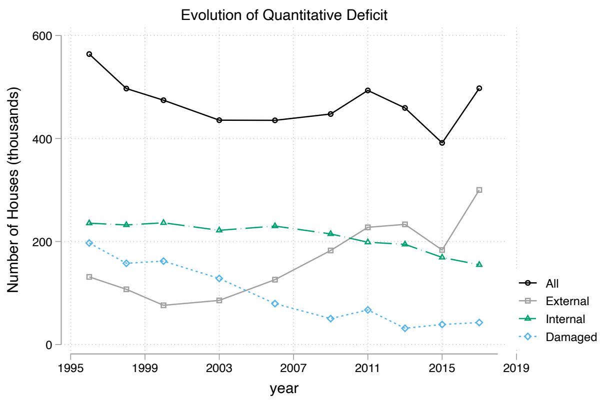
Panel A: By Income | Panel B: By Year



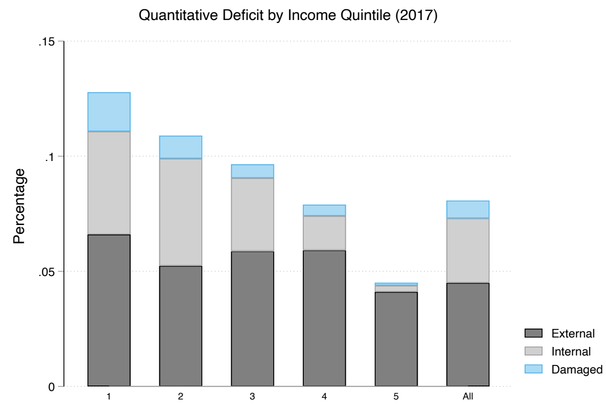

*Notes*: This figure shows the distribution of the housing tenure condition by income quintile and year. In Panel A, we show the distribution by income quintile in the year 2017. In Panel B, we show the aggregated distribution by year, from 2006 to 2017.

**Figure A4:** Quantitative Housing Deficit

Panel A: By Year



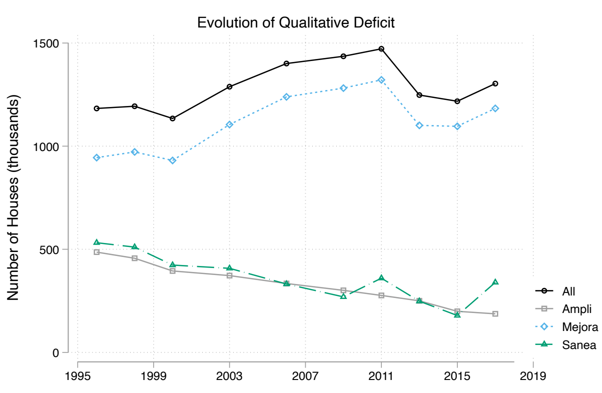

Panel B: By Income



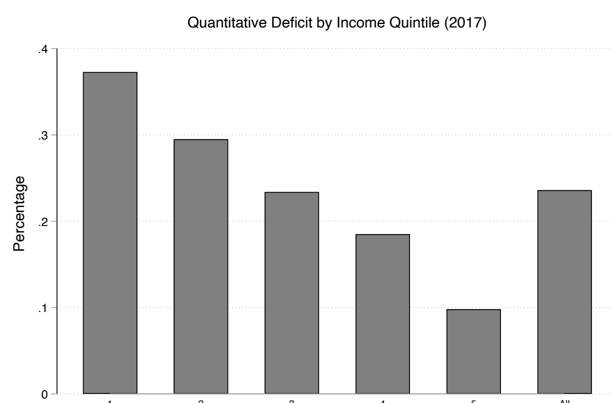

*Notes*: This figure shows the distribution of the quantitative housing deficit by income quintile and year. *External* corresponds to more than one household living in the same unit; *Internal* to more than one family living in the same unit with more than 2.5 persons per bedroom; and *Damaged* corresponds to housing units with irrecoverable damage. Panel A shows the evolution of this deficit by year, while Panel B displays the deficit by income quintile in 2017.

**Figure A5:** Qualitative Housing Deficit

Panel A: By Year

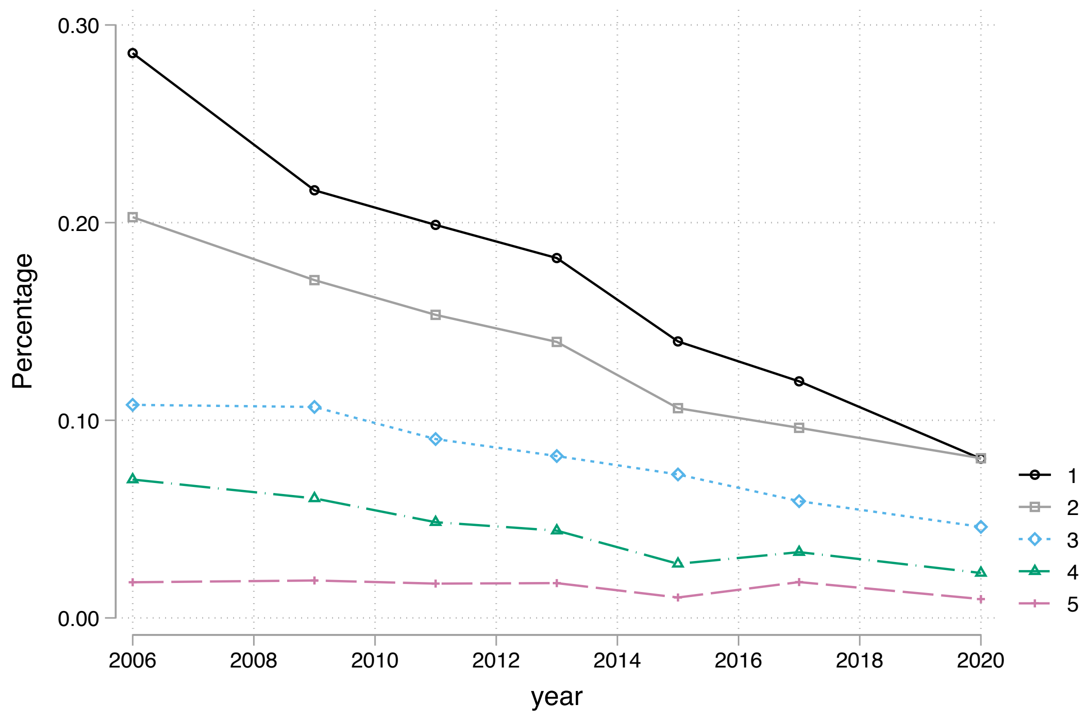



Panel B: By Income



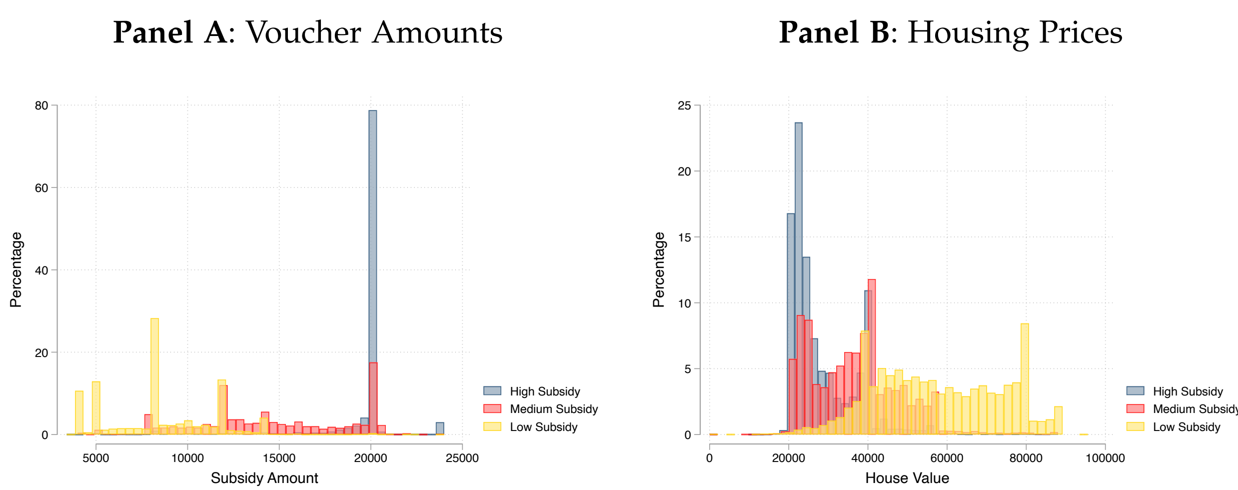

*Notes*: This figure displays the distribution of the qualitative housing deficit by income quintile and year. *Ampli* correspond to overcrowded houses (more than 2.5 persons per bd); *Mejora* to more than one family living in the same unit with more than 2.5 persons per bedroom; and *Z* corresponds to housing units with irrecoverable damage. The total number includes all of the housing units that need at least one of the 3 categories.

**Figure A6:** Evolution of Overcrowding by Income Quintile



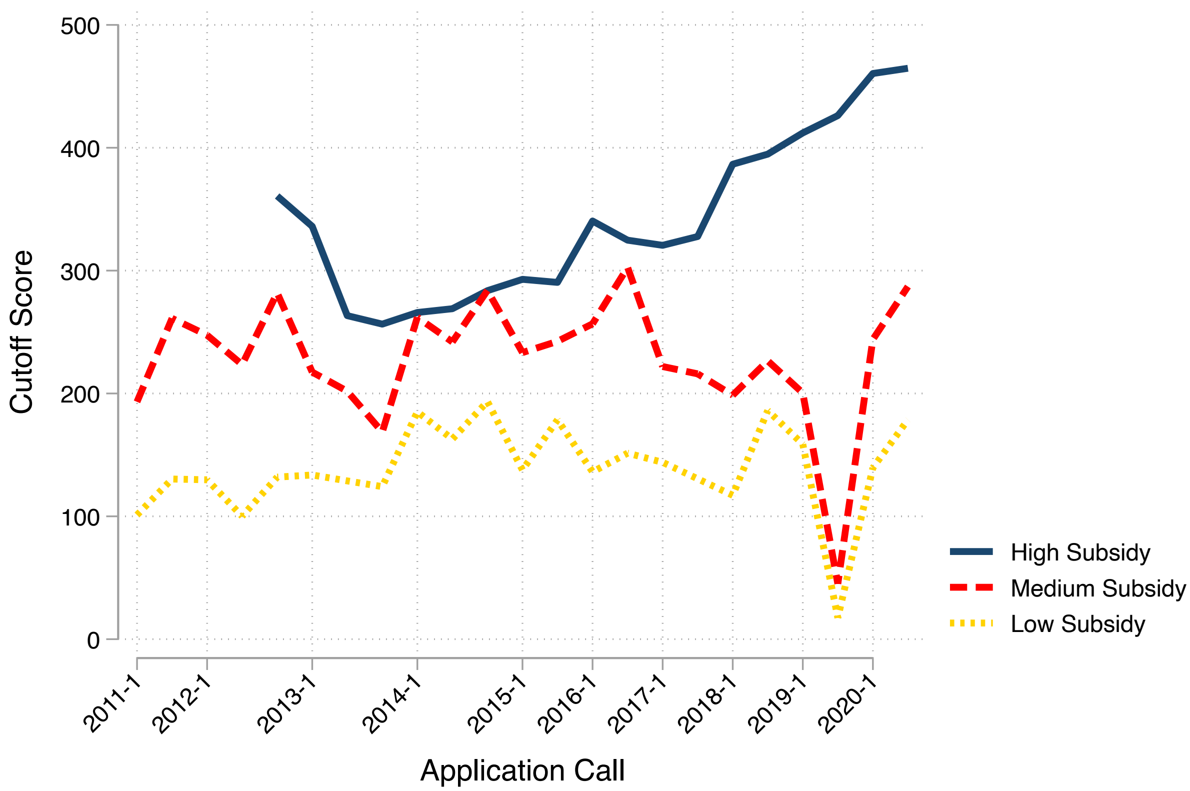

*Notes*: This figure shows the evolution of the distribution of overcrowded households by income quintile over the years, measured as housing units with more than 2.5 people per bedroom. We show that, even in 2020, many families live in overcrowded housing conditions, especially the ones in the lower quintiles of the income distribution.

**Figure A7:** Distribution of Vouchers and Housing Prices for Recipients



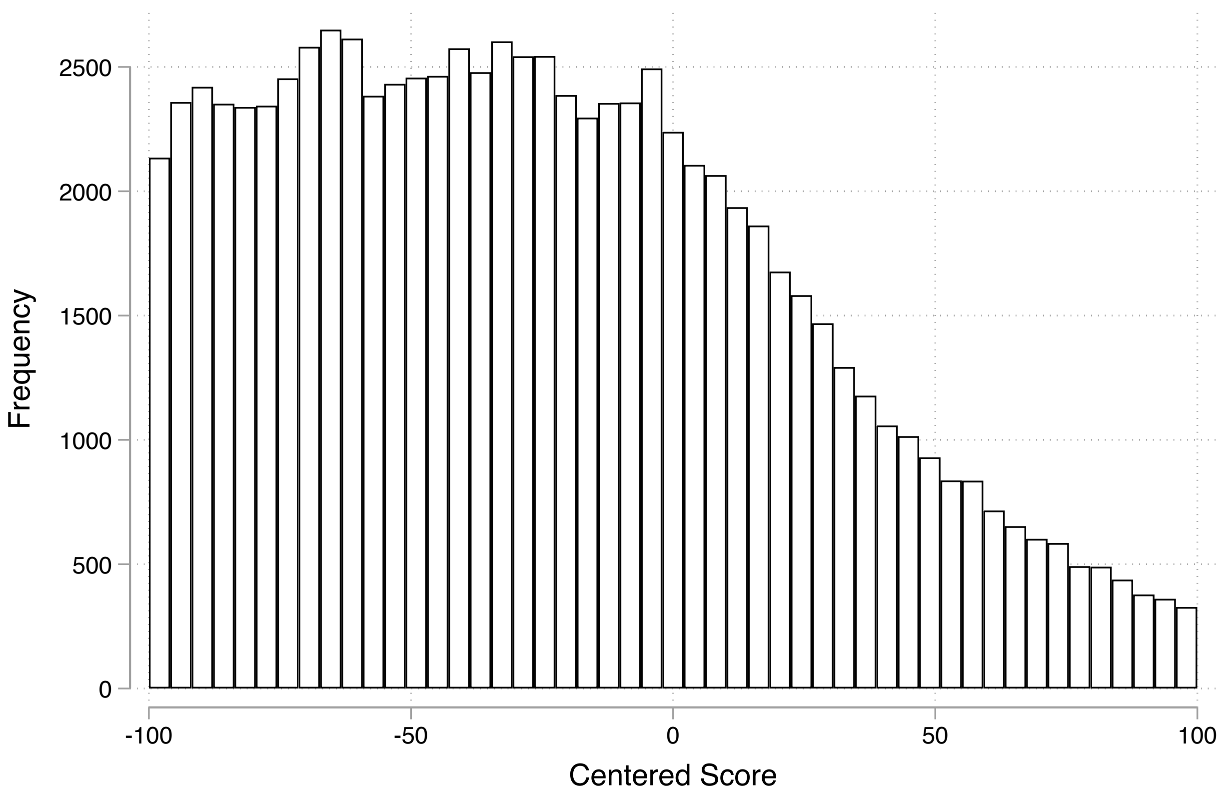

*Notes*: This figure shows the distribution of voucher amounts and housing prices for voucher recipients. Panel A presents the distribution of voucher amounts by subsidy tier, while Panel B shows the distribution of housing prices.

**Figure A8:** Cutoff Evolution by Call and Tier




*Notes*: This figure displays the cutoff scores by application call and tier for Santiago. The variance in cutoff scores by application call is mostly driven by changes in the pool of applicants, as the budget for different regions and tiers is relatively stable over time.

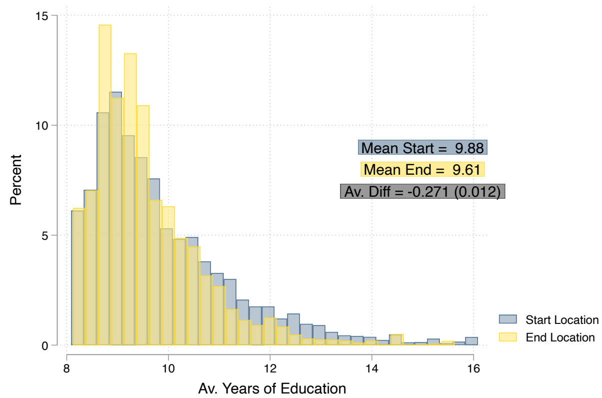
**Figure A9:** Score Distribution



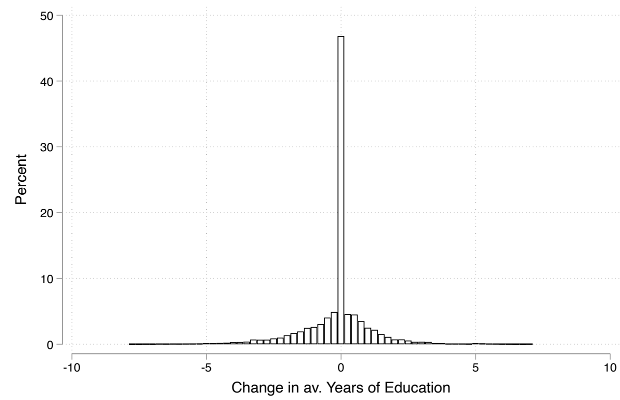

*Notes* This figure shows the distribution of scores relative to the cutoff, pooling across application calls. There is a large mass on both sides of the cutoff, and there is no evidence of bunching at zero. We take this as evidence that there is no manipulation of the scores and that we will have enough power to detect effects with the regression discontinuity

**Figure A10:** Distribution of average neighborhood quality

**Panel A**: Initial v/s ending Location



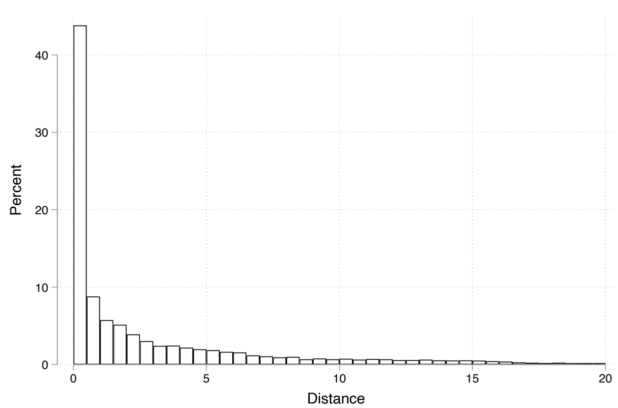

**Panel B**: Difference in NH quality



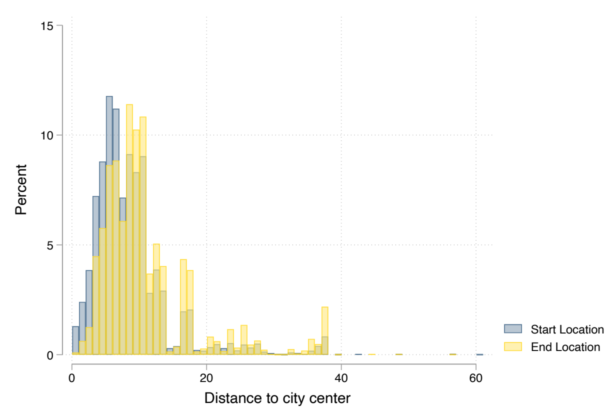

*Notes*: This figure shows the distribution of neighborhood quality measured as average years of schooling in the census tract. Panel A presents the distribution of average years of education associated with the initial and ending locations of voucher users. Panel B shows the distribution of the change in years of education from the initial and ending locations. We show that almost half of voucher users stay in a census tract with the same average years of education. For the ones moving to different neighborhoods, we find that they tend to move to slightly less educated neighborhoods.

**Figure A11:** Distance between houses and to the city center

**Panel A**: Distance between houses



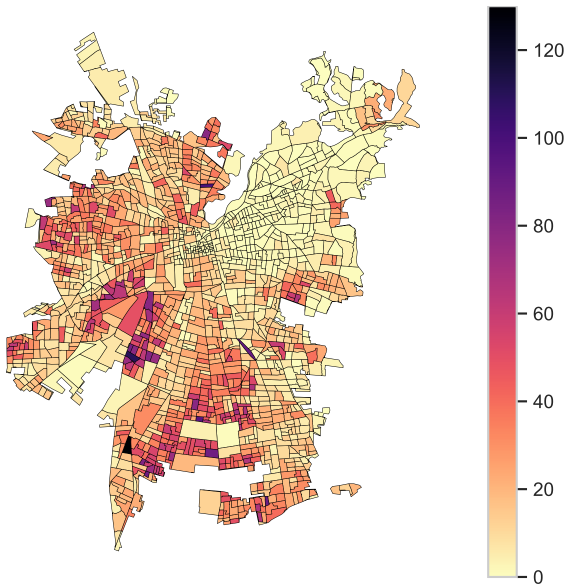

**Panel B**: Distance to city center



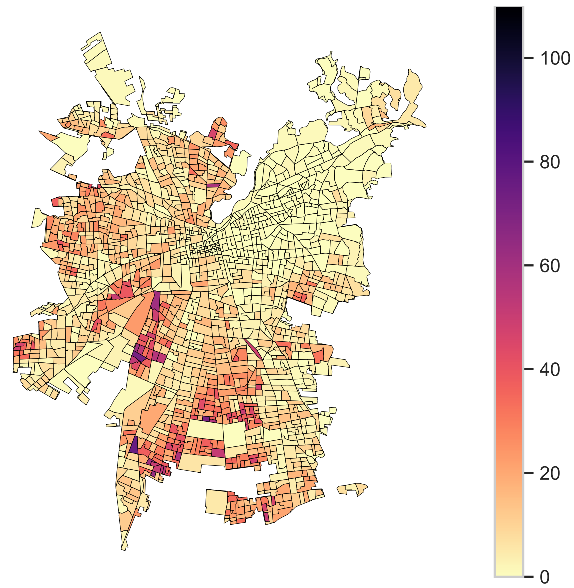

*Notes*: This figure presents the distribution of the distance between the initial and ending locations of the houses for voucher users and the distribution of distances to the city center. Panel A presents the distribution of the distance between former and new housing units. Panel B shows the distribution of the distance from the initial and ending locations to the city center. We show that more than half of voucher users do not move more than one mile away, and most of the remaining move relatively close. However, they move to places slightly further from the city center.

**Figure A12:** Maps of the distribution of winners and users

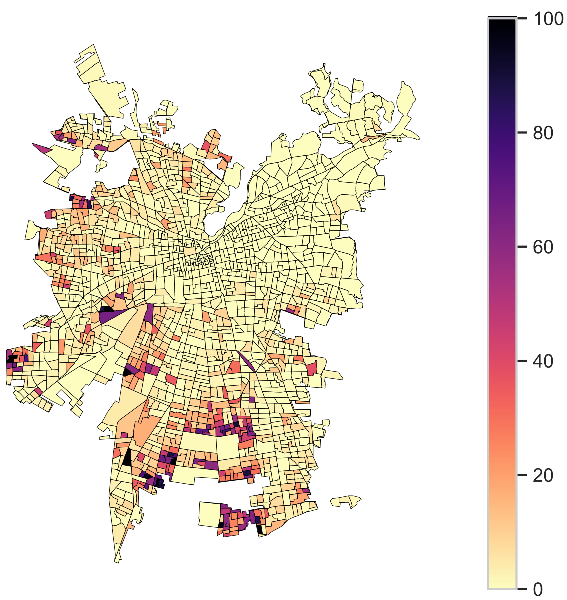
**Panel A:** Initial location of winners



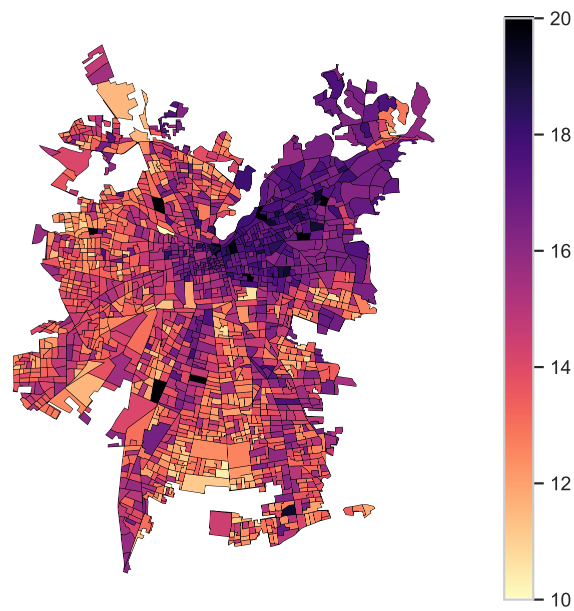

**Panel B:** Initial location of users




**Panel C:** Ending location of users



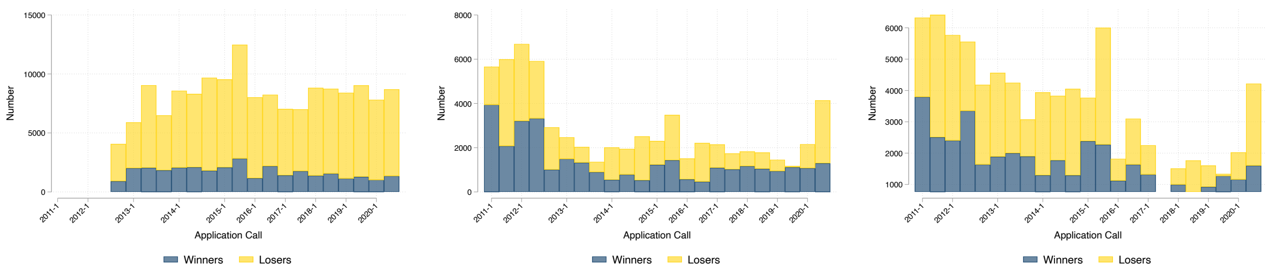

**Panel D:** Av. Years of schooling




*Notes*: This figure displays the distribution of number of households in each census tract. Panel A shows the distribution of the location at the time of application for voucher awarded households, and Panel B for voucher users. Panel C displays the distribution of the final location of voucher users, and panel D presents the average years of schooling by census tract, using census data from 2017.

**Figure A13:** Evolution of winners

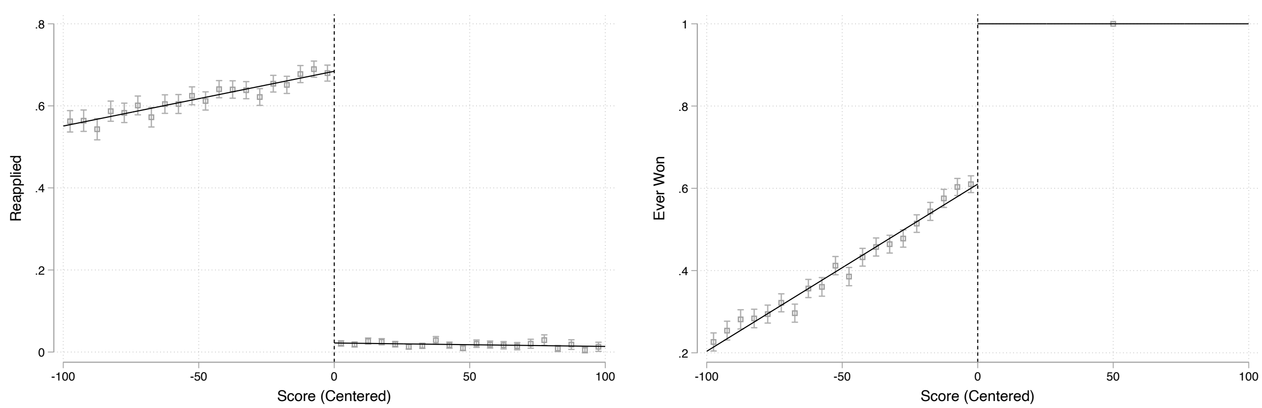
Panel A: High Subsidy | Panel B: Medium Subsidy | Panel C: Low Subsidy




*Notes*: This figure displays the evolution of applicants in Santiago by application call and tier, separated by awarded and non-awarded applicants.

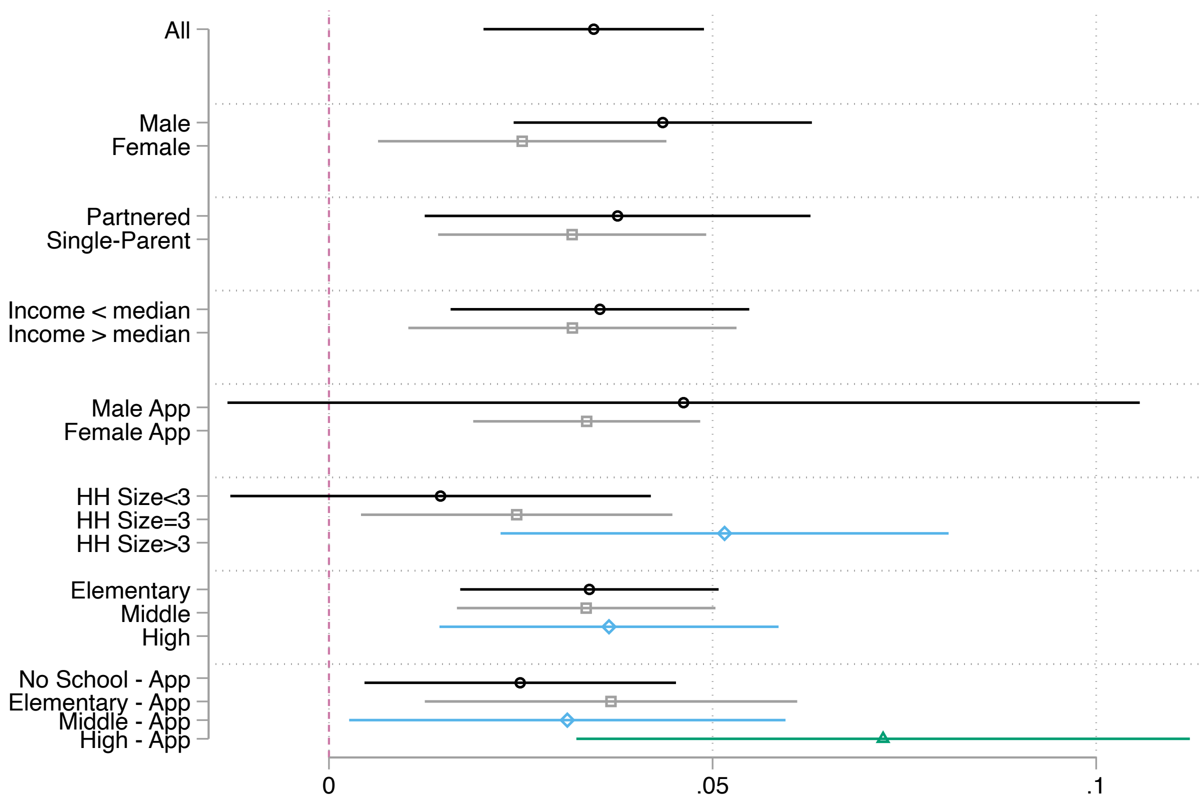
**Figure A14:** Reapplicants and Winners around the cutoff

Panel A: Reapplicants | Panel B: Winners




*Notes*: This figure shows the result of the regression discontinuity, using Equation 1 on the probability of reapplying and winning the subsidy. Panel A uses an indicator of reapplying in the future, and Panel B an indicator of ever winning the subsidy as an outcome. We show that almost 70% of non-awarded applicants end up reapplying in the future, while only 5% of awarded applicants do so. Moreover, over 60% of non-awarded applicants end up winning the voucher in the future.

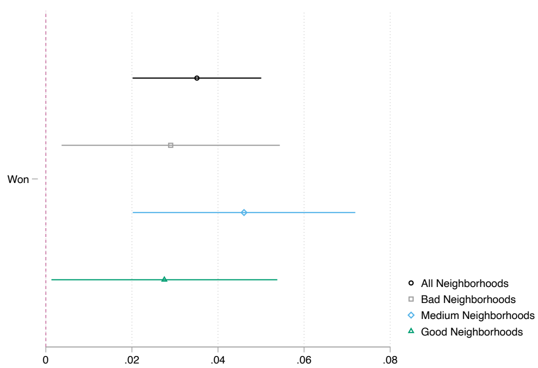
**Figure A15:** Heterogeity by Demographics: Grades



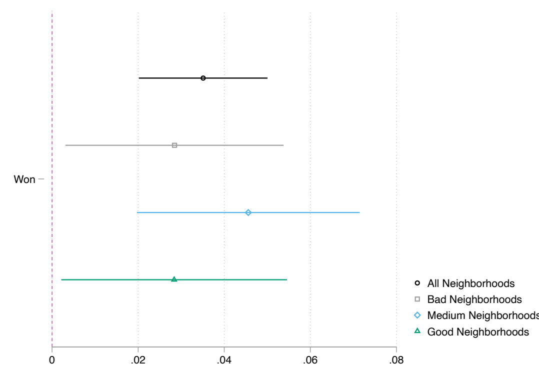

*Notes:* This figure displays the heterogeneous effects depending on demographic characteristics for the ITT estimates on grades. Each horizontal bar reports the coefficient of the jump at the cutoff and the confidence interval of the estimate at the 10% significance level, using Equation 1 and fitting a linear polynomial at each side of the cutoff. All estimates include year and gender by age fixed effects and consider scores the IMSE-optimal bandwidth. Standard errors are clustered at the applicant level.

**Figure A16:** Heterogeneity on Neighborhood: alternative measures

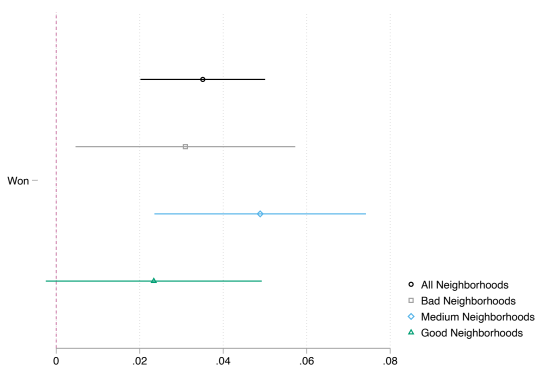
**Panel A:** Av. Years of Schooling



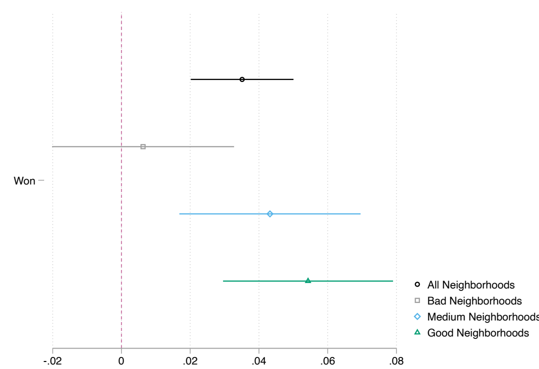

**Panel B:** Socio-Territorial Index




**Panel C:** Overcrowding

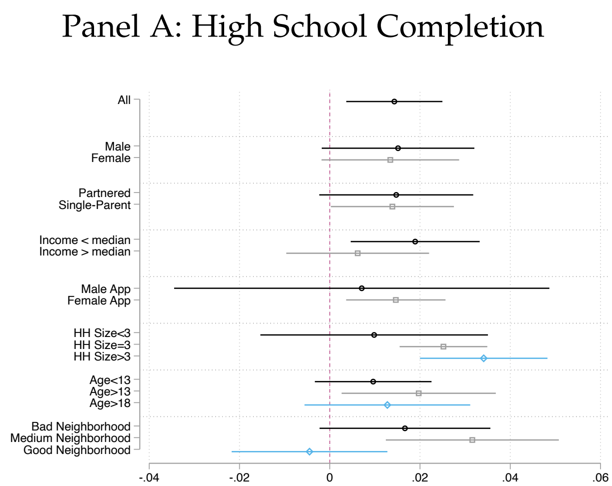


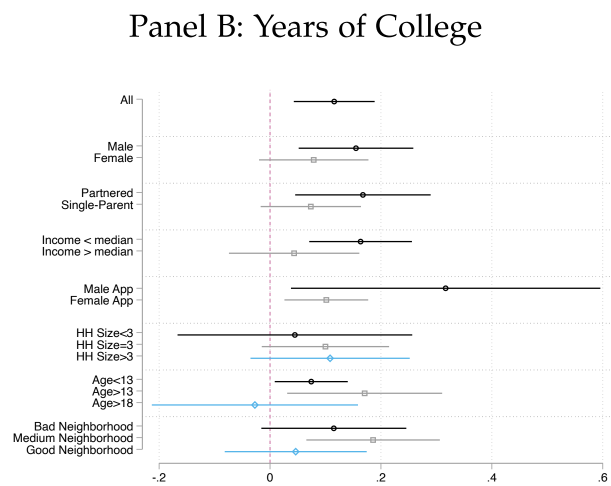

**Panel D:** Material Quality




*Notes*: This figure displays the heterogeneous effects of the result of the estimate of the ITT estimate for grades depending on neighborhood quality, pooling years after the application. Measures of neighborhood quality include average years of schooling (A), socio-territorial index (B), overcrowding index (C), and material quality index (D). Standard errors are clustered at the applicant level, and regression considers scores using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects. ***, **, * indicates significance at 1, 5, and 10%.

**Figure A17:** Heterogeneities in high school attainment and years of college

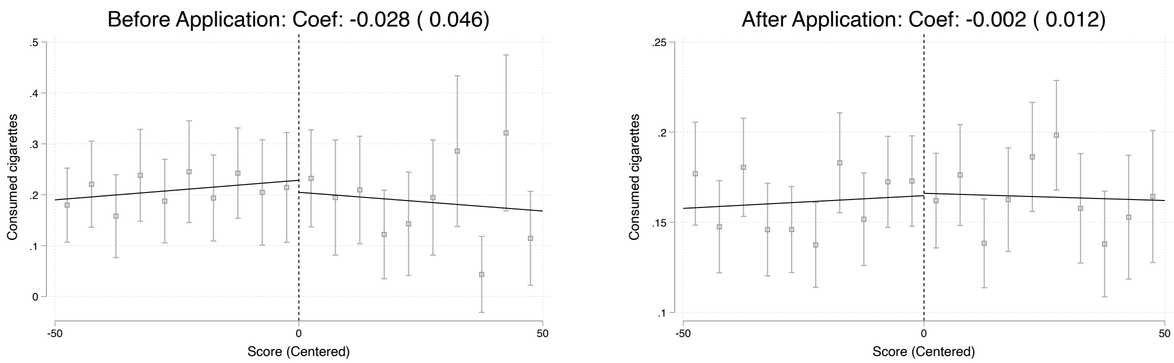


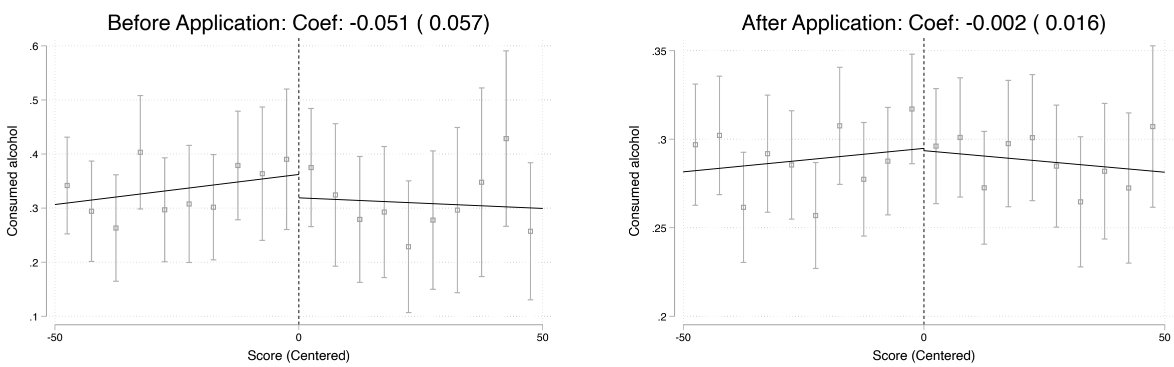

*Notes*: This figure displays the heterogeneous effects depending on demographic characteristics for the ITT estimates on high school completion and years of college. Each horizontal bar reports the coefficient of the jump at the cutoff and the confidence interval of the estimate at the 10% significance level, using Equation 1. All estimates include year and gender by age fixed effects and consider scores the IMSE-optimal bandwidth. Standard errors are clustered at the applicant level.

**Figure A18:** RD of children's behavior regarding drug consumption

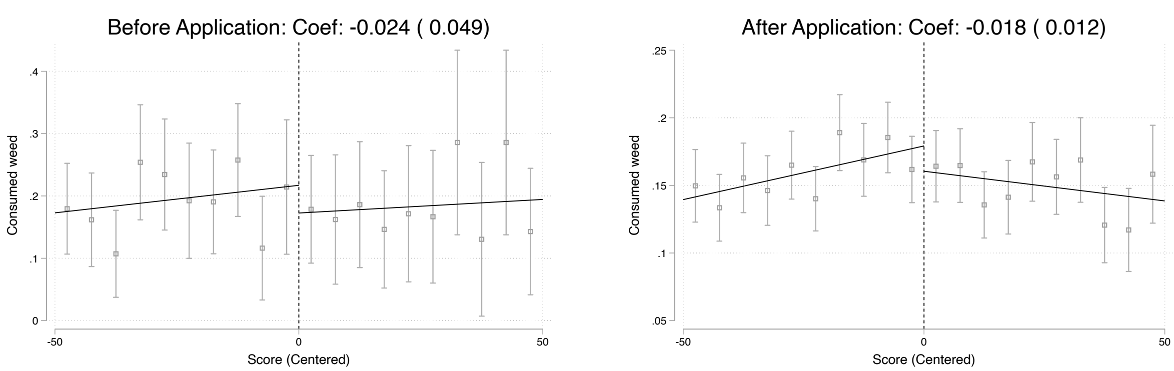
**Panel A:** Cigarette Consumption




**Panel B**: Alcohol Consumption



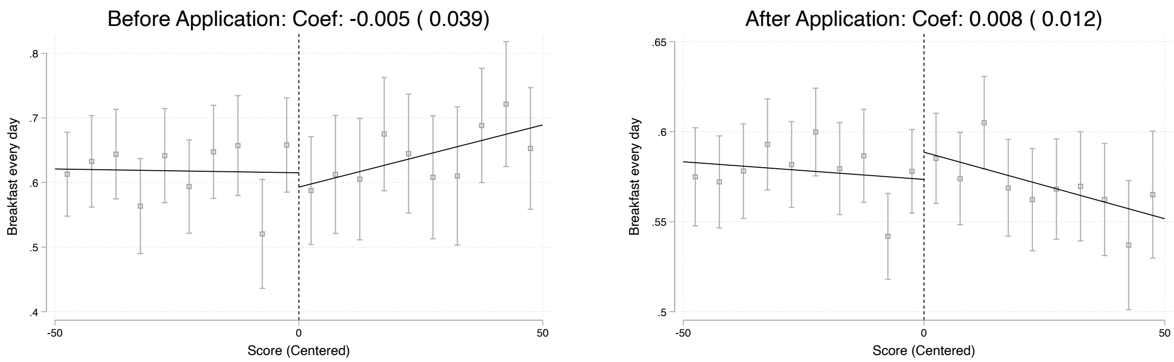

**Panel C:** Weed Consumption



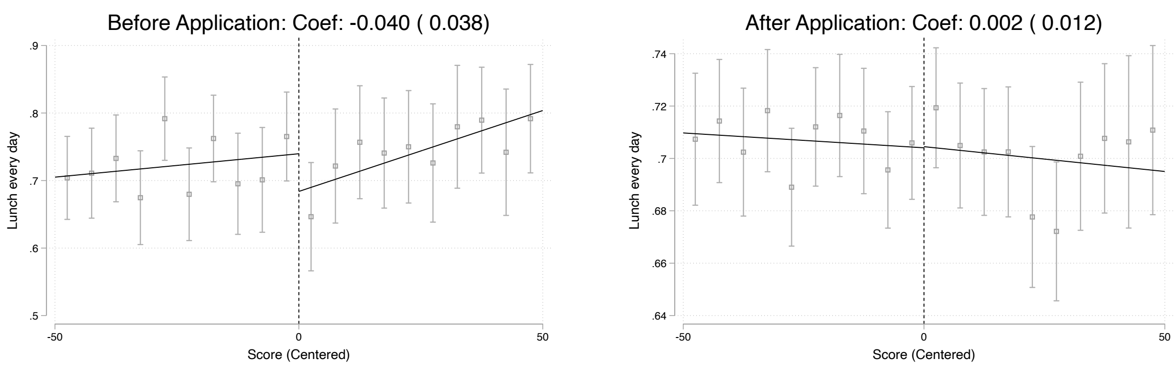

*Notes*: This figure shows the result of the ITT estimate of the regression discontinuity regarding children's drug consumption before and after the application. In Panel A, B, and C, the outcome variable indicates cigarette, alcohol, and weed consumption, respectively, considering consumption at least once a year. Standard errors are clustered at the applicant level, and scores are considered using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects. ***, **, * indicates significance at 1, 5, and 10%.

**Figure A19:** RD of children's behavior regarding food consumption

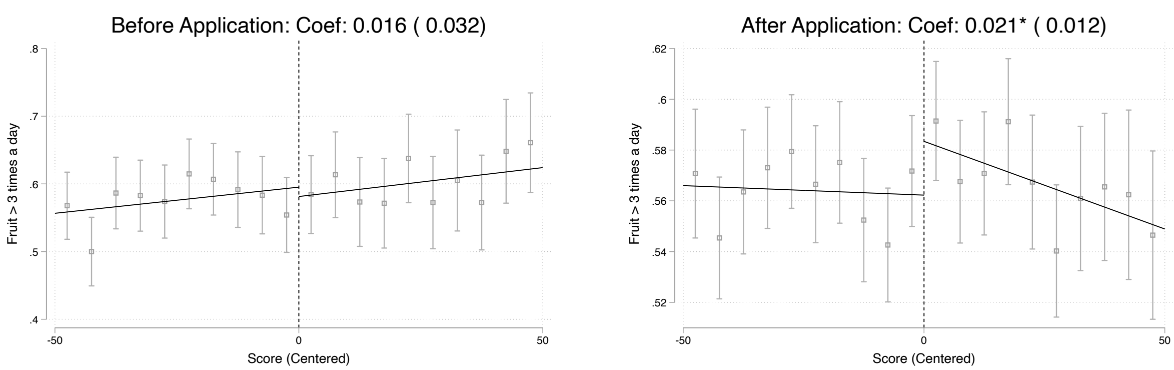
**Panel A:** Breakfast




**Panel B**: Lunch



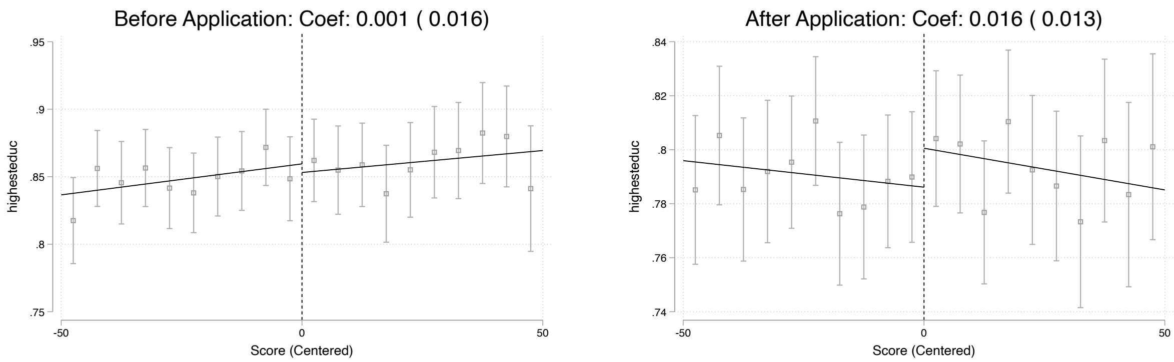

**Panel C:** Fruit Consumption



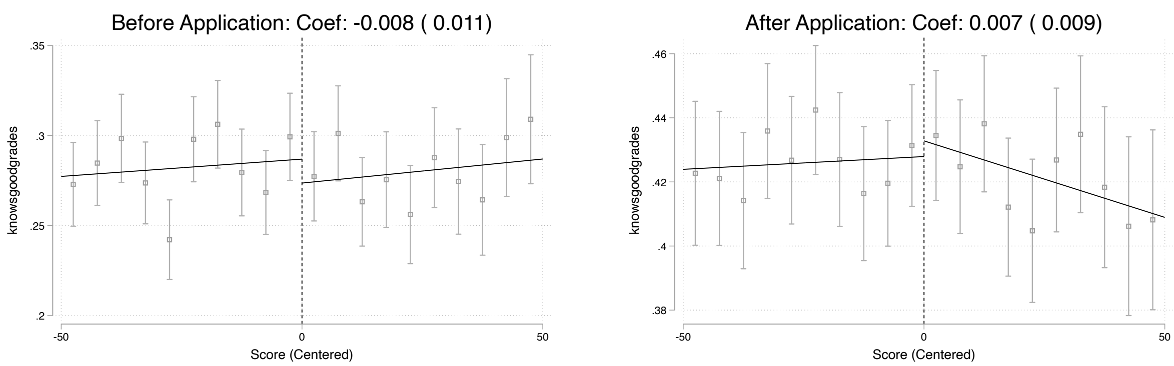

*Notes*: This figure shows the result of the ITT estimate of the regression discontinuity regarding children's food consumption before and after the application. In Panel A, B, and C, the outcome variable indicates breakfast, lunch and fruit consumption, respectively. For breakfast and lunch, the outcome variable indicates having had lunch all school days. For fruit consumption, it indicates consuming two or more times a day. Standard errors are clustered at the applicant level, and scores are considered using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects. ***, **, * indicates significance at 1, 5, and 10%.

**Figure A20:** RD of children's expectations

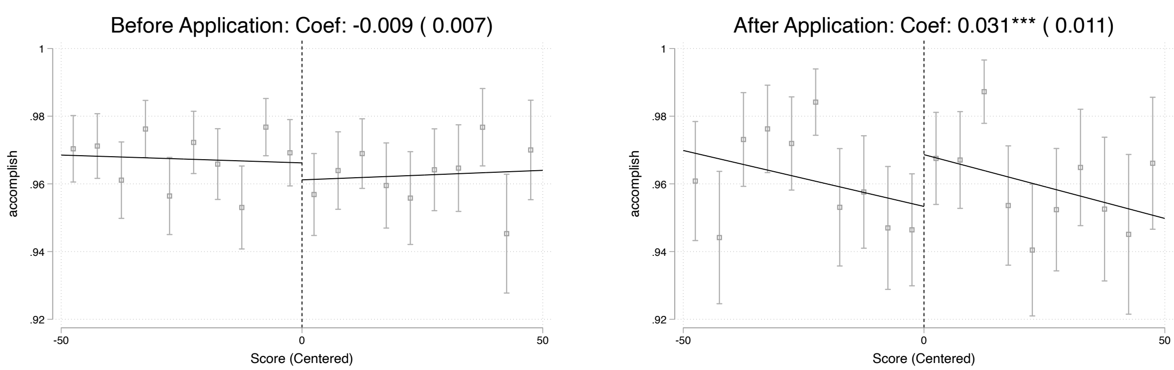
**Panel A:** Will attend post-secondary education




**Panel B**: Knows they can get good grades




**Panel C:** Will accomplish what they want as adults




*Notes*: This figure shows the result of the ITT estimate of the regression discontinuity regarding children's expectations about the future. In Panel A, the outcome variable indicates whether the student thinks they will complete post-secondary education. Panels B and C indicate whether the student believes they can get good grades and will accomplish what they want as adults, respectively. Standard errors are clustered at the applicant level, and scores are considered using the IMSE-optimal bandwidth. Controls include year and gender-by-age fixed effects. ***, **, * indicates significance at 1, 5, and 10%.

# B Appendix Tables

**Table A1:** Score Components

| **Name of the Variable** | **Description** | **Score** | **Average Score** |
|---|---|---|---|
| Household Size | Number of Household Members besides the applicant | 40 | 50 |
| Single-Parent | Indicator applicant is single-parent | 35 | 13.3 |
| Elderly | Number of elderly in the household | 30 | 2.2 |
| Savings | Amount Saved in addition to the minimum | 1 | 40.2 |
| Past Applications | Number of applications in the past | 20 | 35 |
| Vulnerability | Vulnerability Index | 1 | 51 |
| Disability | Number of household members with disabilities | 30 | 1.3 |
| Valech | Part of the Valech Report | 100 | 0.2 |
| Military | Indicator applicant participated in the military | 20 | 0.3 |
| Children $< 5$ | Number of children younger 5 years old | 30 | 9.1 |
| Children $> 5$ | Number of children older than 5 years old | 20 | 10.6 |
| Total Score | Sum of the individual scores | - | 224 |

*Notes*: This table describes the variables used to construct the score, along with their weight on the overall score constructed by the Ministry of Housing. Column (1) displays the name of the variable, column (2) describes it, column (3) shows how much impact it has on the overall score, and column (4) shows the average score considering all applicants.

**Table A2:** Neighborhood characteristics

| Dep. Variable | Initial Location<br>(1) | End Location<br>(2) | Difference<br>(3) | Applicants<br>(4) |
|---|---|---|---|---|
| **Panel A: Census Data** | | | | |
| Education Index | 9.879 | 9.608 | -0.271*** | 16,059 |
| | ( 0.011) | ( 0.009) | ( 0.012) | |
| Socio - Territorial Index | 0.499 | 0.487 | -0.012*** | 16,059 |
| | ( 0.001) | ( 0.000) | ( 0.001) | |
| Overcrowding Index | 1.629 | 1.603 | -0.026*** | 16,059 |
| | ( 0.002) | ( 0.001) | ( 0.002) | |
| Material Quality Index | 8.829 | 8.866 | 0.036*** | 16,059 |
| | ( 0.001) | ( 0.001) | ( 0.001) | |
| Housing Deficit | 0.101 | 0.083 | -0.018*** | 16,059 |
| | ( 0.000) | ( 0.000) | ( 0.000) | |
| Population Density | 191.954 | 216.754 | 24.800*** | 16,059 |
| | ( 0.833) | ( 0.908) | ( 0.987) | |
| People / Houses | 3.363 | 3.375 | 0.012*** | 16,059 |
| | ( 0.004) | ( 0.004) | ( 0.004) | |
| **Panel B: Unidad Vecinal** | | | | |
| Green Area Surface pp | 3.318 | 3.374 | 0.056* | 13,918 |
| | ( 0.026) | ( 0.024) | ( 0.029) | |
| Education Facilities pp | 0.579 | 0.507 | -0.072*** | 13,903 |
| | ( 0.004) | ( 0.003) | ( 0.004) | |
| Supermarkets pp | 0.042 | 0.039 | -0.003*** | 14,120 |
| | ( 0.001) | ( 0.001) | ( 0.001) | |
| Bus Stops pp | 1.543 | 1.256 | -0.287*** | 14,037 |
| | ( 0.008) | ( 0.008) | ( 0.009) | |
| Drugstores pp | 0.149 | 0.111 | -0.037*** | 14,232 |
| | ( 0.002) | ( 0.002) | ( 0.002) | |
| Health Facilities pp | 0.086 | 0.071 | -0.015*** | 14,142 |
| | ( 0.001) | ( 0.001) | ( 0.002) | |
| **Panel C: SII data** | | | | |
| Total Units | 1720.642 | 1782.734 | 62.092*** | 16,027 |
| | ( 10.389) | ( 11.733) | ( 14.546) | |
| Price m2 const. | 21.580 | 17.138 | -4.443*** | 16,027 |
| | ( 0.096) | ( 0.058) | ( 0.100) | |
| Size of Const. | 41.958 | 40.059 | -1.899*** | 16,027 |
| | ( 0.074) | ( 0.062) | ( 0.079) | |
| House Valuation | 683.770 | 562.433 | -121.337*** | 16,027 |
| | ( 3.165) | ( 2.100) | ( 3.401) | |

*Notes*: This table presents the average neighborhood characteristic for awarded applicants who buy a house using the subsidy on a variety of outcomes. Columns (1) and (2) show the neighborhood characteristics of the initial and end locations, respectively, while column (3) shows the difference and column (4) displays the number of users. Panel A shows census outcomes at the census tract level. Panel B shows other outcomes gathered from *Espacio Público* at the *unidad vecinal* level, which is more aggregated than the census tract. Panel C displays characteristics regarding prices using data from the Servicio de Impuestos Internos, also at the census tract level. We find that users of the high subsidy tend to move to slightly worse neighborhoods in terms of average years of schooling and socio-territorial index and have access to fewer amenities. They also move to cheaper places measured as the price of the squared meter.

**Table A3:** Optimal Bandwidths by Outcome

| Dep. Variable | High | Medium | Low |
|---|---|---|---|
| Grades | 55.14 | 59.16 | 35.32 |
| Grades (sd) | 56.32 | 71.64 | 43.56 |
| Percentile | 59.25 | 74.85 | 53.83 |
| Ind. Percentile $> 0.5$ | 57.54 | 69.96 | 35.35 |
| Av. Score | 58.73 | 55.35 | 45.27 |
| Score Verbal | 60.26 | 55.27 | 47.50 |
| Score Math | 71.15 | 51.80 | 47.69 |
| Ind. Progression | 65.30 | 59.32 | 54.25 |
| Ind. at School | 77.34 | 64.69 | 39.88 |
| Ind. Dropout | 76.76 | 63.12 | 34.11 |
| Absenteeism | 75.81 | 70.47 | 41.81 |
| Chronic Absenteeism | 82.95 | 52.30 | 42.71 |
| Ind. Repeated | 81.94 | 53.66 | 54.61 |
| Ind. Priority Student | 50.38 | 37.38 | 44.43 |
| Ind. Public School | 93.04 | 38.86 | 57.37 |
| Ind. Private | 58.74 | 68.54 | 43.56 |
| School Quality | 75.50 | 78.99 | 48.51 |
| Class Size | 74.00 | 68.63 | 48.10 |
| Ind. Change Comuna | 74.98 | 67.14 | 49.94 |
| Ind. Change School 2 | 72.07 | 72.44 | 57.08 |

*Notes*: This table shows the value IMSE-optimal bandwidth at application for the main variables, separated by subsidy tier. It includes year and age by gender fixed effects and clusters the standard errors at the applicant level.

**Table A4:** Differences in demographics for voucher Users

| | All | Winners | Users | Non-Users | Difference |
|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) |
| Applicant's Age | 37.373 | 36.971 | 35.827 | 38.040 | -2.213*** |
| | ( 7.803) | ( 7.281) | ( 6.912) | ( 7.453) | ( 0.086) |
| Applicant's Gender | 0.924 | 0.922 | 0.925 | 0.918 | 0.007** |
| | ( 0.265) | ( 0.269) | ( 0.263) | ( 0.274) | ( 0.003) |
| Married = 1 (Applicant) | 0.307 | 0.319 | 0.318 | 0.321 | -0.003 |
| | ( 0.461) | ( 0.466) | ( 0.466) | ( 0.467) | ( 0.006) |
| Single-Parent | 0.620 | 0.601 | 0.607 | 0.596 | 0.011* |
| | ( 0.485) | ( 0.490) | ( 0.488) | ( 0.491) | ( 0.006) |
| Family Members | 3.130 | 3.835 | 3.825 | 3.843 | -0.018 |
| | ( 1.048) | ( 1.094) | ( 1.094) | ( 1.094) | ( 0.013) |
| Children at School | 1.443 | 1.705 | 1.686 | 1.723 | -0.037*** |
| | ( 0.710) | ( 0.837) | ( 0.810) | ( 0.860) | ( 0.010) |
| Former Applications | 1.191 | 1.221 | 1.031 | 1.398 | -0.367*** |
| | ( 1.972) | ( 1.976) | ( 1.780) | ( 2.128) | ( 0.023) |
| Self-reported Income | 11.831 | 11.923 | 11.394 | 12.417 | -1.023*** |
| | ( 5.201) | ( 5.277) | ( 4.943) | ( 5.525) | ( 0.063) |
| Av. Years Schooling NH | 9.995 | 9.976 | 9.804 | 10.136 | -0.332*** |
| | ( 1.476) | ( 1.470) | ( 1.386) | ( 1.526) | ( 0.017) |
| Normalized score | -47.432 | 66.225 | 58.382 | 73.552 | -15.171*** |
| | ( 106.789) | ( 67.321) | ( 61.227) | ( 71.784) | ( 0.798) |
| Bandwidth | All | All | All | All | All |
| Observations | 90,362 | 28,126 | 13,584 | 14,542 | 28,126 |

*Notes*: This table displays the differences in demographic characteristics for users and non-users among voucher winners. Columns (1), (2), (3), and (4) display the mean and standard deviation for the whole sample, all voucher winners, and split by users and non-users, respectively. Column (5) presents the difference in these demographic characteristics for users vs non-users. We consider all voucher winners and users, without restricting the sample within a bandwidth. ***, **, * indicates significance at 1, 5, and 10%.

**Table A5:** Achievement outcomes: Bandwidth selection

| | Mean | BW = 30 | BW = 40 | BW = 50 | BW = 60 | BW = 70 | BW = 80 | BW = 90 | BW = 100 |
|---|---|---|---|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Grades | 5.685 | 0.035*** | 0.039*** | 0.036*** | 0.035*** | 0.033*** | 0.031*** | 0.028*** | 0.027*** |
| | | ( 0.012) | ( 0.011) | ( 0.010) | ( 0.009) | ( 0.008) | ( 0.008) | ( 0.007) | ( 0.007) |
| Grades (sd) | -0.151 | 0.061*** | 0.066*** | 0.061*** | 0.058*** | 0.055*** | 0.052*** | 0.048*** | 0.045*** |
| | | ( 0.019) | ( 0.017) | ( 0.015) | ( 0.014) | ( 0.013) | ( 0.012) | ( 0.011) | ( 0.011) |
| Percentile | 0.485 | 0.019*** | 0.020*** | 0.018*** | 0.017*** | 0.016*** | 0.015*** | 0.015*** | 0.014*** |
| | | ( 0.006) | ( 0.005) | ( 0.005) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.003) | ( 0.003) |
| Ind. Percentile $> 0.5$ | 0.473 | 0.032*** | 0.031*** | 0.028*** | 0.026*** | 0.024*** | 0.023*** | 0.022*** | 0.021*** |
| | | ( 0.009) | ( 0.008) | ( 0.007) | ( 0.006) | ( 0.006) | ( 0.006) | ( 0.005) | ( 0.005) |
| Av. Score | -0.241 | 0.062** | 0.065** | 0.059** | 0.057*** | 0.054*** | 0.050*** | 0.047*** | 0.045*** |
| | | ( 0.030) | ( 0.026) | ( 0.023) | ( 0.021) | ( 0.019) | ( 0.018) | ( 0.017) | ( 0.016) |
| Score Math | -0.246 | 0.053* | 0.056** | 0.051** | 0.051** | 0.050*** | 0.047*** | 0.045*** | 0.044*** |
| | | ( 0.030) | ( 0.026) | ( 0.023) | ( 0.021) | ( 0.019) | ( 0.018) | ( 0.017) | ( 0.016) |
| Score Verbal | -0.205 | 0.050* | 0.051** | 0.047** | 0.045** | 0.044** | 0.041** | 0.038** | 0.036** |
| | | ( 0.030) | ( 0.026) | ( 0.023) | ( 0.021) | ( 0.020) | ( 0.018) | ( 0.017) | ( 0.017) |
| Ind. Progression | 0.830 | 0.014* | 0.015** | 0.014** | 0.015*** | 0.015*** | 0.014*** | 0.013*** | 0.012*** |
| | | ( 0.008) | ( 0.007) | ( 0.006) | ( 0.006) | ( 0.005) | ( 0.005) | ( 0.005) | ( 0.004) |
| Ind. at School | 0.956 | 0.003 | 0.004 | 0.004* | 0.004* | 0.004** | 0.004** | 0.004** | 0.004** |
| | | ( 0.003) | ( 0.003) | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.002) |
| Ind. Dropout | 0.010 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) |
| Ind. Repeated | 0.044 | -0.003 | -0.003* | -0.003** | -0.003** | -0.003** | -0.003** | -0.002** | -0.002** |
| | | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) |
| Absenteeism | 10.020 | -0.145 | -0.178 | -0.163 | -0.143 | -0.120 | -0.096 | -0.090 | -0.095 |
| | | ( 0.180) | ( 0.156) | ( 0.139) | ( 0.126) | ( 0.116) | ( 0.108) | ( 0.102) | ( 0.097) |
| Chronic Absenteeism | 0.362 | -0.008 | -0.010 | -0.011* | -0.011** | -0.010** | -0.009* | -0.008* | -0.008* |
| | | ( 0.008) | ( 0.007) | ( 0.006) | ( 0.006) | ( 0.005) | ( 0.005) | ( 0.004) | ( 0.004) |
| Observations | - | 227,707 | 291,395 | 348,282 | 399,831 | 449,220 | 491,659 | 528,324 | 560,293 |
| Children | - | 37,676 | 48,361 | 58,060 | 66,793 | 75,298 | 82,628 | 89,177 | 95,020 |
| Bandwidth | - | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
| Controls | - | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: This table shows the differences in our achievement outcomes after application, presenting the ITT estimate of the regression discontinuity using Equation 1. Column (1) shows the control mean, and columns (2)-(9) display the ITT coefficients using different bandwidths from 30 to 100. Results are very stable across bandwidths for all achievement outcomes, suggesting our results are not driven by the bandwidth selection. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table A6:** Achievement outcomes by Age at application

| | No School | | Elementary | | Middle | | High | |
|---|---|---|---|---|---|---|---|---|
| | ITT | ATE | ITT | ATE | ITT | ATE | ITT | ATE |
| Dep. Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Grades (sd) | 0.060*** | 0.245*** | 0.056** | 0.290** | 0.056** | 0.291* | 0.078** | 0.534** |
| | ( 0.020) | ( 0.083) | ( 0.025) | ( 0.135) | ( 0.027) | ( 0.152) | ( 0.038) | ( 0.264) |
| Percentile | 0.021*** | 0.084*** | 0.012* | 0.064* | 0.019** | 0.095** | 0.012 | 0.083 |
| | ( 0.006) | ( 0.024) | ( 0.007) | ( 0.039) | ( 0.008) | ( 0.044) | ( 0.012) | ( 0.081) |
| Av. Score | 0.036 | 0.150 | 0.078** | 0.461** | 0.043 | 0.271 | 0.044 | 0.254 |
| | ( 0.042) | ( 0.195) | ( 0.033) | ( 0.203) | ( 0.036) | ( 0.226) | ( 0.054) | ( 0.317) |
| Ind. Progression | 0.005 | 0.021 | 0.013 | 0.067 | 0.029** | 0.163** | 0.001 | 0.007 |
| | ( 0.006) | ( 0.025) | ( 0.010) | ( 0.054) | ( 0.014) | ( 0.076) | ( 0.020) | ( 0.138) |
| Absenteeism | -0.001 | -0.004 | -0.001 | -0.006 | -0.001 | -0.006 | 0.001 | 0.006 |
| | ( 0.002) | ( 0.006) | ( 0.002) | ( 0.009) | ( 0.002) | ( 0.011) | ( 0.004) | ( 0.025) |
| Mean Grades (sd) | -0.099 | -0.099 | -0.172 | -0.172 | -0.184 | -0.184 | -0.179 | -0.179 |
| Mean Percentile | 0.491 | 0.491 | 0.481 | 0.481 | 0.482 | 0.482 | 0.482 | 0.482 |
| Mean Av. Score | -0.168 | -0.168 | -0.219 | -0.219 | -0.234 | -0.234 | -0.305 | -0.305 |
| Mean Ind. Progression | 0.933 | 0.933 | 0.874 | 0.874 | 0.837 | 0.837 | 0.799 | 0.799 |
| Mean Absenteeism | 0.108 | 0.108 | 0.101 | 0.101 | 0.095 | 0.095 | 0.099 | 0.099 |
| Bandwidth | Opt | Opt | Opt | Opt | Opt | Opt | Opt | Opt |
| Observations | 153,676 | 153,676 | 127,405 | 127,405 | 72,516 | 72,516 | 21,216 | 21,216 |

*Notes*: This table shows the differences in our main achievement outcomes, separated by age at application. Columns (1), (3), (5) and (7) display the ITT estimates of winning the subsidy, while (2), (4), (6) and (8) show the LATE estimates of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table A7:** Achievement outcomes by Household size

| | HH Size<3 | | HH Size=3 | | HH Size>3 | |
|---|---|---|---|---|---|---|
| | ITT | ATE | ITT | ATE | ITT | ATE |
| Dep. Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Grades (sd) | 0.034 | 0.123 | 0.043** | 0.226** | 0.082*** | 0.324*** |
| | ( 0.028) | ( 0.124) | ( 0.020) | ( 0.108) | ( 0.029) | ( 0.120) |
| Percentile | 0.017** | 0.063* | 0.012** | 0.067** | 0.021** | 0.082** |
| | ( 0.008) | ( 0.038) | ( 0.006) | ( 0.031) | ( 0.008) | ( 0.034) |
| Av. Score | 0.006 | 0.000 | 0.059** | 0.377** | 0.056 | 0.258 |
| | ( 0.051) | ( 0.246) | ( 0.029) | ( 0.193) | ( 0.040) | ( 0.184) |
| Ind. Progression | 0.006 | 0.029 | 0.016** | 0.081** | 0.015 | 0.057 |
| | ( 0.010) | ( 0.045) | ( 0.007) | ( 0.038) | ( 0.011) | ( 0.045) |
| Absenteeism | 0.330 | 1.635* | -0.300* | -1.531* | 0.107 | 0.511 |
| | ( 0.204) | ( 0.915) | ( 0.162) | ( 0.829) | ( 0.227) | ( 0.909) |
| Mean Grades (sd) | -0.051 | -0.051 | -0.168 | -0.168 | -0.207 | -0.207 |
| Mean Percentile | 0.506 | 0.506 | 0.480 | 0.480 | 0.476 | 0.476 |
| Mean Av. Score | -0.152 | -0.152 | -0.240 | -0.240 | -0.283 | -0.283 |
| Mean Ind. Progression | 0.865 | 0.865 | 0.832 | 0.832 | 0.792 | 0.792 |
| Mean Absenteeism | 9.671 | 9.671 | 10.076 | 10.076 | 10.416 | 10.416 |
| Bandwidth | Opt | Opt | Opt | Opt | Opt | Opt |
| Observations | 80,418 | 80,418 | 182,496 | 182,496 | 112,291 | 112,291 |

*Notes*: This table shows the differences in our main achievement outcomes, split by household size at application. Columns (1), (3), (5) and (7) display the ITT estimates of winning the subsidy, while (2), (4), (6) and (8) show the LATE estimates of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table A8:** Achievement outcomes by Neighborhood quality

| | **Bad Neighborhood** | | **Medium Neighborhood** | | **Good Neighborhood** | |
|---|---|---|---|---|---|---|
| | ITT | ATE | ITT | ATE | ITT | ATE |
| Dep. Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Grades (sd) | 0.050** | 0.268** | 0.083*** | 0.358*** | 0.039 | 0.150 |
| | ( 0.024) | ( 0.125) | ( 0.025) | ( 0.114) | ( 0.025) | ( 0.123) |
| Percentile | 0.012* | 0.060* | 0.025*** | 0.109*** | 0.015* | 0.061 |
| | ( 0.007) | ( 0.035) | ( 0.007) | ( 0.033) | ( 0.008) | ( 0.037) |
| Av. Score | 0.040 | 0.294 | 0.114*** | 0.545*** | 0.012 | 0.039 |
| | ( 0.035) | ( 0.245) | ( 0.036) | ( 0.184) | ( 0.038) | ( 0.210) |
| Ind. Progression | 0.011 | 0.062 | 0.027*** | 0.115*** | 0.006 | 0.026 |
| | ( 0.009) | ( 0.046) | ( 0.009) | ( 0.042) | ( 0.009) | ( 0.044) |
| Absenteeism | -0.128 | -0.656 | -0.155 | -0.623 | -0.012 | 0.131 |
| | ( 0.194) | ( 0.932) | ( 0.195) | ( 0.871) | ( 0.189) | ( 0.903) |
| Mean Grades (sd) | -0.206 | -0.206 | -0.168 | -0.168 | -0.099 | -0.099 |
| Mean Percentile | 0.484 | 0.484 | 0.482 | 0.482 | 0.486 | 0.486 |
| Mean Av. Score | -0.283 | -0.283 | -0.257 | -0.257 | -0.177 | -0.177 |
| Mean Ind. Progression | 0.829 | 0.829 | 0.824 | 0.824 | 0.824 | 0.824 |
| Mean Absenteeism | 10.379 | 10.379 | 10.175 | 10.175 | 9.751 | 9.751 |
| Bandwidth | Opt | Opt | Opt | Opt | Opt | Opt |
| Observations | 126,812 | 126,812 | 128,350 | 128,350 | 120,043 | 120,043 |

*Notes*: This table shows the differences in our main achievement outcomes, split by neighborhood quality at application using average years of schooling. Columns (1), (3), (5) and (7) display the ITT estimates of winning the subsidy, while (2), (4), (6) and (8) show the LATE estimates of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.

**Table A9:** High School and Post-secondary outcomes by age

| | Control Mean | ITT | ATE | Observations | Bandwidth |
|---|---|---|---|---|---|
| Dep. Variable | (1) | (2) | (3) | (4) | (5) |
| **Panel A: Children < 13 at application** | | | | | |
| Ind. graduated HS | 0.881 | 0.010 | 0.040 | 17,038 | 71.600 |
| | | ( 0.008) | ( 0.037) | | |
| Grades HS | 5.688 | 0.013 | 0.041 | 11,892 | 58.917 |
| | | ( 0.019) | ( 0.092) | | |
| Ind. PSU | 0.827 | 0.018 | 0.080 | 13,176 | 59.357 |
| | | ( 0.013) | ( 0.066) | | |
| Av. Score | -0.287 | 0.021 | 0.111 | 8,941 | 55.438 |
| | | ( 0.029) | ( 0.145) | | |
| Ind. college | 0.486 | 0.029** | 0.147** | 13,027 | 58.387 |
| | | ( 0.013) | ( 0.064) | | |
| Years of college | 1.040 | 0.086** | 0.392* | 13,528 | 61.843 |
| | | ( 0.043) | ( 0.214) | | |
| Ind. University | 0.445 | 0.005 | 0.025 | 6,964 | 66.233 |
| | | ( 0.023) | ( 0.120) | | |
| Years Accredited | 5.705 | 0.018 | 0.112 | 6,146 | 60.243 |
| | | ( 0.063) | ( 0.322) | | |
| **Panel A: Children > 13 at application** | | | | | |
| Ind. graduated HS | 0.823 | 0.020** | 0.080* | 15,147 | 73.359 |
| | | ( 0.010) | ( 0.048) | | |
| Grades HS | 5.515 | 0.072*** | 0.343*** | 8,535 | 56.280 |
| | | ( 0.021) | ( 0.111) | | |
| Ind. PSU | 0.829 | -0.010 | -0.044 | 13,932 | 86.335 |
| | | ( 0.013) | ( 0.057) | | |
| Av. Score | -0.359 | 0.098*** | 0.448*** | 7,436 | 56.556 |
| | | ( 0.034) | ( 0.172) | | |
| Ind. college | 0.715 | 0.007 | 0.034 | 12,691 | 75.338 |
| | | ( 0.012) | ( 0.057) | | |
| Years of college | 2.532 | 0.178** | 0.785** | 12,787 | 76.136 |
| | | ( 0.082) | ( 0.381) | | |
| Ind. University | 0.356 | 0.055*** | 0.251** | 8,364 | 67.507 |
| | | ( 0.021) | ( 0.103) | | |
| Years Accredited | 5.525 | -0.161** | -0.758** | 6,618 | 55.645 |
| | | ( 0.073) | ( 0.352) | | |

*Notes*: This table shows the differences in high school completion and our main post-secondary education outcomes, split by age at application. Panel A considers children who were below 13 years old when applying, while Panel B considers children aged 13 or older. Columns (1), (4), and (5) display the mean of the variable for non-awarded households, the number of applicants, and the bandwidth selected to perform the RD, respectively. Column (2) shows the ITT estimate of the regression discontinuity using Equation 1 by regressing each demographic characteristic on the score, corresponding to the jump at the cutoff. Column (3) presents the LATE estimates, rescaling the ITT estimates by the first stage in Equation 2 and presenting the effects of using the voucher to buy a house. All estimates include year and gender by age fixed effects and clustered standard errors at the application level. ***, **, * indicates significance at 1, 5, and 10%.