Rental Assistance in Middle-Income Countries: Quasi-experimental Evidence from Chile

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October 25, 2025

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Abstract

This paper presents the evaluation of a rental voucher program in a middle-income country: Chile. I estimate treatment effects before and after the COVID-19 outbreak using a local randomization regression discontinuity design and administrative and survey data. Pre-pandemic results mirror U.S. evidence: voucher receipt improved housing conditions and increased mobility but did not lead to relocation to higher-quality neighborhoods. Effects depend on initial tenure and access to local housing authorities. Post-pandemic results (November 2020) show that vouchers helped low-income families cope with the aggregate shock by reducing reliance on debt and enhancing housing stability. Findings highlight a previously underappreciated insurance role of rental subsidies during periods of economic distress. ***JEL Codes:*** H24, I38, R21, R38.

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1 Introduction

Rising rents and stagnant wages have left low-income households increasingly vulnerable to homelessness, overcrowding, and deprived neighborhoods—conditions linked to adverse long-term outcomes for children (Chetty, Hendren and Katz, 2016; Chyn, 2018; Chyn and Katz, 2021; Collinson et al., 2024). The COVID-19 pandemic further strained household finances and intensified the risk of eviction (Ellen, O'Regan and Ganz, 2020). In response, several countries introduced or expanded direct rental assistance–most notably, voucher programs–to mitigate housing insecurity, while improving neighborhood access for disadvantaged families (OECD, 2024). However, little is known about rental voucher effectiveness outside high-income countries and their role in helping families cope with unexpected economic shocks.

In this paper, I present the first evaluation of a rental voucher program in a middle-income country, Chile. Using a unique dataset combining administrative and survey data collected before and during the COVID-19 pandemic, I address two central questions: (i) What are the effects of Chile's rental voucher program on housing and neighborhood characteristics, residential mobility, and demand for subsidized homeownership? and (ii) How does rental assistance influence how families cope with major economic shocks, such as the COVID-19 pandemic?

The *Subsidio de Arriendo* (Rental Subsidy), implemented by the Chilean Ministry of Housing and Urban Planning (MINVU) in December 2013, was the first such policy in the region. It marked a major shift away from long-standing reliance on large-scale, demand-side subsidies for homeownership, and constituted the first national effort to support low-income families in the rental market. Subsequently, Argentina, Brazil, Colombia, Peru, and Uruguay have adopted rental assistance–although with distinct policy designs–making Chile's experience particularly relevant for understanding rental assistance in middle-income settings where rental demand among low-income families is growing (Blanco, Cibils and Miranda, 2014).

Empirical evidence on rental voucher programs–primarily focused on the U.S. Housing Choice Voucher Program (HCVP)–finds that vouchers effectively reduce rent burden, crowding, and homelessness, but have limited success in improving neighborhood quality (Ellen, 2020; Mills et al., 2006; Wood, Turnham and Mills, 2008). In addition, there is causal evidence showing that rental voucher receipt reduced employment rates and earnings, and increased receipt of public assistance, including TANF, Medicaid, and Food Stamps (Jacob and Ludwig, 2012).

Modeled after the HCVP, the Chilean program subsidizes private-market rents for units that meet minimum quality standards and fall below a maximum allowable rent threshold. The program provides a fixed subsidy through two time-limited voucher schemes. First, the regular voucher for young families offers US$6,500 paid in fixed monthly installments of US$123 to cover rents up to the maximum allowable amount of US$353, over approximately four and a half years. Second, the elderly voucher offers a more generous subsidy for a shorter period–US$8,170 paid in fixed monthly installments that cover 95% of the threshold for two years–for individuals aged 60 or older. MINVU offers a form of partial rent insurance for landlords against short-run nonpayment by the voucher recipient.

The theoretical effects of rental vouchers on housing consumption, residential mobility, and homeownership applications are ambiguous. Standard consumer theory predicts vouchers expand budget sets and increase housing consumption, but actual improvements depend on how closely the maximum allowable rent threshold tracks prevailing rents, how landlords respond to payment standards, and enforcement of quality requirements. Families initially paying above the cap may reduce consumption (Collinson, Ellen and Ludwig, 2015; Olsen, 2003). Vouchers may reduce instability by insulating families from income shocks or increase moves if benefits encourage upgrading (Collinson, Ellen and Ludwig, 2015; Olsen, 2003). Effects on homeownership applications depend on whether reduced rent payments free resources for mandatory savings or instead reduce precautionary savings, and whether contact with housing authorities reduces application frictions. The more generous elderly voucher should generate larger effects due to minimal expected labor supply responses and shorter benefit duration, although lower baseline income and housing consumption among elderly applicants may attenuate differences.

Compared to the HCVP, which covers the gap between the maximum allowable rent and 30% of household income and maintains assistance conditional on income eligibility (Collinson, Ellen and Ludwig, 2015), Chile's fixed, time-limited voucher may broaden coverage and avoid labor supply disincentives (Jacob and Ludwig, 2012; Zhang, 2025). By setting national rather than city-level rent caps, it may enable landlords to raise rents to payment standards, reducing quality gains (Aliprantis, Martin and Tauber, 2020; Brewer et al., 2019; Chan and Fan, 2023; Collinson and Ganong, 2018; Gibbons and Manning, 2006; Hyslop and Rea, 2019; Phillips, 2017). Additionally, partial rent insurance may raise landlord participation and reduce housing instability during transitory shocks (Abramson and Van Nieuwerburgh, 2024) by shifting short-run default risk to the program. These design features make Chile's experience informative for voucher reform debates in both high- and middle-income countries.

Beyond program design differences, institutional disparities may affect voucher effectiveness (Colburn, 2021; Ross and Pelletiere, 2014). In Chile, the low-income rental market is small and highly informal. By 2017, only 16% of households in the bottom income quintile rented, and nearly half lacked formal lease agreements (National Socioeconomic Survey, 2017). These conditions likely exacerbate barriers during housing search, contributing to Chile's lower voucher utilization rate (45%) compared to the U.S. (60%) (Ellen, O'Regan and Strochak, 2024).

I use a Regression Discontinuity Design (RDD) exploiting Chile's rental voucher assignment mechanism to estimate causal effects separately for regular and elderly voucher schemes. During the study period, MINVU assigned available vouchers multiple times based on a discrete application score, granting them to families above specific cutoffs. In cases of score ties at the cutoff, MINVU implemented a three-step tie-breaking protocol that included randomization. Given the discrete application score is supported on a small number of mass points, I use the Local Randomization approach to RDD developed by Cattaneo, Idrobo and Titiunik (2019), as traditional local polynomial methods yield inconsistent treatment effect estimates, invalid inference, and problematic bandwidth selection under these conditions (Branson and Mealli, 2018; Díaz and Zubizarreta, 2023; Kolesár and Rothe, 2018).

The evaluation sample comprises 926 and 1,717 applicants immediately above and below the eligibility cutoff in regular and elderly rounds, respectively, between 2017 and 2019. Randomized voucher assignments account for 58% of the sample in regular rounds and 97% in elderly rounds. Pre-pandemic outcome data (December 2019) are obtained from administrative and public data sources, and follow-up outcomes during the COVID-19 pandemic are obtained via a survey implemented with MINVU in November 2020.

Pre-pandemic Intent-to-Treat (ITT) estimates show voucher receipt improved housing quality (more bedrooms and less crowding) and increased residential mobility but did not improve neighborhood characteristics, mirroring U.S. patterns despite design and institutional differences. Among regular recipients, vouchers increased bedrooms by 0.24 (14%), reduced overcrowding by 4.4 p.p. (37%), and increased the likelihood of relocating by 7.1 p.p. (17%). Among elderly recipients, bedrooms increased by 0.44 (33%), overcrowding decreased by 1.4 p.p. (47%), and residential mobility increased by 25.7 p.p. (76%). Recipients moved to neighborhoods similar to their control group counterparts–if anything, regular recipients moved farther from schools while elderly recipients relocated closer to municipal centers. Homeownership applications increased among elderly recipients but remained unchanged for regular recipients.

Heterogeneity analysis indicates that voucher effects depend critically on initial tenure and access to local housing authorities, not only on benefit generosity.

Post-pandemic outcomes–available only for regular recipients–show vouchers significantly helped families cope with the COVID-19 shock. Recipients were 15.3 p.p. (23%) less likely to increase debt and 10.9 p.p. (50%) less likely to miss rent payments, despite the partial rent insurance, suggesting no moral hazard. These findings underscore a previously underappreciated social insurance role of vouchers during economic distress.

This paper departs from most prior studies of rental vouchers, which focus primarily on the U.S. HCVP (Chetty, Hendren and Katz, 2016; Collinson, Ellen and Ludwig, 2019; Ellen, 2020; Jacob and Ludwig, 2012; Kling, Liebman and Katz, 2007; Mills et al., 2006; Pollakowski et al., 2022; Wood, Turnham and Mills, 2008). Related work examines rental assistance in other high-income countries (Brewer et al., 2019; Eerola and Lyytikäinen, 2021; Gibbons, Sanchez-Vidal and Silva, 2020; Hyslop and Rea, 2019) and in lower-income settings (Barnhardt, Field and Pande, 2017), although program designs differ substantially. In Latin America, the limited causal evidence focuses on homeownership programs, the main form of public housing in the region (Chagas and Rocha, 2019; Navarrete and Navarrete, 2016). Closest to this study, Barnhardt, Field and Pande (2017) evaluate a project-based rental housing program in India and find no improvements in socioeconomic outcomes or tenure security, alongside evidence of social isolation and reduced informal insurance. By studying fixed, time-limited vouchers, this paper provides evidence relevant for debates about rental assistance reform (Zhang, 2025). To my knowledge, this is also the first evaluation of rental vouchers targeted to elderly households, a population that has received limited attention despite representing a growing share of U.S. housing subsidy beneficiaries (Collinson, Ellen and Ludwig, 2015; Reina and Aiken, 2022).

This research also contributes to the growing literature on the role of rental assistance in promoting housing stability–defined as access to safe, stable, and affordable living conditions (Abramson, 2023; Abramson and Van Nieuwerburgh, 2024; DeLuca and Rosen, 2022; Ellen, O'Regan and Ganz, 2020; Fetzer, Sen and Souza, 2023). Prior empirical work, largely from pre-pandemic settings and focused on specific subgroups (homeless, welfare recipients, and public housing tenants) yields mixed results (Gubits et al., 2016; Sanbonmatsu et al., 2011; Wood, Turnham and Mills, 2008). In contrast, I examine the behavioral responses of families without prior housing assistance–the most typical voucher applicant–during a period of severe economic distress.

The remainder of the paper is organized as follows. Section 2 details policy design. Section 3 describes the data. Section 4 outlines the identification strategy and sample construction. Section 5 describes the evaluation sample. Section 6 presents the results. Section 7 concludes.

2 Policy Design

The *Subsidio de Arriendo* (Rental Subsidy), launched in 2013 by the Chilean Ministry of Housing and Urban Planning (MINVU), provides a fixed, time-limited subsidy for use in the private market, aiming to reduce overcrowding, improve access to better locations, and delay applications to homeownership subsidies among young families.

Chile administers two rental voucher schemes: regular rounds targeting young families and elderly rounds for adults aged 60 or older. Between 2017 and 2019–the analyzed period–MINVU received approximately 40,000 applications and awarded 23,000 vouchers, with 80% allocated through regular rounds. This is small relative to homeonwership subsidies; only in 2020, 40,000 homeownership subsidies were delivered.

Eligibility is based on a vulnerability index–the National Household Social Registry or RSH[1]–with the program targeting households in the bottom 70% of the distribution who are either renting or doubled up. Regular rounds target 18 or older-headed families with monthly income between 7 UF[2] (US$270) and 25 UF (US$900), with at least 4 UF (US$155) in private savings for home purchase; homeownership programs impose up to 40% higher minimum savings requirements. Elderly rounds of vouchers target individuals aged 60 or older, with monthly income above 3.8 UF (US$145), and require no savings.

Families may apply online or in person at any of the 52 local housing authorities (Housing and Urban Planning Service, or SERVIU).[3] To allocate vouchers to the most vulnerable families, MINVU calculates an application score using a complex formula. As the assignment mechanism is central to identifying causal effects, a detailed description is provided in the next subsection.

[1] Used for the provision of most social assistance. The index, administered by the Ministry of Social Development, is derived from survey and administrative data on educational attainment, income, expenses, health, food security, and living conditions. Families are categorized into 7 groups based on their position in the score distribution: below the 40th, 41st-50th, 51st-60th, 61st-70th, 71st-80th, 81st-90th, and 91st-100th percentiles.

[2] The inflation-indexed unit of account in Chile, adjusted daily based on changes in the Consumer Price Index.

[3] MINVU oversees administrative decisions, assigns vouchers, and pays rent to landlords. SERVIUs provide information, assist with application and lease validation, and coordinate housing inspections. Municipalities may also support application processes.

Voucher holders in regular rounds receive a total subsidy of 170 UF (US$6,500), paid in fixed monthly installments to cover rents up to the maximum allowable threshold, over four and a half years. The subsidy cannot exceed 80% of the monthly rent. Elderly recipients receive higher monthly benefits for a shorter period: 213 UF (US$8,170), paid in fixed monthly installments, covering up to 95% of the rent below the threshold, for two years.[4]

From 2017 to 2019, the regular monthly subsidy rose from 3 UF (US$114) to 3.2 UF (US$123) in February 2018 and to 4.2 UF (US$161) in December 2019. The maximum allowable rent amount–common to both voucher schemes–rose from 8.6 UF (US$330) to 9.2 UF (US$353) and then to 11 UF (US$422). For elderly recipients paying the cap, the monthly voucher increased from US$314 to US$401 (95% of the cap). These adjustments applied to both new and existing recipients upon updating their leases. Thresholds apply nationally except in 30 designated high-cost counties (out of 346), located in the far north and south, where thresholds are slightly higher. In these areas, the monthly subsidy increased from 3.5 UF (US$134) to 4.2 UF (US$161) and then to 4.9 UF (US$188), while the maximum allowable rent increased from 10 UF (US$384) to 12 UF (US$460) and then to 13 UF (US$499). Although the number of high-cost counties has increased over time, the core structure of the program remains unchanged, making the findings in this paper directly relevant to its current design.

A 2016 internal report by MINVU shows that the maximum allowable rent is often binding; it averaged 74% of the median rent, ranging from 52% to 128% across regional rental markets, with higher prices in the extreme north and south of the country. In contrast, under the HCVP, the maximum allowable rent is set at the city level, between 90% and 110% of the area's Fair Market Rent (FMR), updated annually (Collinson, Ellen and Ludwig, 2015). This rent cap is binding only during the first year of participation in the HCVP. Appendix Figure A.1 illustrates how Chilean and U.S. vouchers shift budget constraints.

Recipients have 24 months to begin using the voucher–four to twelve times longer than the lease-up period in the U.S. program (Collinson, Ellen and Ludwig, 2015)–and both schemes allow families to flexibly spread their monthly payments over an eight-year window. Minimum unit standards are consistent across voucher types. Eligible units must have three separated spaces, a residential use certificate issued by the municipality, and a Chilean tax registration number; additionally, the landlord must not be a member of the beneficiary's extended family. Families already in qualifying units may lease up in place, whereas applicants who do not initially meet requirements–i.e., those doubled up, in lower-quality hous-

[4]In elderly rounds, total subsidy and voucher vary slightly across RSH groups. The benefits described are those received by the most vulnerable group, which represents 99% of elderly applicants in the evaluation sample.

ing, paying above the rent cap, or renting from relatives–must relocate to use their vouchers. Therefore, voucher effects on out-of-pocket rent payments vary by initial tenure and housing quality.

Recipients generate a lease through an online platform, and if the landlord provides the necessary documentation, the process is typically quick. Unlike the HCVP, there is no rent negotiation with government officials, and unit inspections are rare. The voucher is activated once the tenant makes the first co-payment, after which MINVU transfers the full rent to the landlord.

The program includes a partial rent insurance: if a tenant misses the required co-payment, MINVU continues voucher payments to the landlord for up to three consecutive months—and for any number of additional nonconsecutive one- or two-month periods. If the tenant fails to pay for three consecutive months, the subsidy is terminated, although the landlord may not evict the family. By November 2022, approximately 10% of recipients from the 2017-2019 rounds who used their vouchers had a terminated lease with outstanding debt.

In 2019, the reported annual cost per active beneficiary was US$2,357 (transfers plus administration).[5] Administrative costs represented 5.8% of transfers, below other Chilean housing subsidies (9.7%) (Ministerio de Desarrollo Social, 2019).

2.1 Voucher Assignment Mechanism

Rounds remain open for two to nine months. During each round, MINVU assigns 1,000 to 3,000 rental vouchers every one or two months by screening applicants using an application score based on multiple data sources (Appendix Table A.1). In each applicant screening, vouchers are awarded to those with the highest scores.

MINVU uses a rolling application system. Applicants not selected in a screening are automatically rescreened together with new applicants in the subsequent assignment period. This process continues until a family receives a voucher or the round closes. To be reconsidered in a future round, applicants must reapply; only 15% do so.

The number of available vouchers and the timing and number of assignment periods are set by decree before each round opens, but both can be modified for administrative or political reasons outside the

[5] Computed as total expenditures on transfers and administration (US$28 million) divided by the number of beneficiaries actively using their vouchers (11,888).

control of the rental policy team. Importantly, such adjustments are not publicly announced. Of the three elderly rounds in the analysis period, two had a single assignment period, and the third added an unanticipated second period. In contrast, regular rounds had between two and seven assignment periods.

In 2017, a reform to the national vulnerability index used in MINVU's application score (Appendix Table A.1) transformed the continuous score into a categorical one. Total application scores became discrete–multiples of five–creating frequent ties at the cutoff. MINVU adopted a three-step tie-breaking protocol: (1) re-rank tied applicants using their family size score; (2) if needed, re-rank again using the vulnerability score–which generated the ties in the first place; and (3) if ties persist, randomly assign remaining vouchers among applicants with identical family size and social vulnerability scores. I do not rely exclusively on the randomized sample because of its small size in regular rounds, but I report results for this subsample as a robustness check in Section 6.3.

3 Data

This paper builds a unique data set by linking administrative, survey and public data from three different time periods: baseline (at application), December 2019 (pre-pandemic), and September-November 2020 (six to eight months after the COVID-19 outbreak).

Baseline data comprise administrative data from the RSH, the Civil Registry, and the Pension Fund Superintendency, along with self-reported information collected by MINVU to assess applicants' eligibility and calculate their application score. It includes applicants' socioeconomic, demographic, and housing characteristics, and geographic location.

I complement this data with an online survey, administered in partnership with MINVU, to all applicants in regular rounds between March 2017 and October 2019. The survey, conducted prior to the announcement of voucher assignment results, elicited information on residential mobility, housing and neighborhood experiences, as well as preferences and beliefs. The average response rate was 78%.

Also, I assembled a unique geocoded dataset combining location from multiple data sources provided by MINVU with baseline survey information. This data was linked to public geocoded records on municipalities, local housing authorities (SERVIUs), and county-level information–including poverty rates from the 2017 National Socioeconomic Household Survey (CASEN), and density from the 2012 Census. Finally, MINVU supplied administrative data on household applications to the two largest homeownership

programs, *Fondo Solidario de Vivienda (DS49)* and *Subsidio Clase Media (DS1)*. While DS49 provides fully funded housing for the most vulnerable families, DS1 offers partial funding to less vulnerable families, with a down payment that decreases with house price and household income.

Pre-pandemic outcomes draw on administrative records from RSH data updated in December 2019. The data include unit characteristics (number of bedrooms), household composition (size, gender of the household head), and location. In addition, MINVU provided updates through December 2019 on applications to DS1 and DS49 and on the status (active or inactive) of private savings accounts required for homeownership applications. I also construct neighborhood variables by linking applicant location in 2019 to geocoded data on schools, healthcare centers, and county-level assault, robbery, theft, and poverty rates.

In partnership with MINVU, I implemented a follow-up survey between September and November 2020 to construct pandemic outcomes. The survey elicited information on housing and neighborhood characteristics, satisfaction, income, employment, household composition (size and marital status), and behavioral responses during the first eight months following the COVID-19 outbreak. It also included retrospective questions regarding residential mobility, which I used to complement and asses the quality of pre-pandemic outcomes. Appendix D provides an English translation of the questionnaire items used to build the COVID-19 outcomes.

The survey was conducted during Chile's COVID-19 response, which combined broad cash support and job protection for vulnerable households with targeted housing relief for the middle class. Beginning in April 2020, low-income households received cash transfers (US$80 per household member in May 2020, with two additional allowances distributed after survey data collection), in-kind food assistance, and access to unemployment insurance benefits and a temporary wage subsidy for formal workers. All benefits were tied to the RSH and thus available to both voucher and non-voucher holders.[6]

Housing-specific policies included a temporary moratorium on utility disconnections (with arrears prorated over future bills) and 150,000 three-month rent subsidies for middle-income households (covering up to US$330 per month for rents up to US$800). Although targeted to the middle class, existing voucher recipients could apply. However, take-up among voucher holders was limited given higher income and housing-quality requirements; according to MINVU officials, applications in the first few months totaled

[6]Liquidity was further expanded through three extraordinary pension fund withdrawals and middle-class grants/soft loans. The first withdrawal occurred in August 2020, although voucher applicants were unlikely to have sufficient pension funds to access it. The remaining two withdrawals occurred after survey data collection.

only about 25,000 nationally. MINVU also granted temporary extensions for voucher expiration in 2020: unused vouchers set to expire received an additional 12 months, and subsidies fully utilized by 2020 were extended by six months. These changes are unlikely to affect the main analysis since they applied to earlier voucher cohorts than those included in this study.

4 Identification Strategy

I exploit exogenous variation in voucher assignment from surpassing the score cutoff $X_i > c$ and actual randomization at the cutoff within screening $s_t \in S$ across 2017-2019 rounds to estimate causal treatment effects of the rental voucher program using a sharp multi-cutoff Regression Discontinuity Design (RDD). The design mimics a stratified quasi-random assignment conducted sequentially, with each screening s_t forming a strata within which applicants at the cutoff are independently assigned to treatment or control. Figure I shows the distribution of application scores by round type, pooling all applicant screenings s_t.

In the Chilean rental voucher program, the running variable is discrete, with the number of mass points varying across screenings (Section 2.1). In regular rounds, it ranges from 20 to 119 mass points per screening, and in elderly rounds varies from 22 to 92 mass points per screening.[7] When the running variable has few mass points, continuity-based methods yield inconsistent estimates, invalid inference and bandwidth selection (Branson and Mealli, 2018; Cattaneo, Idrobo and Titiunik, 2019; Díaz and Zubizarreta, 2023; Kolesár and Rothe, 2018).[8] I therefore adopt the Local Randomization Approach to Regression Discontinuity Design (LRRD), developed by Cattaneo, Idrobo and Titiunik (2019).[9]

4.1 Local Randomization Approach to RDD

The LRRD assumes that within a narrow window $W = [c - e, c + e]$, treatment (D_i) is as good as randomized. Within W, the distribution of the forcing variable is assumed to be known and the same across units, satisfying score ignorability, i.e., that potential outcomes depend on the score only through

[7] Appendix Tables A.2 and A.3 show the number of mass points per screening and Appendix Figure A.2 presents the distribution of normalized scores for screenings included in the evaluation sample.

[8] Let $Y_i(1)$ and $Y_i(0)$ be the potential outcomes under treatment and control, and let $D_i = D_i(X_i) = I(X_i \geq c^*) \in \{0,1\}$ be the treatment indicator. The observed outcome for individual is $Y_i = D_i Y_i(1) + (1 - D_i)Y_i(0)$. The continuity assumption implies that regression functions $\mathbb{E}\{Y_i(1)|X_i = 0\}$ and $\mathbb{E}\{Y_i(0)|X_i = 0\}$ at the cutoff ($X_i = 0$) can be used to approximate the average outcome that units just above the threshold would have experienced in the absence of treatment. The average treatment effect at the cutoff is $\tau_{Cont} = \mathbb{E}\{Y_i(1) - Y_i(0)|X_i = 0\} = \lim_{x \downarrow c} \mathbb{E}\{Y_i(1)|X_i = 0\} - \lim_{x \uparrow c} \mathbb{E}\{Y_i(0)|X_i = 0\}$ (Lee and Lemieux, 2010). However, when the running variable is discrete, the specification bias in the average treatment effect ($\mathbb{E}\{Y_i(0)|X_i = c\} - \mathbb{E}\{Y_i(0)|X_i = c_k\}$) is no longer negligible at the cutoff.

[9] See Branson and Mealli (2018) for a review of alternative RDD estimation methods.

treatment: $Y_{i\in W}(X_{i\in W}, D_{i\in W}) = Y_{i\in W}(D_{i\in W})$. The design also requires no interference across units (SUTVA). While interference could occur through neighborhood spillovers or market interactions, this seems unlikely given the small program size and broad geographic distribution of applicants within each screening.

Under LRRD, causal treatment effects (τ_{LRRD}) can be identified without parametric modeling assumptions–as in an experimental setting–as $\tau_{LRRD} = \bar{Y}_{i\in W}(1) - \bar{Y}_{i\in W}(0) \approx$
$\mathbb{E}\{Y_i(1) - Y_i(0)|X_i \in W\}$. Similar to the standard continuity approach, the key step in LRRD is selecting a valid W where i) treatment is plausibly randomized i.e. there is no manipulation of the score, and ii) treatment and control groups are balanced on pre-treatment covariates.

Manipulation in the LRRD is tested using a binomial test of the treatment assignment probability in a narrow window around the cutoff (Cattaneo, Idrobo and Titiunik, 2019). If applicants cannot manipulate their score precisely, treatment probability q should be consistent with the assumed assignment mechanism (complete randomization) within this window. Appendix Table A.4 shows that the observed treatment probability does not differ significantly from $q = 0.5$, consistent with non-manipulation, which would require anticipating voucher availability, one's own score, and the entire score distribution–highly unlikely in this setting.

In order to use the LRRD, groups at both sides of the cutoff in W must be balanced. Specifically, I use the data-driven window selection procedure developed by Cattaneo, Idrobo and Titiunik (2019), that identifies the largest window around each cutoff where LRRD conditions hold by testing for balance in pre-treatment covariates across treated and control applicants in progressively larger windows. The selected W is the largest window where the minimum p-value from balance tests remains above a predetermined significance threshold ($\alpha = 10\%$).

4.2 Window Selection

I replicate the voucher assignment process for each applicant screening s_t conducted between March 2017 and September 2019.[10] The initial dataset includes 95,553 observations corresponding to 56,715 unique applicants across 82 screenings in 21 assignment periods, spanning eight rounds. Columns 1 to 5 of Appendix Tables A.2 and A.3 summarize the number of participants, score ranges, available vouchers, and cutoffs per screening.

[10]The rolling application system implies that some individuals are screened multiple times, only within the same round (Section 2).

After two data restrictions excluding 57,074 observations (31,317 applicants), the final sample for window selection comprises 38,847 observations (32,789 applicants) across 12 screenings–seven in regular and five in elderly rounds–spanning nine assignment periods from 2017 to 2019. Appendix C details sample construction.

I apply the data-driven window selection procedure separately for each applicant screening s_t, yielding screening-specific windows W_{s_t}. I test for balance in multiple pre-treatment covariates, including variables that did not enter the application score formula directly. These additional covariates were created using administrative data from other government agencies or departments within MINVU, or were obtained from survey and geocoded data not observed by MINVU officials during voucher assignment.

Following Cattaneo, Idrobo and Titiunik (2019), I split pre-treatment covariates into two sets: the first set to select W_{s_t} and the second set for additional falsification tests within s_t. The first set includes pre-treatment variables that vary within screenings[11] and are observed for the full sample: family income, gender, tenure type–and whether tenure is missing–, household poverty status (based on income per capita)[12], prior application to homeownership programs, and an indicator for non-missing geolocation. Additional round-specific variables include savings, online application, and local housing authority (SERVIU) presence in the county (regular rounds), and marital status (elderly rounds).

The second set includes indicators for Chilean nationality, prior applicants within 500 meters, housing quality (number of bedrooms, crowding indicator, and shelter type[13]), household size, county-level poverty, county-level density, five macro-regional dummies, distance to nearest SERVIU office, and an indicator for applications to previous rounds of the program. Round-specific variables include an indicator for participating in multiple screenings within the same round, age range (25-35), marital status, housing costs (rent for tenants or amount paid for doubled-up families), rent burden–total housing costs divided by family income–baseline survey response, and survey-based measures of housing satisfaction and preference to stay in place (regular rounds), as well as age range indicator (70-79) and SERVIU county-presence (elderly rounds). Variables in both sets are correlated with voucher utilization, housing and neighborhood outcomes, and household pandemic response.

[11] In some screenings, certain covariates are constant within the smallest window around cutoff: overcrowding, marital status, and low-quality housing (April 2018 regular); nationality, overcrowding, baseline survey response, and low-quality housing (October 2019 O'Higgins and Los Lagos regular).

[12] According to the 2017 CASEN, the poverty line adjusted by family size was US$210, US$342, US$455, US$556 for a family of one, two, three, and four, respectively. The national poverty rate was 8.6%.

[13] Formal (house or apartment) or informal (informal settlement, room, or other).

Eight windows W_{s_t} are selected using these covariates and the *rdwinselect* Stata package, and then aggregated into the evaluation sample W_0.[14] Section 5 presents balance tests and characterizes the treatment and control groups.

4.3 Empirical Specification

Causal treatment effects for outcome Y of applicant i in screening s_t within W_0 are estimated using:

$$Y_{i,s_t} = \alpha + \tau_{LRRD} D_{i,s_t} + Z'_{i,s_t}\beta + \gamma_{s_t} + \epsilon_{i,s_t} \tag{1}$$

Where D_{i,s_t} is an indicator of voucher assignment (treatment indicator) ($X_{i,s_t} > 0$), γ_{s_t} are dummies for each applicant screenings s_t which absorb time- and cutoff-specific heterogeneity across s_t, and Z_{i,s_t} is a subset of baseline covariates used for window selection.[15]

The parameter of interest, τ_{LRRD}, is the Intent-to-Treat (ITT) effect of voucher assignment. Specifically, τ_{LRRD} is the weighted average of s_t-specific ITT effects. This is the reduced form estimate using the discontinuity in voucher assignment as the instrument. Figure II shows the first stage: a sharp discontinuity in voucher assignment at the score cutoff, using normalized scores in each screening to have a cutoff $c_{s_t} = 0$.

While I focus on ITT estimates, I present Local Average Treatment Effects (LATE) in Section 6. Since compliance is one-sided–the control group cannot receive the voucher–LATE corresponds to ITT estimates scaled by the estimated compliance rate (Angrist and Pischke, 2008).

The sample only includes screenings in which the control group has never-treated–i.e., s_t with no later treated near the cutoff (Appendix C). Hence, τ_{LRRD} is the effect of voucher receipt relative to never receipt, rather than the effect of holding the voucher for a longer period of time. While also interesting, I do not have the power to estimate both effects separately.

[14] Nine windows were initially selected using the first set of covariates. Additional balance tests within s_t using the second set led to two adjustments: (1) narrower windows for April 2018 and October 2019 regular screenings in O'Higgins–originally $[-5,5]$ and $[-15,10]$, respectively–and (2) the exclusion of the July 2019 elderly screening in Santiago. In total, 303 observations were dropped from the sample.

[15] Income, and dummy variables for SERVIU presence in the county, high poverty county, female, Chilean nationality, family poverty status, age range, married, macro-regional dummies, non missing geocoded data, tenant, baseline crowding and unit quality, previous voucher recipients within 500 meters, and previous rental voucher and homeownership applications. Online application, savings for home purchase, baseline survey response, and multiple screening participation are included in regular rounds only.

Because each screening s_t occurs at a different point in time–with a distinct cutoff–disentangling variation across cutoffs (i.e., social vulnerability) from differences in policy exposure is nontrivial. In Section 6.4 I exploit voucher random assignment at the cutoff to explore heterogeneity across different groups of applicants through the following specification:

$$Y_{i,s_t} = \alpha + \delta_{g_0} D_{i,s_t} + \sum_{g \in \mathcal{G}} \delta_g \left(D_{i,s_t} \times Group_{ig} \right) + Z'_{i,s_t} \beta + \gamma_{s_t} + \varepsilon_{i,s_t} \tag{2}$$

where $Group_{ig}$ are pre-treatment subgroup indicators, δ_{g_0} is the treatment effect for the omitted subgroup g_0, and δ_g captures differences in treatment effects relative to g_0.

5 Evaluation Sample

Tables I and II summarize the selected windows by voucher type, reporting the assignment period, region, cutoff, sample size, number of treated and control units, minimum p-value from balance tests, and the normalized score range in each W_{s_t}.

The evaluation sample W_0 includes 2,643 observations from 2,622 unique applicants: 926 observations (910 applicants) from 5 regular screenings and 1,717 observations (1,712 applicants) from 3 elderly screenings. The maximum window length is $[-15, 15]$ in regular and $[-5, 5]$ in elderly rounds. The 2017–2018 samples include national screenings and 2019 screenings are concentrated in southern regions for regular and in central regions for elderly rounds. Randomized assignment accounts for 58% of the regular and 97% of the elderly sample.

5.1 Balance

Given limited within-screening variation in some pre-treatment covariates, I assess overall balance between treatment and control groups in the evaluation sample using two regression models corresponding to distinct hypothesis tests: (1) a weaker test of the null hypothesis that covariate differences average to zero across screenings, and (2) a stricter test of the null that covariate differences are zero across screenings (Young, 2019). These tests are estimated as follows:

$$X_{i,s_t} = \alpha + \sum_s \gamma_{s_t} \times \mathbf{1}\{s_t = s\} + \delta D_{i,s_t} + \epsilon_{i,s_t} \tag{3}$$

$$X_{i,s_t} = \alpha + \sum_s \gamma_{s_t} \times \mathbf{1}\{s_t = s\} + \sum_s \delta_{s_t} \times D_{i,s_t} \cdot \mathbf{1}\{s_t = s\} + \epsilon_{i,s_t} \tag{4}$$

Where X_{i,s_t} includes both sets of baseline covariates, D_{i,s_t} is the treatment indicator, γ_{s_t} denotes a set of screening indicators, δ denotes the pooled treatment effect, and δ_{s_t} the screening-specific treatment effect. Tables III and IV present the results. Columns 7 and 8 report the first test–whether δ in equation 3 is zero–and Columns 9 and 10 report the second test–whether all δ_{s_t} in equation 4 are jointly zero. The bottom panel presents joint significance tests from a regression of treatment on pre-treatment covariates available for the full sample, using both large-sample and randomization-based inference.

Treated and control units are balanced on key pre-treatment characteristics not used in voucher assignment. Differences are small and generally not statistically significant, and joint tests fail to reject the null of balance. Additionally, treatment effects in Section 6 remain stable after controlling for these covariates, which is consistent with balanced treated and control groups. Appendix Table A.5 presents differences in score components and total scores between the treatment and control groups within W_0. Differences are small, especially in elderly rounds. Based on the score formula in Appendix Table A.1, the observed differences are minimal for program eligibility.

5.2 Descriptive Statistics

Columns 4 and 5 of Tables III and IV present descriptive statistics for regular and elderly voucher holders in the evaluation sample. In regular rounds, the evaluation sample comprises applicants who are predominantly Chilean (97%), female (91%), and single (88%), with 65% aged 25-35. Most rent (77%), with average family income of 13.19 UF (US$516). About 15% have previously applied for a homeownership subsidy. Applicants live in high-poverty counties but report low housing vulnerability: 6% in an informal shelter, although initial housing quality relative to the minimum quality standard is unknown.

Average housing costs–available only from late 2018 for regular rounds–were 5.24 UF (US$205), with rent burden at 51%. Among tenants, only 4% had rents above the maximum allowable rent, suggesting the rent cap was non-binding for most recipients and there was potential room for quality improvements. A majority expressed housing satisfaction (66%) and a preference to remain in place (56%).

In elderly rounds, the sample is more evenly split by gender (61% female), marital status (43% with a spouse), and age (41% aged 60-75). Average family income is lower than among regular applicants at 5.43 UF (US$212), and only 5% have previously applied for homeownership subsidies. These voucher holders live in worse housing conditions as they are more likely to reside in informal shelters. They also tend to live in less poor counties and in closer proximity to a local housing authority than younger

voucher holders.

Voucher utilization varies across voucher scheme and, within schemes, by region and cohort. Appendix Table A.6 shows average lease-up rates by screening in December 2019, March, and November 2020. In regular screenings, lease-up was 29% by December 2019 and rose to 49% by November 2020. In elderly screenings, average lease-up remained stable at 54% through November 2020. Higher lease-up rates among elderly recipients are consistent with both more generous voucher and informal institutional support: interviews indicate SERVIU officials often help elderly recipients engage with landlords who contact SERVIU seeking tenants.

5.3 External Validity

Multiple cutoffs can mitigate the local nature of RDD estimates by averaging treatment effects across the score distribution (Cattaneo et al., 2016). To assess external validity, I compare recipients in W_0 to all recipients in the eight screenings s_t included in W_0. Descriptive statistics in Appendix Tables A.7 and A.8 show that while W_0 includes recipients with lower application scores, both groups have similar income, demographics, bedrooms, tenure type, access to local housing authorities, exposure to prior applicants within 500 meters, and prior rental voucher and homeownership applications. Among regular recipients, groups are also similar in baseline survey response, online application rate, housing cost burdens, housing satisfaction, and preference to remain in place. However, recipients in W_0 have lower housing vulnerability score. In particular, they are 11-14 p.p. more likely to live in formal shelters. Among regular rounds, recipients in the W_0 are also less crowded.

This may limit external validity of housing consumption effects, as households in W_0 could experience smaller consumption gains than more vulnerable recipients. However, similar utilization rates across families with varying housing vulnerability and low baseline rents (Section 5.2) suggest substantial room for quality improvements despite lower measured vulnerability.[16] Similarities in bedrooms, tenure type, and housing satisfaction further suggest compositional differences may not substantially affect program effectiveness.

The COVID-19 policy response (Section 3) could also limit external validity. Because both groups received pandemic support, estimated voucher effects represent impacts relative to government assistance rather than no support, potentially underestimating effects during non-aggregate shocks (job loss or child-

[16] By November 2020, lease-up rate among regular recipients were 53% for those with zero housing vulnerability score and 48% for those with positive scores. Among elderly recipients, rates were 56% and 54%, respectively.

birth). Importantly, most voucher holders leased up before March 2020 (Appendix Table A.6), limiting differential pandemic effects on housing search.

6 Results

This section presents the causal effects of the rental voucher program. For December 2019, outcomes include housing and neighborhood characteristics, household composition (household size and probability of a female household head), residential mobility, and application to homeownership programs. For November 2020, the analysis focuses on housing and neighborhood characteristics, and broader socioeconomic impacts, including income, employment, and how families coped with the shock induced by the pandemic.

Tables V and VI present Intent-to-Treat (ITT) effects–τ_{LRRD} in equation 1–estimated before the pandemic (December 2019), separately for regular and elderly rounds. Table VII presents corresponding ITT effects during the COVID-19 pandemic (November 2020). Each table reports the counterfactual mean and standard deviation (Column 2); estimates of τ_{LRRD} with standard errors clustered at the individual level (Column 3); p-values from OLS estimation (Column 4); randomization-based p-values (Column 5); and Romano-Wolf p-values adjusting for multiple hypothesis testing (Column 6).[17] Column 3 corresponds to my preferred specification, which includes baseline covariates Z_{i,s_t} used in balance tests (Section 4.3). Appendix Tables A.9, A.10, and A.11 present estimates excluding these covariates (Column 4) and show that including them yields efficiency gains and has minimal impact on the coefficients.

I focus primarily on ITT estimates–the effect of voucher assignment–throughout the analysis. However, Column 6 in Appendix Tables A.9, A.10, and A.11 show Local Average Treatment Effects (LATE) using two-stage least squares estimates (2SLS), employing the discontinuity at the cutoff as an instrument for voucher utilization. As described in Section 5, LATE are larger than ITT estimates, reflecting partial compliance with voucher assignment.

The next subsections present the main findings grouped by outcome categories.

[17] The randomization-t exact test developed by Young (2019) is implemented using the Stata package *randcmd*, and Romano-Wolf p-values are computed using *rwolf* by Clarke, Romano and Wolf (2020). In both cases, I use 1,000 iterations and re-randomize the data by screening of applicants, as in a stratified experimental design.

6.1 Results in December 2019

6.1.1 Housing and neighborhood characteristics before COVID-19 pandemic

Among the control group, overcrowding almost doubled between application and December 2019 in regular rounds–rising from 7% to 12%–and more than doubled for elderly households, although it remained low at 3% (Column 2 in Tables V and VI). Voucher receipt significantly increased the number of bedrooms and reduced crowding for both round types. In regular rounds, voucher recipients had 0.24 additional bedrooms (14% increase relative to the control group) and 0.16 (9%) fewer people per bedroom, reducing overcrowding by 4.5 percentage points (p.p.) (38%). In elderly households, recipients had 0.44 (33%) additional bedrooms and 0.30 (24%) fewer people per bedroom, reducing overcrowding by 1.4 p.p. (47%), although the latter is not statistically significant (Rand-t p-value=0.133). Given rising counterfactual crowding trends, preventing overcrowding deterioration represents an important program benefit.

Among elderly recipients, the reduction in crowding reflects both an increase in bedrooms and a decrease in household size (-0.156). In contrast, for regular voucher holders the reduction is driven primarily by an increase in the number of bedrooms, with no significant change in household size (coefficient is positive (0.119), yet not statistically significant). Effects on the probability of a female household head have opposite signs across rounds–positive for elderly and negative for regular recipients–but are not statistically significant in either round.

The improvement in housing conditions was not matched by improved access to higher-quality locations. Tables V and VI report treatment effects on seven neighborhood quality outcomes measured as of December 2019: (i) access to early childhood educational institutions and (ii) access to schools, both measured by the distance (km) to the closest institutions; (iii) school quality, proxied by the average math and language standardized test scores of nearby schools[18]; (iv) access to health care, measured by the distance to primary care centers and hospitals; (v) distance to the closest municipality, which tend to be in denser areas with more commercial activity; (vi) county-level poverty; and (vii) safety, measured as the county-level share of individuals 18 years or older who reported being victims of assault, robbery, or theft in police records. All outcomes are expressed as standardized z-scores.

The voucher did not affect overall neighborhood quality but did influence specific neighborhood char-

[18]Based on the three closest (pre)schools within a one-kilometer radius, or the closest available if no (pre)schools exist within this distance.

acteristics, with important differences across rounds. In regular rounds, voucher receipt increased the distance to early childhood education centers by 0.210 standard deviations and to schools by 0.248 standard deviations, with no significant change in school quality. These effects correspond to an average increase of 0.43 and 0.41 kilometers relative to the counterfactual, respectively. Among elderly recipients, voucher receipt reduced the distance to a municipality by 0.102 standard deviations–an average reduction of 0.8 kilometers–suggesting increased relocation to denser areas with greater commercial activity. However, this effect is not statistically significant after adjusting for multiple hypothesis testing (Romano-Wolf p-value=0.159). Effects of voucher receipt on crime, poverty, and health care access are not statistically significant in either voucher scheme.

6.1.2 ***Residential mobility before COVID-19 pandemic***

Regular voucher receipt increased residential mobility–measured by an indicator for nonzero distance between baseline and December 2019 location–by 7.3 p.p. (17%) and led to relocation farther from origin. Voucher holders were 7.7 p.p. (11%) less likely to remain within one kilometer, 6.2 p.p. (52%) more likely to move more than ten kilometers, and 5.9 p.p. (84%) more likely to relocate across county boundaries.

Elderly recipients show larger effects: 25.7 p.p. (76%) more likely to relocate to a different housing unit, 19.4 p.p. (26%) less likely to stay within one kilometer, 8.4 p.p. (76%) more likely to move more than ten kilometers, and 5.5 p.p. (61%) more likely to move to a different county. These effects are substantial relative to national residential mobility rates for low-income families, indicating high housing-mobility pressures among program applicants.[19]

Taken together, both voucher schemes increased within-unit housing consumption and residential mobility but did not improve access to better neighborhoods. The substantially more generous elderly voucher generates modestly larger impacts, although baseline differences between regular and elderly recipients (Section 5.2) make it impossible to isolate the effect of subsidy generosity alone. Section 6.4 examines heterogeneity across applicants with varying initial tenure and varying local market conditions to explore underlying mechanisms.

[19] According to the 2018 National Survey on Urban Quality of Life, only 9% of individuals in the lowest socioeconomic groups in urban areas aged 30-59, and 2.5% of those aged 60 or older, moved over the previous two years. In contrast, 43% of untreated regular applicants and 34% of untreated elderly applicants in the voucher evaluation sample moved between application and December 2019 (Column 2 in Tables V and VI).

6.1.3 *Homeownership applications before COVID-19 pandemic*

One explicit policy goal of the rental voucher program was to discourage applications to homeownership programs, especially by younger families. However, theoretical effects of the voucher on applications to other housing programs are ambiguous, depending on its impact on labor supply, savings capacity, and application frictions. Among the control group, applications doubled between application and December 2019: from 15% to 31% among regular applicants and from 6% to 12% among elderly applicants (Column 2 in Tables V and VI).

The voucher did not reduce applications to homeownership subsidies. Voucher assignment had no significant effect on applications to any major homeownership programs or on the likelihood of maintaining an active savings account for homeownership among regular voucher holders. However, it increased applications by 4.8 p.p. (40%) among elderly recipients, driven primarily by a significant rise in applications to the fully subsidized program targeting most vulnerable households–*Fondo Solidario* (DS49)–which typically provides housing on the urban periphery (Blanco, Cibils and Miranda, 2014).

These results suggest the more generous elderly voucher expanded savings capacity and/or reduced application frictions, whereas the smaller voucher for younger households did not. Section 6.4 examines heterogeneity by access to local housing authorities and initial tenure.

6.2 Results from November 2020

This section presents treatment effects (τ_{LRRD} in equation 1) using the subset of the evaluation sample who responded to the online survey conducted between September and November 2020. Appendix D describes the questions included in the survey.

The survey was sent to 716 unique regular applicants in the evaluation sample (W_0) with valid email addresses, 65% of whom responded. The follow-up sample includes 465 unique applicants (corresponding to 496 observations): 282 in the control group and 183 in the treatment group. I focus on regular vouchers due to the small number of elderly applicants who responded; only 37% of those in W_0 had valid email addresses, with a 38% response rate.

I find no evidence of selective attrition in the follow-up survey data.[20] Compared to the full sample, the

[20] Appendix Tables C.1 and C.2 show that voucher assignment did not affect response rates and that treatment and control groups remained balanced on baseline covariates. This supports the validity of the local randomization assumptions in this subset of the evaluation sample.

counterfactual mean and estimated treatment effects are similar, although some point estimates are not statistically significant in the smaller sample.[21]

I first present effects of voucher assignment on housing and neighborhood characteristics and then the impact on household behavioral responses during the COVID-19 pandemic. Table VII presents ITT effects and Table A.11 presents LATE estimates. Estimates remain stable with and without baseline controls, further suggesting no selective attrition.

*6.2.1 **Housing and neighborhood characteristics post COVID-19 pandemic***

Table VII examines housing and neighborhood characteristics during the pandemic period, including satisfaction measures and housing consumption indicators such as heating systems, Wifi, and cable TV. The voucher did not affect total rent levels–suggesting that overall housing quality remained unchanged–while reducing out-of-pocket rent payments by 10 p.p. (21%). In addition, the voucher improved several specific housing features. Voucher holders were 14.6 p.p. (19%) more likely to have an independent kitchen–a program housing quality requirement–and 9.3 p.p. (12%) more likely to have some form of heating in their homes, while access to cable TV and WiFi remained unchanged.

The absence of changes in total rent and improvements in specific housing features suggests that, unlike in HCVP, landlords in Chile did not widely respond to the regular voucher by matching rents to program rent caps during the period of analysis, despite the nationally fixed rent payment standard (Collinson and Ganong, 2018).[22]

The effect on crowding remains negative (-3.5 p.p., a 32% decrease) but is not statistically significant. In addition to power limitations in this smaller sample, the number of bedrooms increased among the control group between December 2019 and November 2020–from 1.96 (Appendix Table C.3) to 2.24–suggesting non-recipients also moved to larger units. However, voucher holders moved faster and achieved higher overall housing consumption, as evidenced by greater access to independent kitchens and heating systems. The smaller effect on crowding may also reflect changes in household composition: voucher receipt seemed to increase the likelihood of living with a partner by 8.9 p.p. (28%) and of having others move in due to the pandemic by 4.9 p.p. (82%) (Rand-t p-values=0.086 and 0.131, respectively), although these effects are not statistically significant after adjusting for multiple hypothesis testing (Romano-Wolf

[21] Appendix Table C.3 replicates Table A.9 using pre-pandemic outcomes of survey respondents.

[22] Appendix Figure A.3 is consistent with this: there is no bunching at the rent cap in the distribution of total monthly rent among voucher recipients who leased by November 2020.

p-values=0.294 and 0.170, respectively).

To measure treatment effects on neighborhood outcomes, I constructed two neighborhood quality indices (z-scores): one capturing the number of accessible amenities within a four-block radius of the home and another reflecting the number of disamenities in respondents' self-identified neighborhoods. Amenities include childcare, schools, public transportation, and primary care, whereas disamenities encompass drug dealing and consumption, destroyed properties, graffiti, gang fights, armed violence, public alcohol consumption, and prostitution. The voucher did not affect either index.

Improvements in housing conditions without corresponding gains in neighborhood characteristics are reflected in modest changes in satisfaction: a 7 p.p. (9%) increase in housing satisfaction (Rand-t p-value=0.074) and a 4 p.p. (5%) decrease in neighborhood satisfaction (Rand-t p-value=0.277), neither statistically significant after accounting for multiple hypothesis testing.

The voucher increased residential mobility–having lived in the unit for less than two years–by 12.7 p.p. (27%) as of November 2020. Recipients were also 10 p.p. (35%) less likely to report they could ask neighbors for childcare help. These findings are consistent with prior evidence that rental vouchers improve housing conditions but do not improve access to higher-opportunity neighborhoods for low-income families (Ellen, 2020), and that rental policy in low-income settings may increase social isolation (Barnhardt, Field and Pande, 2017).

I cannot separately identify longer-term voucher impacts from broader pandemic effects. However, as explained in Section 3, no policies differentially helped the control group (pushing down the true long-term effect) or the treatment group (pushing up the true long-term effect). Moreover, while the pandemic could have differentially affected housing search across groups, most families who used the voucher in the period of analysis had already leased up by March 2020 (Appendix Table A.6). I now examine whether the voucher helped families cope with the aggregate COVID-19 pandemic shock.

6.2.2 ***Household behavioral responses during COVID-19 pandemic***

The survey elicited information on the magnitude of the shock and the strategies that families employed to cope. The data reveal a substantial negative impact of the pandemic: 80% of non-voucher holders in the sample experienced partial or total household income loss, 18% were temporarily unemployed, and 95% resorted to extraordinary measures to adapt to the new circumstances. Common strategies included reducing food expenses (57%), relying on emergency support (57%), using household savings (49%),

and missing monthly bill payments (44%)–including rent payments (22%) (Column 2 in Table VII).

I examine voucher effects on household income, individual employment, and the reported employment and income losses due to COVID-19. By November 2020–between one and two-and-a-half years after voucher assignment–the fixed monthly voucher had small, statistically insignificant effects on employment (-3.2 p.p. or 4.5%; Rand-t p-value=0.526) and monthly household income (US$12 or 2.5%; Rand-t p-value=0.610), consistent with null effects on the marginal income tax rate from fixed-benefit design (Jacob and Ludwig, 2012).

The rental voucher did not prevent income loss during the pandemic, nor did it reduce temporary unemployment, although it changed how families coped with the negative shock.

I group behavioral responses into five categories and create indicator variables equal to one if respondent engages in any strategy within each category: (i) new income generation (cash from sales or new remunerated activity), (ii) increased debt (via formal or informal loans, or missed bill payments), (iii) reduced expenses on food, healthcare, or utilities, (iv) emergency support application, (v) residential adjustments (moving out, others moving in, missing rent payments). I report these three residential responses separately to further understand voucher impacts on housing instability. Table VII presents the results.

Voucher holders were less likely to face financial distress and housing instability: they were 15.1 p.p. (23%) less likely to increase debt–also 12.3 p.p. (18%) less likely to experience debt overload–and were 10.8 p.p. (49%) less likely to miss rent payments. Point estimates suggest beneficial effects on generating new income (-4 p.p. or 9%; Rand-t p-value=0.561), applying to emergency support (-7 p.p. or 12%; Rand-t p-value=0.243), or moving out of their homes (-3.3 p.p. or 47%; Rand-t p-value=0.230), although none are statistically significant. Voucher receipt also increased the likelihood of having a formal lease by 11.6 p.p. (19%), potentially offering additional protection against eviction during the pandemic. These results are consistent with the voucher's impact on housing affordability and null effect on employment or household income.

The reduction in missed rent payments and debt relative to the control group suggests the partial rent insurance did not undermine precautionary savings. Administrative data on rent co-payments–available for the subset of recipients who used their vouchers–indicate that overall rent co-payment behavior remained stable during the first eight months of the pandemic, with no increase in delayed or skipped payments.[23]

[23] Appendix Figure A.4 shows the likelihood of skipping rent payments, timing, and co-payment method in regular rounds before and after the pandemic. Payment delays in July 2020 appear to reflect a change in method.

Voucher impacts on financial stability may reflect not only increased affordability through lower out-of-pocket rent, but also shifted preferences toward housing stability and greater risk aversion during a period of heightened uncertainty.

These findings highlight a previously underappreciated social insurance role of rental vouchers during economic downturns, limiting the need to take on additional debt and helping stabilize housing conditions for low-income families.

6.3 Robustness Checks

I test whether the results are robust to the choice of the window or bandwith used to define the evaluation sample. Specifically, I estimate treatment effects for the pre-pandemic period using the smallest window around the cutoff ($W = [-1, 1]$), including only the randomized sample.

The randomized sample includes 539 regular applicants and 1,672 elderly applicants. Appendix Tables A.12 and A.13 assess balance between treatment and control groups within this subset of the evaluation sample. The sample remains balanced on baseline covariates used in Section 4. Voucher utilization–both overall and by applicant screening–also remains comparable. Among regular recipients, utilization was 32% by December 2019 and 47% by November 2020. Among elderly recipients, utilization remained stable at 54% through November 2020.

Tables A.14 and A.15 present treatment effects in the period before the pandemic (December 2019) in $W = [-1, 1]$ in regular and elderly rounds. Specifically, these tables present the OLS Intent-to-Treat (ITT) effects with and without baseline controls, and Local Average Treatment Effects (LATE), using the discontinuity at the cutoff as an instrument for voucher utilization. Compared to the full sample (Tables A.9 and A.10), results are robust to alternative bandwidth or window selection. Coefficients remained stable, although some standard errors increased using the smaller sample.

In the next subsection, I use the randomized sample to study heterogeneity in pre-pandemic housing outcomes, residential mobility, and homeownership applications.

6.4 Heterogeneity

Using equation 2, I examine heterogeneity in treatment effects in December 2019 along three dimensions that should mediate voucher effectiveness: (1) initial tenure (doubled-up versus tenants), which determines voucher effects on out-of-pocket rent payments; (2) access to local housing authorities (SERVIUs),

which may reduce frictions to voucher utilization and applications to homeownership programs; and (3) macroregional rental markets featuring different rental market sizes and rent levels that may affect housing consumption. The analysis reveals that voucher effects vary substantially across household types and institutional contexts, with striking differences between regular and elderly recipients.

6.4.1 Initial Tenure

Tables VIII and X examine heterogeneity by tenure for regular and elderly rounds, restricting to the randomized sample. Column 2 reports the control mean for doubled-up families; Column 3 for tenants; Column 4 the ITT effects for doubled-up families (δ_0); Column 5 the treatment$\times$tenant interaction (δ_g); and Column 6 the implied total effect for tenants ($\delta_0 + \delta_g$).

Voucher receipt had no differential effect on housing consumption by tenure: bedrooms increased and crowding fell for both tenure types, with no changes in neighborhood characteristics. Among elderly voucher holders, effects on household composition, residential mobility, and homeownership applications are also homogeneous across tenure types. These results are consistent with similar rent payment obligations for tenants and doubled-up elderly recipients.

In contrast, regular recipients show meaningful heterogeneity. Relative to tenants, doubled-up families–who must relocate–move farther from their initial location (to neighborhoods with similar characteristics) and are less likely to be in a female-headed household. This is consistent with the increase in the presence of a partner or spouse by November 2020 (Section 6.2.2), suggesting that aggregate composition changes are driven by initially doubled-up applicants. Savings for homeownership also vary by tenure: tenants are 10.4 p.p. (11%) more likely to report an active savings account for home purchase than doubled-up families, consistent with larger reductions in out-of-pocket rent among initial renters. Point estimates suggest that some of this additional savings among tenants translate into homeownership applications for DS1 (which requires a down payment and offers better housing quality)–although differences across tenure type are not statistically significant.

6.4.2 Access to Local Housing Authorities (SERVIUs)

SERVIUs process homeownership applications and leases to activate rental vouchers. Offices are typically located in provincial capitals–denser, less-poor counties with more competitive rental markets. Tables IX and XI examine whether SERVIU access differentially affects recipients, revealing large heterogeneity by local institutional capacity.

Among regular recipients, SERVIU access does not affect housing consumption or residential mobility despite differences in local rental market characteristics. However, SERVIU access strongly affects homeownership applications: applications remained unchanged in non-SERVIU counties but increased by 10.8 p.p. (35%) in SERVIU counties, suggesting proximity to housing authorities reduces application frictions for younger families. Among elderly recipients, the pattern reverses. Homeownership applications are homogeneous, but housing consumption and mobility outcomes vary. Overcrowding was reduced only in non-SERVIU counties, where families moved farther but to similar neighborhoods. Families in SERVIU counties moved shorter distances and into slightly lower-poverty counties (8% decrease in poverty rate), consistent with informal institutional support helping elderly recipients navigate housing search.

6.4.3 Macroregional Rental Markets

Table XII analyzes heterogeneity among elderly recipients across five macroregions: Santiago; North (Tarapacá, Arica, Atacama, Coquimbo); Valparaíso; Center-South (O'Higgins, Maule, Biobío); and South (Araucanía, Los Ríos, Los Lagos, Aysén). The sample is restricted to randomized vouchers from the 2017-2018 cohorts; 2019 is excluded as it covers only Valparaíso. Column 1 reports effects for Santiago (δ_0); Columns 2-5 report treatment interactions with other macroregions (δ_g). Regular recipients are excluded due to small sample sizes.

Elderly voucher receipt increased bedrooms and mobility (both whether to move and where) nationwide, with larger effects outside Santiago–except in the North, where bedroom gains were even greater but mobility patterns resembled Santiago. Nationwide housing improvements suggest the maximum allowable rent cap was often non-binding, enabling access to better units without landlords systematically matching rents to payment standards during this period. However, neighborhood characteristics did not improve in any macroregion.

Impacts on household composition, crowding, and homeownership applications vary by region. Household size and crowding fell everywhere except in the Center-South. The likelihood of female-headed households increased everywhere but not in the North, consistent with more couples securing housing together in more expensive counties (Section 2). Homeownership applications increased outside Santiago: differences relative to Santiago are statistically significant in Valparaíso and the Center–South.

Heterogeneity analysis reveals that initial tenure matters for regular recipients: doubled-up families form

independent households farther away, while tenants move closer and are more likely to save for homeownership. SERVIU access reduces homeownership-application frictions for younger families, while eases voucher-utilization frictions for elderly recipients. Finally, nationwide housing improvements with no neighborhood-quality gains point to substantive supply and demand constraints during housing search. Together, findings indicate voucher effects depend critically on household circumstances and local institutions, not only on benefit generosity.

7 Discussion

This paper presents the first evaluation of rental vouchers in a middle-income country. Voucher receipt improved within-unit quality nationwide but did not improve neighborhood quality, mirroring U.S. findings despite fundamental differences: Chile provides longer search windows (24 versus 2-4 months), partial landlord rent insurance, and fixed benefits that avoid work disincentives. The persistence of null neighborhood improvements across contexts points to structural constraints beyond affordability that transfers alone cannot overcome: limited affordable housing in better neighborhoods, landlord discrimination, information frictions, location preferences, and transaction costs.

Combined with differential effectiveness by tenure and SERVIU access, these findings suggest vouchers require complementary policies: housing search assistance for doubled-up families and expanded SERVIU capacity in underserved areas.

Beyond housing quality, vouchers play a previously underappreciated social insurance role, helping low-income households cope with economic shocks. During the pandemic, informal settlement populations rose 74% nationally (Techo Chile, 2021). At an annual cost of US$2,357 per beneficiary, vouchers delivered sustained housing improvements and helped preserve stability by reducing debt and maintaining housing stability despite income losses, likely reducing longer-term negative consequences of evictions. Importantly, co-payment rates remained stable, suggesting no moral hazard from the partial rent guarantee. These findings suggest rental vouchers can be cost-effective crisis interventions when housing stability is the policy target.

8 Acknowledgements

Special thanks to Rajeev Dehejia, Ingrid Gould Ellen, Tatiana Homonoff, Daniel Waldinger, Kathy O'Regan and Patrick Button for valuable comments; to conference participants at the 2024 AREUEA National, 2023 LACEA LAMES Meeting, 2022 First LACEA Urban Annual Meeting, 2022 Summer Institute of the National Bureau of Economic Research, 2021 APPAM Fall Research Conference, and the UEA 11th EU Meeting.

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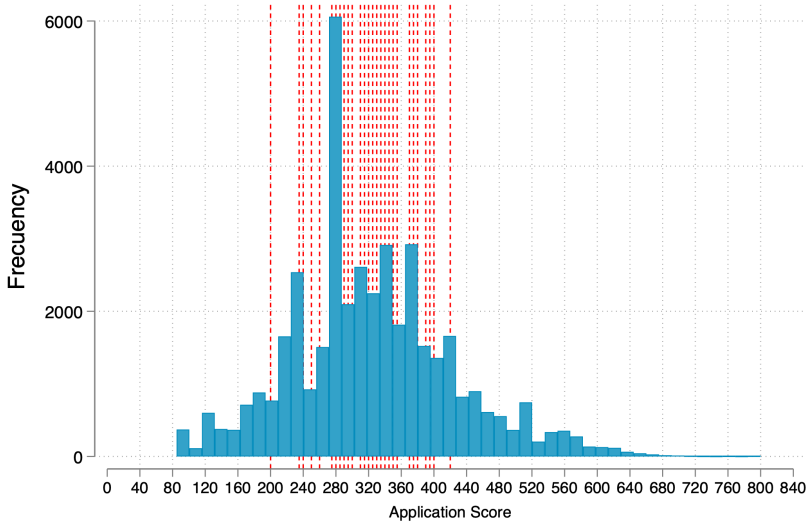
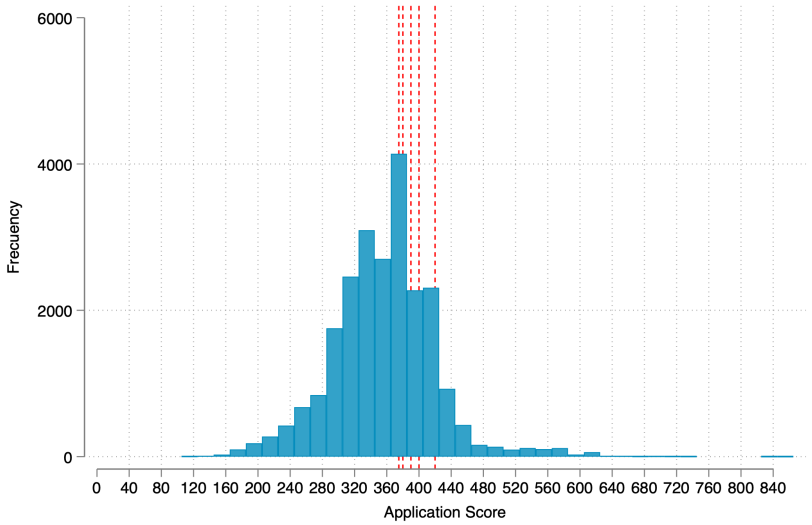
Figures

FIGURE I. Multiple Cutoff Regression Discontinuity Design



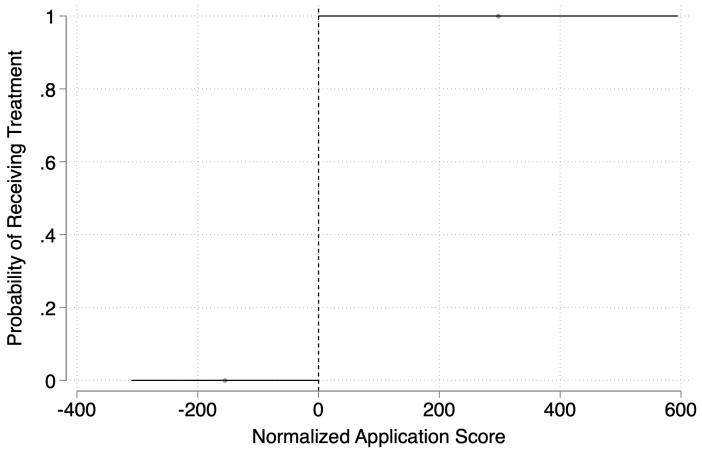
(a) Regular Rounds



(b) Elderly Rounds

This figure shows the distribution of the application score and cutoffs in regular (Panel a) and elderly (Panel b) rounds in the pooled data.

FIGURE II. Sharp RD Design



This figure shows treatment probability in the pooled data from regular and elderly screenings in the 2017–2019 rounds of the program. Scores are normalized such that the cutoff in each screening is $c_{st} = 0$.

Tables

TABLE I. Window Selection Results Regular Rounds

Assignment Date	Region (1)	Cutoff (2)	Total (3)	Controls (4)	Treated (5)	Min pvalue (6)	Left (7)	Right (8)
11apr2018	All	285	144	66	78	0.114	-2	2
28dec2018	All	345	375	295	80	0.208	-5	2
10oct2019	6	285	65	47	18	0.114	-5	2
10oct2019	9	285	275	153	122	0.400	-15	15
10oct2019	10	275	67	47	18	0.262	-1	1

This table describes each applicant screenings in regular rounds of the program within the evaluation sample. Column 1 indicate whether the screening was national or region-based. Column 2 presents the cutoff. Columns 3 to 5 report the total sample size, and the number of individuals below (control) and above (treated) the cutoff. Columns 6 to 8 summarize the selected window: the minimum p-value from all balance tests using covariates explained in Section 4, and the minimum and maximum value of the running variable within the window.

TABLE II. Window Selection Results Elderly Rounds

Assignment Date	Region (1)	Cutoff (2)	Total (3)	Controls (4)	Treated (5)	Min pvalue (6)	Left (7)	Right (8)
04sep2017	All	380	1,173	337	836	0.284	-5	2
11apr2018	All	380	355	248	107	0.144	-2	2
05jul2019	5	380	189	159	30	0.188	-5	5

This table replicates Table I for applicant screenings in elderly rounds within the evaluation sample.

TABLE III. Balance in Baseline Characteristics in Regular Rounds

		Control		Treated			Balance Test 1		Balance Test 2	
	N	Mean	SD	Mean	SD	Diff	F-test (p)	Rand-t (p)	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	926	0.89	0.31	0.91	0.29	0.01	0.628	0.693	0.197	0.226
Poor	926	0.20	0.40	0.22	0.42	0.02	0.518	0.518	0.966	0.368
Tenant	926	0.82	0.39	0.77	0.42	-0.04	0.896	0.849	0.929	0.970
Family income (UF)	926	13.10	4.57	13.19	4.98	0.09	0.286	0.272	0.178	0.945
Saving balance (UF)	926	17.15	37.42	15.77	15.82	-1.38	0.409	0.487	0.430	0.195
Previous app. to ownership subsidy	926	0.14	0.34	0.15	0.36	0.01	0.568	0.545	0.863	0.479
Geocoded location	926	0.91	0.28	0.92	0.26	0.01	0.609	0.661	0.147	0.864
SERVIU county presence	926	0.49	0.50	0.45	0.50	-0.04	0.467	0.474	0.563	0.228
Online Application	926	0.36	0.48	0.35	0.48	-0.01	0.825	0.800	0.402	0.571
Multiple screenings within round	926	0.67	0.47	0.60	0.49	-0.07	0.083*	0.084*	0.000***	0.412
Age 25-35	926	0.59	0.49	0.65	0.48	0.06	0.192	0.179	0.132	0.129
Chilean	926	0.93	0.25	0.97	0.18	0.04	0.072*	0.081*	0.003***	0.149
Spouse/partner	926	0.14	0.35	0.12	0.33	-0.02	0.892	0.871	0.601	0.016**
Household Size	926	2.63	1.06	2.75	1.13	0.12	0.075*	0.075*	0.292	0.634
Number of bedrooms	926	1.61	0.76	1.66	0.82	0.05	0.634	0.632	0.265	0.368
Informal Shelter	926	0.10	0.29	0.06	0.23	-0.04	0.915	0.990	0.037**	0.312
Crowding	926	1.77	0.52	1.78	0.42	0.01	0.179	0.162	0.284	0.469
Previous app. in neighborhood (500mts)	926	0.45	0.50	0.47	0.50	0.02	0.144	0.169	0.565	0.290
County poverty rate	926	0.12	0.07	0.13	0.07	0.01	0.589	0.581	0.321	0.599
Santiago	926	0.13	0.34	0.11	0.31	-0.02	0.585	0.541	0.687	0.336
North	926	0.06	0.24	0.03	0.18	-0.02	0.466	0.434	0.745	0.419
Valparaiso	926	0.08	0.27	0.06	0.24	-0.02	0.527	0.511	0.403	0.837
Center South	926	0.26	0.44	0.23	0.42	-0.03	0.186	0.178	0.393	0.646
South	926	0.47	0.50	0.56	0.50	0.09	0.924	0.913	0.973	0.633
High density county	926	0.39	0.49	0.35	0.48	-0.04	0.370	0.392	0.875	0.178
Answered Baseline Survey	926	0.71	0.45	0.72	0.45	0.01	0.893	0.855	0.026**	0.883
Previous round applications	926	0.29	0.53	0.26	0.48	-0.04	0.061*	0.048**	0.061*	0.041**
KM to closest SERVIU	849	18.67	23.92	21.62	27.24	2.95	0.436	0.433	0.735	0.057*
Rent burden	696	0.48	0.27	0.51	0.22	0.02	0.822	0.811	0.555	0.751
Rent (UF)	860	5.32	3.15	5.24	2.70	-0.08	0.935	0.954	0.869	0.423
Desire to stay in place	558	0.57	0.50	0.56	0.50	-0.02	0.477	0.489	0.679	0.201
Satisfied with housing	602	0.66	0.47	0.66	0.48	-0.00	0.833	0.823	0.144	0.697
SCREENING INDICATORS							Yes	Yes	Yes	Yes
SCREENING INDICATORSxTREAT							No	No	Yes	Yes
Joint Significance (p)									0.573	0.414

This table presents summary statistics and balance tests between treatment and control groups in the evaluation sample in regular rounds. Columns 1-5 report baseline characteristics. Columns 7-8 show results from the first balance test using the weaker null hypothesis from equation 3, and Columns 9-10 report results from the second test including interaction terms from equation 4. April 2018 is the omitted category. Columns 7 and 9 use large-sample inference (F-test); Columns 8 and 10 report Fisherian randomization inference p-values (Randomization-t exact test), computed using 1,000 iterations in the Stata package randcmd (Young, 2019). P-values are not adjusted for multiple hypotheses testing to remain conservative. The bottom panel reports joint significance tests regressing treatment on baseline covariates using both inference methods: dummy variables for female, poor, age 25-35, chilean, married, tenant, informal shelter, prior homeownership application, missing geocoded data, baseline response, SERVIU presence, multiple screenings, online application, prior recipients within 500 meters, macroregion, county level density, and income, savings, the number of bedrooms, county level poverty rate, and household size. See Section 4 for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE IV. Balance in Baseline Characteristics in Elderly Rounds

		Control		Treated			Balance Test 1		Balance Test 2	
	N	Mean	SD	Mean	SD	Diff	F-test (p)	Rand-t (p)	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	1,717	0.60	0.49	0.61	0.49	0.01	0.368	0.342	0.644	0.656
Poor	1,717	0.56	0.50	0.52	0.50	-0.04	0.159	0.169	0.551	0.550
Tenant	1,717	0.55	0.50	0.52	0.50	-0.03	0.937	0.946	0.285	0.291
Family income (UF)	1,717	6.10	2.60	6.35	2.88	0.25	0.186	0.198	0.456	0.472
Previous app. to ownership subsidy	1,717	0.06	0.23	0.05	0.23	-0.00	0.777	0.776	0.808	0.822
Geocoded location	1,717	0.92	0.27	0.89	0.32	-0.03	0.963	0.989	0.795	0.847
Spouse/partner	1,717	0.39	0.49	0.43	0.50	0.04	0.918	0.942	0.999	1.000
SERVIU county presence	1,717	0.51	0.50	0.56	0.50	0.04	0.029**	0.033**	0.055*	0.083*
Age 60-75	1,717	0.57	0.50	0.41	0.49	-0.16	0.885	0.848	0.331	0.321
Chilean	1,717	0.98	0.13	0.99	0.12	0.00	0.662	0.683	0.723	0.877
Household Size	1,717	1.53	1.01	1.50	0.83	-0.03	0.081*	0.074*	0.070*	0.124
Number of bedrooms	1,717	1.34	0.66	1.30	0.61	-0.04	0.039**	0.037**	0.209	0.234
Informal Shelter	1,717	0.18	0.38	0.19	0.39	0.01	0.927	0.901	0.439	0.441
Crowding	1,717	1.17	0.46	1.20	0.47	0.02	0.831	0.834	0.288	0.343
Previous app. in neighborhood (500mts)	1,717	0.60	0.49	0.71	0.45	0.11	0.234	0.223	0.608	0.598
County poverty rate	1,717	0.09	0.05	0.09	0.05	0.00	0.548	0.558	0.535	0.537
Santiago	1,717	0.22	0.42	0.26	0.44	0.03	0.146	0.129	0.211	0.743
North	1,717	0.09	0.29	0.13	0.34	0.04	0.396	0.418	0.400	0.688
Valparaiso	1,717	0.36	0.48	0.23	0.42	-0.13	0.671	0.672	0.751	0.893
Center South	1,717	0.20	0.40	0.21	0.41	0.01	0.721	0.738	0.750	0.893
South	1,717	0.12	0.33	0.17	0.38	0.05	0.320	0.309	0.024**	0.824
High density county	1,717	0.51	0.50	0.50	0.50	-0.01	0.727	0.717	0.833	0.841
Previous round applications	1,717	0.20	0.50	0.05	0.23	-0.15	0.269	0.267	0.269	0.299
KM to closest SERVIU	1,549	12.78	17.73	12.26	19.03	-0.52	0.258	0.262	0.200	0.212
SCREENING INDICATORS							Yes	Yes	Yes	Yes
SCREENING INDICATORSxTREAT							No	No	Yes	Yes
Joint Significance F-Test (p)									0.515	0.555

This table replicates the analysis in Table III using data from elderly rounds. The bottom panel reports joint significance tests regressing treatment on baseline covariates using both inference methods: dummy variables for female, poor, age 60-75, chilean, married, tenant, informal shelter, prior homeownership application, missing geocoded data, SERVIU presence, multiple screenings, online application, prior recipients within 500 meters, macroregion, county level density, and income, savings, the number of bedrooms, county level poverty rate, and household size. See Table III for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE V. Effect of Regular Voucher Before the COVID-19 Pandemic (2019)

Outcome Variable	N (1)	Control Mean [SD] (2)	ITT (3)	OLS (4)	Rand-t (5)	RWolf (6)
Household size	925	2.85	0.119	0.162	0.170	0.931
		[1.21]	(0.085)			
Number of bedrooms	921	1.76	0.243***	0.000	0.001	0.001
		[0.83]	(0.056)			
Number of people per bedroom	921	1.80	-0.162***	0.000	0.004	0.001
		[0.69]	(0.042)			
Overcrowing indicator	921	0.12	-0.045**	0.034	0.034	0.024
		[0.33]	(0.021)			
Female head of household	925	0.73	-0.013	0.623	0.630	0.931
		[0.44]	(0.027)			
Moved to diff. unit	849	0.43	0.073*	0.054	0.049	0.077
		[0.50]	(0.038)			
Stayed in 1km radius	849	0.71	-0.077**	0.030	0.035	0.077
		[0.46]	(0.036)			
Moved +10km away	849	0.12	0.062**	0.022	0.022	0.077
		[0.33]	(0.027)			
Moved to another county	849	0.07	0.059***	0.006	0.010	0.073
		[0.26]	(0.021)			
County level poverty	856	-0.05	-0.028	0.640	0.228	0.770
		[1.00]	(0.060)			
County crime victims	856	0.02	0.048	0.279	0.092	0.317
		[0.83]	(0.045)			
School Quality	816	0.02	-0.028	0.695	0.703	0.930
		[0.94]	(0.072)			
Distance to school	849	-0.08	0.248**	0.016	0.012	0.050
		[0.69]	(0.103)			
Distance to early childhood educ.	849	-0.07	0.210**	0.022	0.025	0.081
		[0.76]	(0.091)			
Distance to health care	849	-0.05	0.162*	0.099	0.123	0.317
		[0.78]	(0.098)			
Kms to closest municipality	921	0.00	0.016	0.808	0.836	0.930
		[1.01]	(0.064)			
Application to Ownership Programs	926	0.31	0.005	0.884	0.854	0.859
		[0.46]	(0.031)			
Application DS1	926	0.23	-0.001	0.971	0.696	0.957
		[0.42]	(0.029)			
Application DS49	926	0.12	-0.002	0.910	0.840	0.957
		[0.32]	(0.022)			
Active ownership savings account	926	0.92	0.012	0.521	0.529	0.957
		[0.27]	(0.018)			

This table presents estimates of equation 1 using outcomes measured in December 2019. Column 2 shows the control group mean with the standard deviation in square brackets. Column 3 reports Intent-to-Treat (ITT) estimates, including applicant screenings fixed-effects and baseline controls (described in Section 6). OLS standard errors are in parenthesis. Column 4 shows OLS p-values, Column 5 presents Fisherian randomization inference, and Column 6 exhibits Romano-Wolf adjusted for multiple hypothesis testing p-values. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE VI. Effect of Elderly Voucher Before the COVID-19 Pandemic (2019)

Outcome Variable	N (1)	Control Mean [SD] (2)	ITT (3)	OLS (4)	Rand-t (5)	RWolf (6)
Household size	1,717	1.60	-0.156***	0.002	0.003	0.013
		[1.11]	(0.051)			
Number of bedrooms	1,604	1.35	0.439***	0.000	0.000	0.001
		[0.74]	(0.045)			
Number of people per bedroom	1,604	1.24	-0.300***	0.000	0.000	0.001
		[0.59]	(0.027)			
Overcrowing indicator	1,604	0.03	-0.014	0.128	0.133	0.122
		[0.17]	(0.009)			
Female head of household	1,717	0.49	0.026	0.106	0.118	0.254
		[0.50]	(0.016)			
Moved to diff. unit	1,549	0.34	0.257***	0.000	0.000	0.001
		[0.47]	(0.028)			
Stayed in 1km radius	1,549	0.76	-0.194***	0.000	0.001	0.001
		[0.43]	(0.026)			
Moved +10km away	1,549	0.11	0.084***	0.000	0.001	0.001
		[0.31]	(0.020)			
Moved to another county	1,549	0.09	0.055***	0.002	0.002	0.002
		[0.29]	(0.018)			
County level poverty	1,577	-0.03	-0.050	0.290	0.259	0.859
		[0.98]	(0.047)			
County crime victims	1,575	-0.01	-0.007	0.847	0.781	0.953
		[0.80]	(0.039)			
School Quality	1,509	-0.02	0.001	0.992	0.975	0.953
		[0.99]	(0.055)			
Distance to school	1,549	0.04	-0.066	0.199	0.208	0.755
		[1.27]	(0.051)			
Distance to early childhood educ.	1,549	0.04	-0.066	0.192	0.209	0.767
		[1.24]	(0.051)			
Distance to health care	1,549	0.04	-0.067	0.208	0.227	0.753
		[1.24]	(0.053)			
Kms to closest municipality	1,624	0.04	-0.102**	0.049	0.047	0.159
		[1.11]	(0.052)			
Application to Ownership Programs	1,717	0.12	0.048***	0.008	0.003	0.008
		[0.33]	(0.018)			
Application DS1	1,717	0.07	0.023	0.103	0.072	0.153
		[0.26]	(0.014)			
Application DS49	1,717	0.07	0.034**	0.016	0.012	0.008
		[0.25]	(0.014)			

This table replicates the analysis in Table V using elderly rounds data. See Table V for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE VII. Effect of Regular Voucher During COVID-19 (2020)

Outcome Variable	N (1)	Control Mean [SD] (2)	ITT (3)	OLS (4)	Rand-t (5)	RWolf (6)
Shelter Deprived	464	0.17	-0.029	0.412	0.430	0.898
		[0.38]	(0.035)			
Formal Lease	402	0.60	0.116**	0.027	0.026	0.089
		[0.49]	(0.052)			
Total rent (unit)	326	6.80	0.040	0.886	0.953	0.912
		[2.81]	(0.277)			
Rent burden (rent paid)	284	0.48	-0.100***	0.001	0.002	0.005
		[0.27]	(0.031)			
Employed	344	0.69	-0.032	0.573	0.526	0.930
		[0.47]	(0.056)			
Family Income	340	13.42	0.336	0.586	0.610	0.930
		[5.71]	(0.618)			
Debt overload	342	0.69	-0.123**	0.035	0.039	0.097
		[0.46]	(0.058)			
Spouse/Partner	339	0.32	0.089	0.107	0.086	0.294
		[0.47]	(0.055)			
Household Size	428	3.28	-0.066	0.641	0.625	0.739
		[1.40]	(0.141)			
Number of people per bedroom	417	1.58	-0.099	0.159	0.172	0.678
		[0.69]	(0.070)			
Overcrowding indicator	418	0.11	-0.035	0.262	0.253	0.739
		[0.31]	(0.032)			
Number of bedrooms	417	2.24	0.019	0.811	0.830	0.908
		[0.88]	(0.081)			
Laundry Room	415	0.36	0.034	0.485	0.497	0.908
		[0.48]	(0.049)			
Kitchen Room	415	0.75	0.146***	0.001	0.001	0.043
		[0.43]	(0.042)			
Heat system	415	0.80	0.093***	0.003	0.003	0.051
		[0.40]	(0.031)			
Cable, Wifi	412	0.59	-0.018	0.632	0.649	0.908
		[0.35]	(0.038)			
Satisfaction current housing unit	459	0.77	0.070*	0.075	0.074	0.532
		[0.42]	(0.039)			
2 or more years current house	459	0.47	-0.127**	0.011	0.008	0.094
		[0.50]	(0.050)			
Household income loss after COVID-19	343	0.80	-0.068	0.206	0.205	0.401
		[0.40]	(0.054)			
Temporary unemployment due to COVID-19	344	0.18	0.058	0.240	0.227	0.514
		[0.39]	(0.050)			
COVID-19: Expenses	340	0.69	-0.019	0.732	0.727	0.704
		[0.46]	(0.056)			
COVID-19: Debt	340	0.67	-0.151**	0.012	0.013	0.014
		[0.47]	(0.060)			
COVID-19: New Income Source	340	0.43	-0.040	0.515	0.561	0.530
		[0.50]	(0.061)			
COVID-19: Applied to Emergency Support	340	0.57	-0.070	0.248	0.243	0.401
		[0.50]	(0.061)			
COVID-19: Moved out	340	0.07	-0.033	0.196	0.230	0.244
		[0.25]	(0.025)			
COVID-19: Others moved in	340	0.06	0.049	0.132	0.131	0.170
		[0.23]	(0.032)			
COVID-19: Delayed rent payments	340	0.22	-0.108**	0.012	0.015	0.079
		[0.42]	(0.043)			
Positive Ammenities	450	-0.02	-0.043	0.684	0.663	1.000
		[1.02]	(0.105)			
Negative Ammenities	328	-0.00	-0.013	0.912	0.867	1.000
		[1.01]	(0.115)			
Would ask neighbors for childcare	427	0.29	-0.100**	0.028	0.028	0.139
		[0.45]	(0.045)			
2 or more years current neighborhood	451	0.55	-0.084	0.101	0.108	0.367
		[0.50]	(0.051)			
Satisfaction current neighborhood	443	0.82	-0.040	0.309	0.277	0.806
		[0.38]	(0.040)			

This table replicates the analysis in Table V using survey data for regular rounds collected between September and November 2020. See Table V for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE VIII. Heterogeneity Analysis in Regular Rounds Before the COVID-19 Pandemic: Tenure

Outcome Variable	N	Control Mean Doubled-up	Control Mean Tenant	ITT Doubled-up	TreatxTenant	ITT Tenant
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	538	2.82	2.59	0.285	-0.350	-0.065
				(0.241)	(0.257)	(0.126)
Number of bedrooms	536	1.59	1.58	0.285**	0.013	0.299***
				(0.145)	(0.158)	(0.084)
Number of people per bedroom	536	1.90	1.81	-0.132	-0.179	-0.311***
				(0.094)	(0.114)	(0.064)
Overcrowing indicator	536	0.11	0.09	-0.042	-0.022	-0.064**
				(0.050)	(0.056)	(0.029)
Female head of household	538	0.82	0.88	-0.172**	0.194**	0.022
				(0.076)	(0.078)	(0.031)
Moved to diff. unit	480	0.41	0.50	0.061	0.013	0.074
				(0.095)	(0.107)	(0.058)
Stayed in 1km radius	480	0.71	0.65	-0.102	0.041	-0.062
				(0.087)	(0.101)	(0.056)
Moved +10km away	480	0.04	0.17	0.162***	-0.160**	0.002
				(0.061)	(0.073)	(0.042)
Moved to another county	480	0.06	0.10	0.097*	-0.066	0.031
				(0.050)	(0.059)	(0.033)
County level poverty	485	-0.32	-0.24	0.008	-0.099	-0.091
				(0.135)	(0.154)	(0.092)
County crime victims	485	0.10	0.05	0.152	-0.113	0.039
				(0.111)	(0.125)	(0.065)
School Quality	467	0.03	-0.01	-0.010	-0.018	-0.028
				(0.184)	(0.200)	(0.100)
Distance to school	480	-0.15	-0.05	0.358**	-0.016	0.341
				(0.176)	(0.221)	(0.217)
Distance to early childhood educ.	480	-0.17	-0.05	0.289*	0.047	0.336*
				(0.169)	(0.218)	(0.187)
Distance to health care	480	-0.12	-0.01	0.195	0.107	0.302
				(0.157)	(0.205)	(0.206)
Kms to closest municipality	536	-0.09	0.13	-0.080	0.108	0.029
				(0.147)	(0.181)	(0.120)
Application to Ownership Programs	539	0.45	0.30	-0.027	0.078	0.051
				(0.081)	(0.093)	(0.045)
Application DS1	539	0.33	0.21	-0.035	0.079	0.044
				(0.076)	(0.085)	(0.041)
Application DS49	539	0.24	0.13	-0.066	0.075	0.009
				(0.068)	(0.076)	(0.036)
Active ownership savings account	539	0.95	0.91	-0.064	0.104*	0.040
				(0.049)	(0.057)	(0.029)
COVARIATES				YES	YES	YES
SCREENING FE				YES	YES	YES

This table presents heterogeneity analysis by initial tenure using equation 2 with outcomes measured in December 2019 (regular rounds). Column 1 lists the number of observations. Column 2 reports the control mean for the omitted group (doubled-up) and Column 3 for the other group (tenants). Column 4 shows the ITT estimates for the omitted group (δ_0) and Column 5 the interaction term (δ_g in equation 2). Column 6 reports the implied total effect for the included group ($delta_0 + \delta_g$). Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE IX. Heterogeneity Analysis in Regular Rounds Before the COVID-19 Pandemic: SERVIU access

Outcome Variable	N	Control Mean No SERVIU	Control Mean SERVIU	ITT No SERVIU	TreatxSERVIU	ITT SERVIU
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	538	2.71	2.60	-0.000	0.050	0.050
				(0.177)	(0.212)	(0.141)
Number of bedrooms	536	1.62	1.55	0.243**	0.099	0.342***
				(0.107)	(0.142)	(0.101)
Number of people per bedroom	536	1.85	1.82	-0.254***	-0.020	-0.274***
				(0.077)	(0.103)	(0.071)
Overcrowing indicator	536	0.11	0.08	-0.066*	0.014	-0.052
				(0.038)	(0.047)	(0.032)
Female head of household	538	0.85	0.88	-0.015	-0.025	-0.040
				(0.046)	(0.059)	(0.041)
Moved to diff. unit	480	0.45	0.51	0.062	0.017	0.079
				(0.070)	(0.094)	(0.068)
Stayed in 1km radius	480	0.66	0.68	-0.051	-0.043	-0.093
				(0.067)	(0.092)	(0.066)
Moved +10km away	480	0.18	0.09	0.011	0.065	0.076
				(0.052)	(0.069)	(0.046)
Moved to another county	480	0.12	0.06	0.080*	-0.063	0.017
				(0.042)	(0.056)	(0.037)
County level poverty	485	-0.13	-0.38	-0.036	-0.057	-0.093
				(0.128)	(0.138)	(0.077)
County crime victims	485	-0.18	0.29	0.059	0.018	0.077
				(0.079)	(0.108)	(0.079)
School Quality	467	-0.07	0.07	-0.119	0.188	0.069
				(0.142)	(0.183)	(0.119)
Distance to school	480	-0.06	-0.09	0.121	0.446	0.567*
				(0.109)	(0.271)	(0.301)
Distance to early childhood educ.	480	-0.06	-0.10	0.210	0.227	0.437*
				(0.129)	(0.241)	(0.245)
Distance to health care	480	0.03	-0.10	0.040	0.466*	0.506*
				(0.130)	(0.256)	(0.273)
Kms to closest municipality	536	0.01	0.14	-0.018	0.035	0.017
				(0.120)	(0.168)	(0.139)
Application to Ownership Programs	539	0.37	0.31	-0.053	0.162**	0.108*
				(0.055)	(0.077)	(0.056)
Application DS1	539	0.24	0.23	-0.008	0.061	0.053
				(0.051)	(0.070)	(0.050)
Application DS49	539	0.20	0.12	-0.092**	0.157**	0.065
				(0.043)	(0.061)	(0.045)
Active ownership savings account	539	0.95	0.89	0.024	-0.020	0.004
				(0.030)	(0.049)	(0.039)
COVARIATES				YES	YES	YES
SCREENING FE				YES	YES	YES

This table replicates Table VIII for regular rounds, replacing tenure with SERVIU access. The omitted group is households in counties without a SERVIU; the other group is households in counties with a SERVIU. Column definitions follow Table VIII. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE X. Heterogeneity Analysis in Elderly Rounds Before the COVID-19 Pandemic: Tenure

Outcome Variable	N	Control Mean Doubled-up	Control Mean Tenant	ITT Doubled-up	TreatxTenant	ITT Tenant
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	1,672	1.71	1.50	-0.189**	-0.012	-0.201***
				(0.076)	(0.086)	(0.056)
Number of bedrooms	1,562	1.37	1.34	0.387***	0.085	0.473***
				(0.063)	(0.079)	(0.060)
Number of people per bedroom	1,562	1.31	1.19	-0.283***	-0.056	-0.339***
				(0.040)	(0.050)	(0.034)
Overcrowing indicator	1,562	0.03	0.03	-0.006	-0.019	-0.025**
				(0.014)	(0.016)	(0.011)
Female head of household	1,672	0.43	0.55	0.039*	-0.020	0.019
				(0.023)	(0.029)	(0.021)
Moved to diff. unit	1,509	0.37	0.30	0.241***	0.047	0.288***
				(0.039)	(0.050)	(0.037)
Stayed in 1km radius	1,509	0.72	0.80	-0.196***	-0.010	-0.206***
				(0.038)	(0.048)	(0.034)
Moved +10km away	1,509	0.13	0.09	0.088***	-0.021	0.067***
				(0.029)	(0.036)	(0.025)
Moved to another county	1,509	0.11	0.07	0.046*	0.014	0.060***
				(0.027)	(0.032)	(0.021)
County level poverty	1,537	0.09	-0.12	-0.050	0.001	-0.049
				(0.070)	(0.083)	(0.057)
County crime victims	1,535	-0.05	0.03	-0.043	0.064	0.021
				(0.055)	(0.070)	(0.051)
School Quality	1,471	-0.01	-0.00	0.005	-0.029	-0.024
				(0.081)	(0.102)	(0.070)
Distance to school	1,509	0.04	0.04	0.014	-0.150	-0.136*
				(0.074)	(0.110)	(0.078)
Distance to early childhood educ.	1,509	0.04	0.04	0.001	-0.133	-0.132*
				(0.073)	(0.108)	(0.078)
Distance to health care	1,509	0.04	0.04	0.013	-0.145	-0.132*
				(0.078)	(0.109)	(0.076)
Kms to closest municipality	1,582	0.04	0.03	-0.010	-0.166*	-0.175**
				(0.068)	(0.097)	(0.075)
Application to Ownership Programs	1,672	0.14	0.11	0.033	0.027	0.060**
				(0.026)	(0.034)	(0.024)
Application DS1	1,672	0.08	0.07	0.022	-0.005	0.017
				(0.020)	(0.026)	(0.019)
Application DS49	1,672	0.07	0.06	0.012	0.044	0.056***
				(0.019)	(0.027)	(0.020)
COVARIATES				YES	YES	YES
SCREENING FE				YES	YES	YES

This table replicates Table VIII for elderly rounds. See Table VIII for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE XI. Heterogeneity Analysis in Elderly Rounds Before the COVID-19 Pandemic: SERVIU Access

Outcome Variable	N	Control Mean No SERVIU	Control Mean SERVIU	ITT No SERVIU	TreatxSERVIU	ITT SERVIU
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	1,672	0.08	0.09	-0.180***	-0.028	-0.208***
				(0.069)	(0.090)	(0.066)
Number of bedrooms	1,562	0.08	0.09	0.439***	-0.013	0.425***
				(0.065)	(0.081)	(0.060)
Number of people per bedroom	1,562	0.08	0.09	-0.331***	0.036	-0.295***
				(0.037)	(0.047)	(0.035)
Overcrowing indicator	1,562	0.08	0.09	-0.034***	0.035**	0.001
				(0.013)	(0.015)	(0.011)
Female head of household	1,672	0.08	0.09	0.030	-0.004	0.027
				(0.022)	(0.029)	(0.022)
Moved to diff. unit	1,509	0.08	0.09	0.263***	0.005	0.268***
				(0.038)	(0.050)	(0.037)
Stayed in 1km radius	1,509	0.08	0.09	-0.194***	-0.015	-0.208***
				(0.036)	(0.048)	(0.036)
Moved +10km away	1,509	0.08	0.09	0.113***	-0.071**	0.043*
				(0.029)	(0.036)	(0.025)
Moved to another county	1,509	0.08	0.09	0.076***	-0.045	0.031
				(0.027)	(0.032)	(0.020)
County level poverty	1,537	0.08	0.09	0.053	-0.201**	-0.147***
				(0.073)	(0.082)	(0.053)
County crime victims	1,535	0.08	0.09	-0.004	-0.012	-0.015
				(0.055)	(0.070)	(0.051)
School Quality	1,471	0.08	0.09	0.008	-0.036	-0.028
				(0.075)	(0.101)	(0.076)
Distance to school	1,509	0.08	0.09	-0.038	-0.052	-0.091
				(0.051)	(0.100)	(0.088)
Distance to early childhood educ.	1,509	0.08	0.09	-0.053	-0.031	-0.084
				(0.055)	(0.099)	(0.086)
Distance to health care	1,509	0.08	0.09	-0.046	-0.032	-0.079
				(0.059)	(0.098)	(0.085)
Kms to closest municipality	1,582	0.08	0.09	-0.083	-0.025	-0.108
				(0.068)	(0.095)	(0.074)
Application to Ownership Programs	1,672	0.08	0.09	0.032	0.028	0.060**
				(0.026)	(0.034)	(0.024)
Application DS1	1,672	0.08	0.09	0.011	0.017	0.027
				(0.020)	(0.027)	(0.019)
Application DS49	1,672	0.08	0.09	0.033*	0.002	0.035*
				(0.019)	(0.026)	(0.019)
COVARIATES				YES	YES	YES
SCREENING FE				YES	YES	YES

This table replicates Table IX for elderly rounds. See Table IX for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

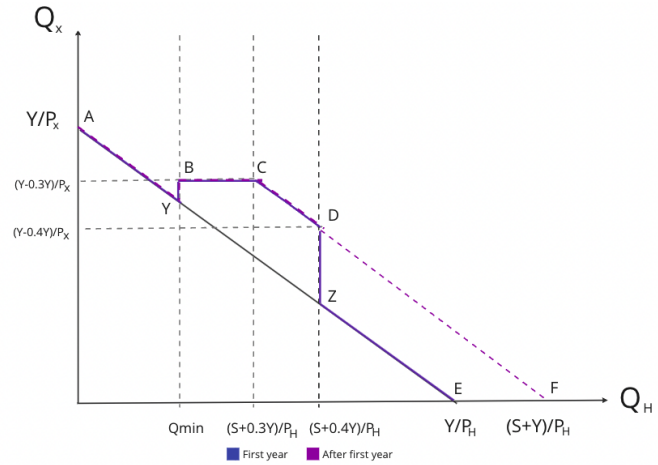
TABLE XII. Heterogeneity Analysis in Elderly Rounds Before the COVID-19 Pandemic: Regional Markets (Macrozones)

Outcome Variable	Control Mean	Santiago	TreatxNorth	TreatxValparaiso	TreatxCenter South	TreatxSouth
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	1.73	-0.352***	0.199	0.128	0.353***	0.177
		(0.095)	(0.155)	(0.140)	(0.137)	(0.143)
Number of bedrooms	1.40	0.230***	0.481***	0.216*	0.367***	0.182
		(0.088)	(0.140)	(0.125)	(0.121)	(0.134)
Number of people per bedroom	1.33	-0.329***	-0.076	-0.012	0.041	0.072
		(0.061)	(0.103)	(0.085)	(0.078)	(0.089)
Overcrowing indicator	0.04	-0.032*	0.021	0.009	0.044*	0.016
		(0.019)	(0.034)	(0.026)	(0.026)	(0.026)
Female head of household	0.50	0.056*	-0.126**	-0.010	-0.028	-0.008
		(0.030)	(0.049)	(0.048)	(0.043)	(0.053)
Moved to diff. unit	0.29	0.162***	0.023	0.167**	0.190**	0.206**
		(0.050)	(0.094)	(0.076)	(0.075)	(0.083)
Stayed in 1km radius	0.78	-0.097**	-0.114	-0.142**	-0.139*	-0.238***
		(0.046)	(0.088)	(0.072)	(0.072)	(0.079)
Moved +10km away	0.11	-0.001	0.063	0.149***	0.086	0.157***
		(0.034)	(0.062)	(0.056)	(0.055)	(0.054)
Moved to another county	0.12	0.040	-0.048	0.038	0.023	0.045
		(0.036)	(0.054)	(0.053)	(0.051)	(0.048)
County level poverty	-0.63	-0.012	-0.025	-0.013	-0.081	-0.129
		(0.065)	(0.107)	(0.104)	(0.120)	(0.200)
County crime victims	0.56	-0.042	0.001	0.043	0.133	-0.006
		(0.094)	(0.113)	(0.122)	(0.118)	(0.122)
School Quality	0.23	-0.078	-0.150	0.270*	0.164	-0.072
		(0.096)	(0.167)	(0.152)	(0.159)	(0.169)
Distance to school	-0.12	-0.041	0.004	-0.002	-0.021	-0.210
		(0.095)	(0.210)	(0.114)	(0.140)	(0.321)
Distance to early childhood educ.	-0.14	-0.036	-0.048	0.011	-0.012	-0.244
		(0.090)	(0.211)	(0.110)	(0.148)	(0.303)
Distance to health care	-0.16	-0.038	0.052	-0.000	-0.089	-0.134
		(0.094)	(0.242)	(0.123)	(0.153)	(0.271)
Kms to closest municipality	-0.21	-0.030	-0.132	-0.004	-0.142	-0.153
		(0.052)	(0.252)	(0.089)	(0.132)	(0.195)
Application to Ownership Programs	0.15	-0.002	0.072	0.112**	0.089	0.028
		(0.035)	(0.054)	(0.051)	(0.054)	(0.059)
Application DS1	0.07	0.017	0.031	0.038	0.018	-0.054
		(0.028)	(0.038)	(0.037)	(0.045)	(0.048)
Application DS49	0.08	-0.013	0.043	0.103**	0.075*	0.049
		(0.026)	(0.047)	(0.041)	(0.042)	(0.045)
Observations		409	192	293	350	252
COVARIATES		YES	YES	YES	YES	YES
SCREENING FE		YES	YES	YES	YES	YES

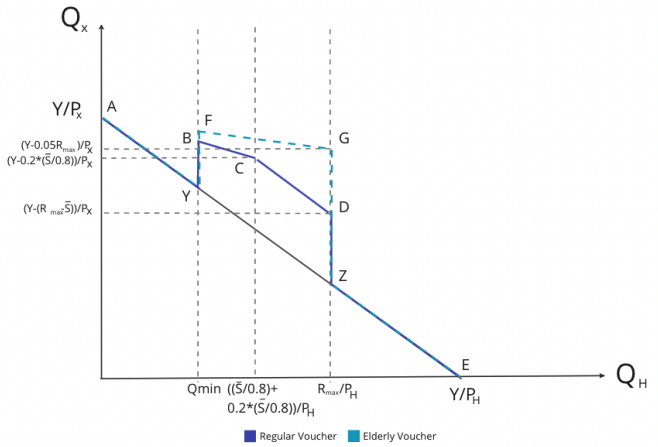
This table presents heterogeneity analysis across five macroregions using equation 2 with outcomes measured in December 2019 (regular rounds). Column 1 lists the number of observations. Column 2 reports the control mean for the omitted group (Santiago). Column 3-6 report the interaction term (δ_g in equation 2) for the other macroregions. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

A Appendix: Additional Tables and Figures

FIGURE A.1. Budget Set in the Rental Voucher Program



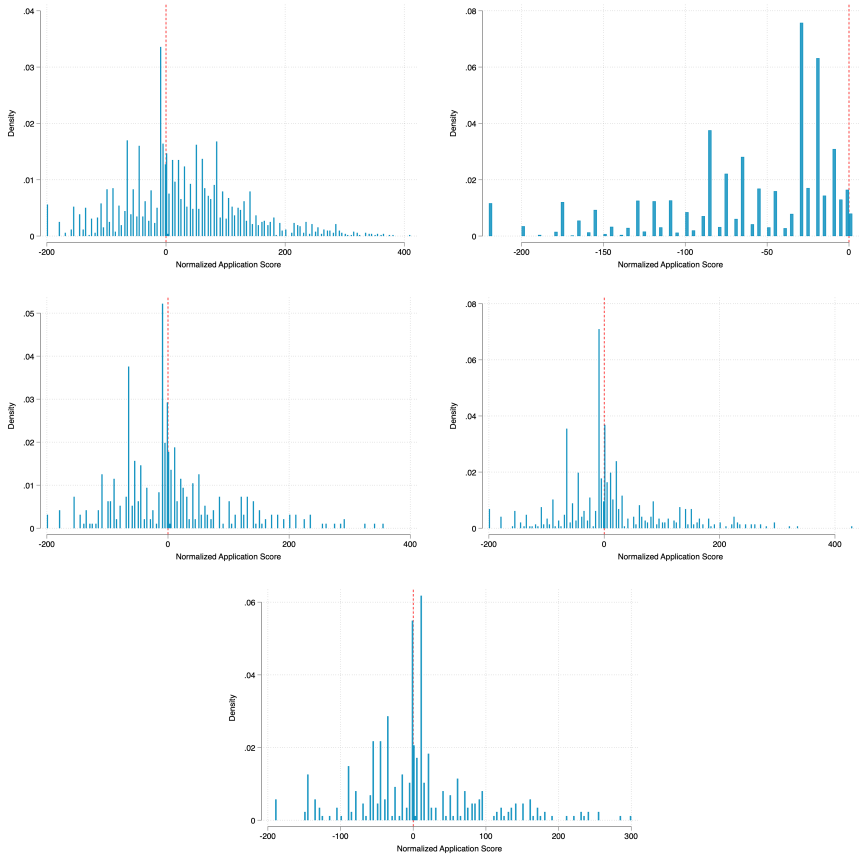
(a) US Housing Choice Voucher Program



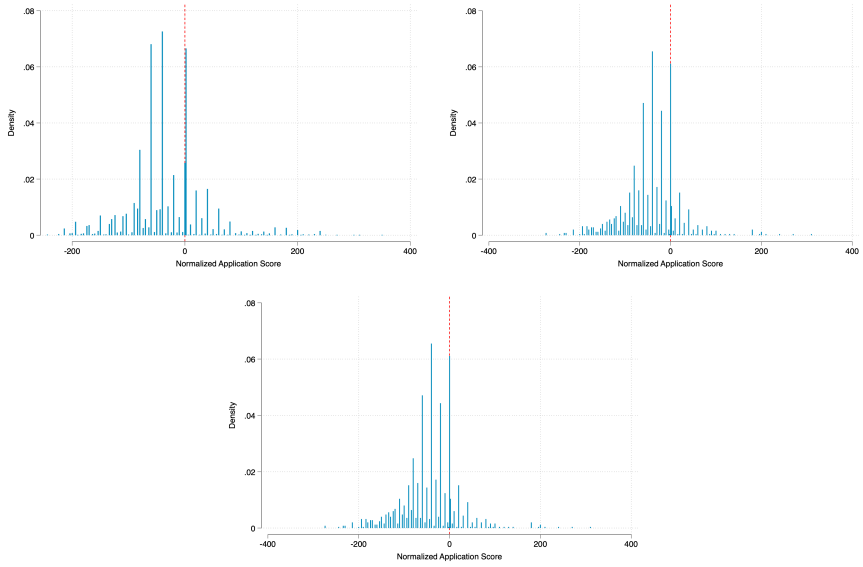
(b) Chilean Rental Voucher

The figure illustrates how the introduction of the rental voucher changes the budget set in the U.S. (a) and Chile (b). In the U.S., recipients initially pay 30% of income (Y) toward rent in units meeting a minimum quality threshold ($Q_{\min}$). The government covers the gap between Fair Market Rent (FMR) and 30% of family income, denoted by S. In the first year, households face the budget constraint AYBCDZE, as rent payments cannot exceed 40% of income. In subsequent years, this restriction is lifted, expanding the budget set to AYBCDF. In Chile, the regular voucher provides a fixed subsidy, capped at 80% of rent, and can only be used in units below the maximum allowable rent ($R_{\max}$), generating the budget set AYBCDZE. In elderly rounds, recipients pay 5% of rent in qualifying units. The resulting budget set is AYFGZE. In both voucher types, doubled-up households are assumed to start below $Q_{\min}$.

FIGURE A.2. Normalized Score Distribution by Applicant Screenings in W_0



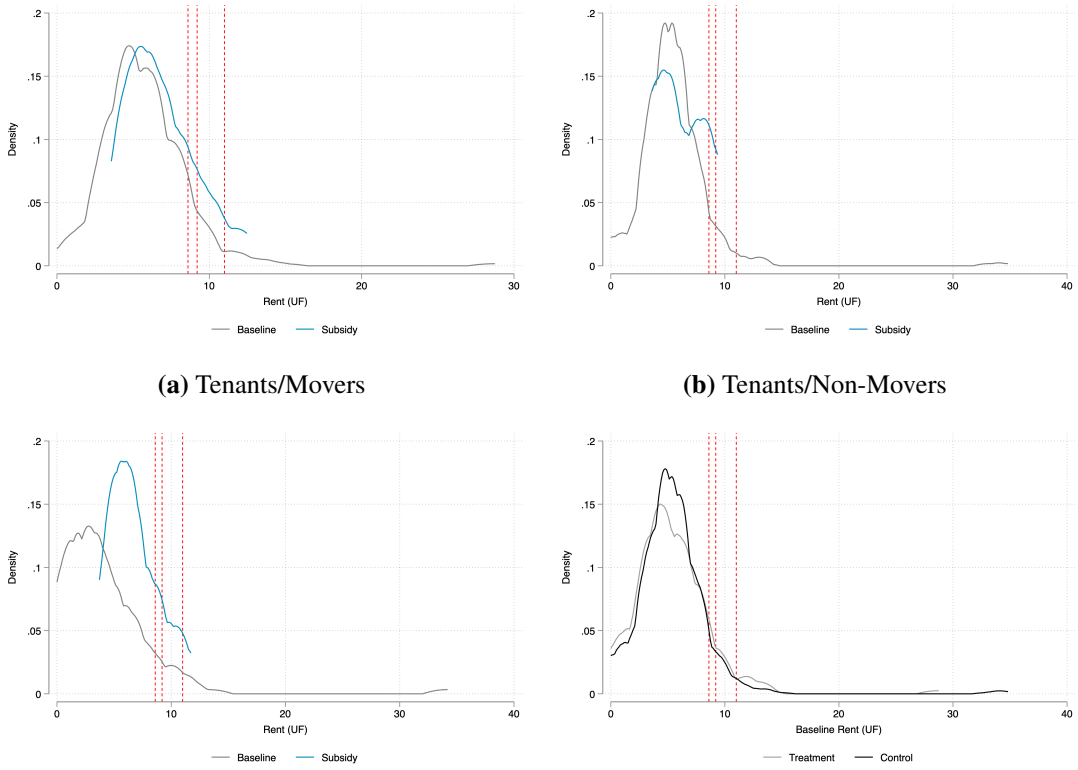
(a) Regular Applicant Screenings



(b) Elderly Applicants Screenings

This figure presents the normalized score distribution by applicant screening in the evaluation sample W_0 in regular rounds (a) and elderly rounds (b).

FIGURE A.3. Total Rent Amount (Administrative Data)



(a) Tenants/Movers

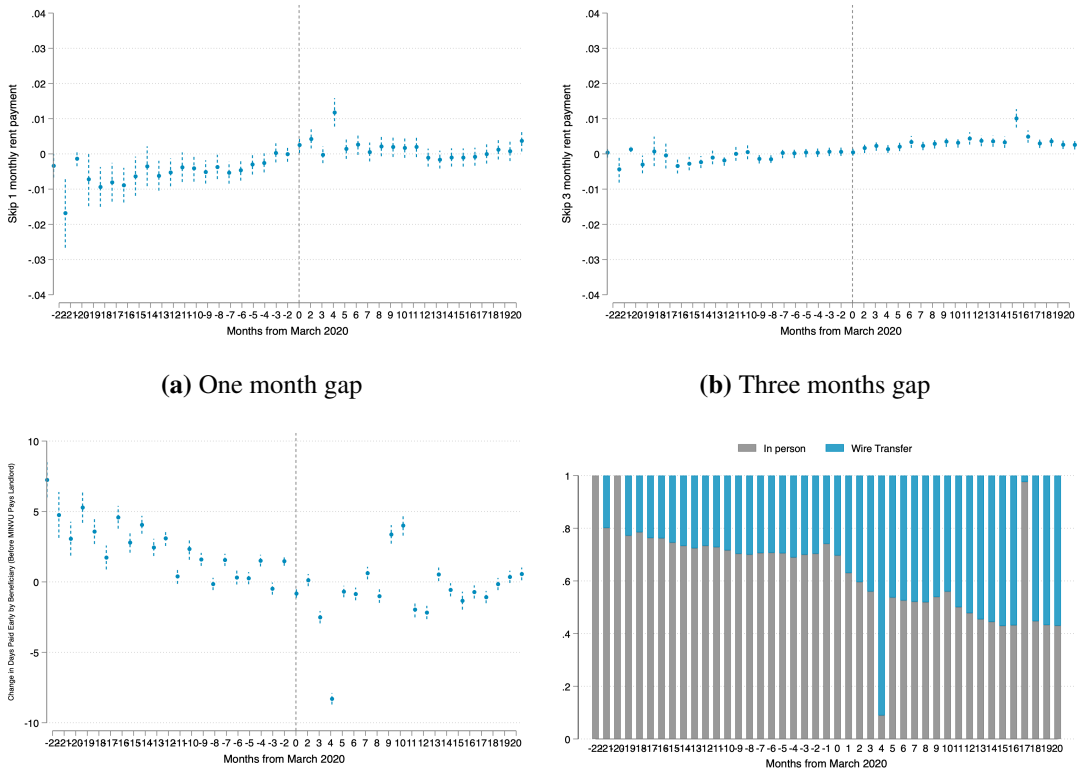
(b) Tenants/Non-Movers

(c) Doubled-up or other (Non-tenants)

(d) No voucher utilization

The figure uses administrative data from MINVU on all leases signed by voucher recipients. Panels (a)–(c) plot the distribution of total monthly rent at baseline and in November 2020 for recipients who had leased with the voucher since assignment. Panels (a) and (b) report distributions separately for applicants who were tenants at baseline and used their voucher in a different unit ("movers") and in the same unit as at application ("non-movers"), respectively. Panel (c) reports the distribution for recipients who were not renting at baseline. Panel (d) shows baseline rent for the control group and for treated applicants who had not yet used their voucher by November 2020. All rent amounts are in UF. Red dashed lines denote the maximum allowable rent; see Section 2 for details on these thresholds.

FIGURE A.4. Rent Co-Payment Behavior (Administrative Data)



(a) One month gap

(b) Three months gap

(c) Payment Timing

(d) Payment Method

This Figure analyzes payment behavior during the period before and after the onset of the COVID-19 pandemic ($t = 0$ corresponds to March 20th 2020). Panel (a) reports the probability of skipping one monthly payment; Panel (b), the probability of skipping three consecutive payments; Panel (c) shows overall delays in rent co-payment, and Panel (d) presents the distribution of payment methods used by voucher holders.

TABLE A.1. Application Score

	Score Component	Regular Rounds	Differences in Elderly Rounds
1	Household member[1]	40 per member	=
2	Children under 5[2]	30 per member	=
3	Children between 6 and 18	20 per member	=
4	Elderly*	30 per member	60 per member
5	Single Parent of 18 or younger children	35	=
6	Physical disability	30 per member	=
7	Tortured in dictatorship (applicant and/or partner)	100 per member	=
8	Military Service	20 per member	=
9	Gendarmerie Service (applicant and/or partner)	40 per member	=
10	Previous Applications (up to 3)	20 per prev application	=
11	Social Vulnerability (RSH Index)	0 (81-100th), 45 (71-80th), 90 (61-70th) 135 (51-60th), 180 (40-50th)	=
12	Housing Vulnerability[3]	0, 20, 40, 60, 80, 100, 120, 140, 160	=
13	Applicant's age (60-64, 65-69, 70-74, >75)	No	20, 40, 60, 100

Notes: (1) Applicant not counted in household size in regular rounds; (2) Age is measured as of December of the application year; (3) Sum of pre-defined scores for crowding, shelter type (house, apartment, informal settlement, room, or other), and access to reliable water and basic sanitation.

TABLE A.2. Assignments in Regular Rounds

Assignment Date	N (1)	Min Xi (2)	Max Xi (3)	Vouchers (4)	Cutoff (5)	R1 (6)	R2 (7)	Region (8)
26apr2017	2,093	85	665	957	300	50	1.00	All
17may2017	2,217	85	720	1,000	275	18	1.00	All
21jun2017	2,374	85	720	1,001	275	3	1.00	All
24jul2017	2,343	85	705	999	240	25	1.00	All
24aug2017	2,495	85	685	1,000	240	22	1.00	All
27sep2017	2,715	85	650	1,000	235	14	1.00	All
19oct2017	3,086	85	695	1,935	200	28	0.00	All
13dec2017	5,754	85	790	900	395	5	0.00	All
11apr2018	2,591	85	695	1,500	285	64	0.00	All
01jun2018	6,848	85	755	1,500	370	13	0.00	All
21sep2018	3,023	125	700	1,000	355	38	1.00	All
26oct2018	4,162	125	800	1,000	375	4	1.00	All
20nov2018	7,175	125	800	2,158	350	76	0.33	All
28dec2018	5,017	125	345	80	345	56	0.00	All
03jun2019	83	130	665	46	285	3	1.00	15
03jun2019	95	85	700	72	285	2	1.00	1
03jun2019	146	85	615	48	390	1	1.00	2
03jun2019	74	140	595	40	325	1	1.00	3
03jun2019	126	150	595	66	325	1	1.00	4
03jun2019	533	85	635	240	315	2	1.00	5
03jun2019	868	85	675	426	315	3	1.00	13
03jun2019	317	85	630	114	345	5	1.00	6
03jun2019	462	85	585	142	350	7	1.00	7
03jun2019	192	85	575	40	370	1	1.00	16
03jun2019	657	85	670	300	325	2	1.00	8
03jun2019	534	85	640	200	350	3	1.00	9
03jun2019	162	85	650	62	335	2	1.00	14
03jun2019	317	85	635	124	325	4	1.00	10
03jun2019	66	85	595	40	275	2	1.00	11
03jun2019	25	105	605	25	105	0		12
19aug2019	77	130	505	46	270	1	1.00	15
19aug2019	80	85	640	72	205	1	1.00	1
19aug2019	181	85	625	48	340	1	1.00	2
19aug2019	77	140	480	40	280	2	1.00	3
19aug2019	129	130	605	66	280	1	1.00	4
19aug2019	555	85	650	240	285	24	1.00	5
19aug2019	905	85	635	426	275	9	1.00	13
19aug2019	367	85	680	114	310	1	1.00	6
19aug2019	558	85	640	142	330	1	1.00	7
19aug2019	265	85	550	40	350	4	1.00	16
19aug2019	676	85	640	300	285	6	1.00	8
19aug2019	579	85	645	200	315	1	1.00	9
19aug2019	171	85	675	62	290	2	1.00	14
19aug2019	359	85	625	124	295	3	1.00	10
19aug2019	67	85	605	40	245	1	1.00	11
19aug2019	30	85	680	30	85	0		12
10oct2019	84	85	635	84	85	0		15
10oct2019	93	85	675	93	85	0		1
10oct2019	271	85	645	90	320	1	0.00	2
10oct2019	103	130	665	73	235	1	0.00	3
10oct2019	169	85	740	121	240	2	0.00	4
10oct2019	721	85	680	437	260	1	0.00	5
10oct2019	1,256	85	685	762	250	5	0.00	13
10oct2019	479	85	640	202	285	17	0.00	6
10oct2019	705	85	665	260	295	8	0.00	7
10oct2019	372	85	730	125	315	2	0.00	16
10oct2019	845	85	635	524	260	2	0.00	8
10oct2019	733	85	715	353	285	14	0.00	9
10oct2019	236	85	625	113	275	8	0.00	14
10oct2019	437	85	575	219	275	18	0.00	10
10oct2019	72	85	525	72	85	0		11
10oct2019	32	125	465	32	125	0		12
Total	68,234	85	800	23,565	315			

This table reports, for each regular screening, the number of participants, the minimum and maximum scores (X_i), the number of available vouchers, and the score cutoff. Columns 6-7 reflect sample restrictions: Column 6 shows the minimum number of observations on either side of the cutoff within the smallest estimation window; Column 7 reports the share of later-treated applicants within the $[-5, 5]$ window. Column 8 lists the region (post-2019 reform). Regions are ordered from north to south. Region codes follow official administrative numbering (e.g., Region 15 = Arica y Parinacota; Region 12 = Magallanes; Region 13 = Santiago.)

TABLE A.3. Assignments in Elderly Rounds

Assignment Date	N (1)	Min Xi (2)	Max Xi (3)	Vouchers (4)	Cutoff (5)	R1 (6)	R2 (7)	Region (8)
04sep2017	6,281	135	730	1,860	380	323	0.00	All
11apr2018	2,061	175	645	1,000	380	102	0.00	All
25jun2018	3,789	175	860	1,000	420	22	0.79	All
19oct2018	8,087	145	710	1,000	420	259	0.00	All
05jul2019	242	165	640	38	400	1	0.00	15
05jul2019	204	150	600	30	420	1	0.00	1
05jul2019	171	145	580	30	400	3	0.00	2
05jul2019	96	175	480	15	400	1	0.00	3
05jul2019	232	165	560	35	380	1	0.00	4
05jul2019	1,252	105	690	175	380	23	0.00	5
05jul2019	1,975	105	740	260	400	13	0.00	13
05jul2019	268	180	580	45	380	2	0.00	6
05jul2019	430	185	620	60	400	9	0.00	7
05jul2019	231	195	620	40	390	4	0.00	16
05jul2019	797	125	620	111	400	1	0.00	8
05jul2019	506	150	620	75	390	1	0.00	9
05jul2019	255	170	620	34	400	3	0.00	14
05jul2019	345	165	610	55	400	4	0.00	10
05jul2019	53	170	545	15	380	3	0.00	11
05jul2019	44	225	580	15	375	1	0.00	12
Total	27,319	105	860	5,893	401			

This table replicates the analysis in Table A.2 using data from elderly screenings. See Table A.2 for details.

TABLE A.4. Density Test

	Binomial Test (q=0.5)				
Sample	N (1)	Observed T (2)	Expected T (3)	Observed q (4)	p-value (5)
All screenings	4,099	2,023	2,050	0.49	0.417
Screenings in Wo	2,679	1,318	1,340	0.49	0.417

This table reports binomial tests for manipulation in the running variable using data within the small window $W = [-5, 5]$ around the cutoff. It presents the results for all screenings considered in window selection, followed by those in the evaluation sample. The null hypothesis assumes a probability of success $q = 0.5$. See Section 4 for more details.

TABLE A.5. Descriptive Statistics of Score Components in the Evaluation Sample

		Control		Treated		Difference
	N	Mean	SD	Mean	SD	(5)-(3)
	(1)	(2)	(3)	(4)	(5)	(6)
Regular Rounds						
Family size score	926	45.16	5.87	47.80	8.89	2.64
Single parenthood score	926	29.16	5.44	30.71	3.77	1.55
Number of children under 5 score	926	14.63	12.03	21.89	13.06	7.26
Number of children 6 to 18 score	926	9.24	8.09	10.07	10.31	0.83
Number of elderly score	926	0.91	0.87	0.05	0.11	-0.86
Number of people with disability score	926	0.40	0.66	6.05	13.39	5.65
Social vulnerability score	926	175.97	2.62	174.24	6.01	-1.73
Housing vulnerability score	926	13.82	22.60	10.68	20.25	-3.14
Application score	926	292.45	28.46	296.04	27.92	3.59
Elderly Rounds						
Family size score	1,717	40.24	0.41	42.62	2.42	2.39
Single parenthood score	1,717	0.03	0.06	0.00	0.00	-0.03
Number of children under 5 score	1,717	0.00	0.00	0.00	0.00	0.00
Number of children 6 to 18 score	1,717	0.04	0.07	1.14	1.90	1.10
Number of elderly score	1,717	57.31	3.56	56.89	4.26	-0.42
Number of people with disability score	1,717	0.92	0.50	1.02	0.91	0.10
Social vulnerability score	1,717	178.64	0.87	177.72	3.25	-0.92
Housing vulnerability score	1,717	20.77	16.60	22.69	17.98	1.93
Application score	1,717	379.88	0.11	380.22	0.38	0.34

This table reports summary statistics of total application scores and components in the evaluation sample for regular and elderly rounds. Columns 6 shows the difference in means between treatment and control group.

TABLE A.6. Lease-up rate by screening of applicants in the Evaluation Sample

		Screening				
Regular	All	Apr 2018	Dec 2018	Oct 2019	Oct 2019	Oct 2019
				O'Higgins	Araucania	Los Lagos
By December 2019	0.29	0.46	0.29	0.17	0.22	0.11
By March 2020	0.38	0.49	0.35	0.33	0.36	0.21
By November 2020	0.48	0.53	0.36	0.39	0.57	0.32
Elderly	All	Sept 2017	Apr 2018	Jul 2019		
				Valparaiso		
By December 2019	0.54	0.53	0.61	0.47		
By March 2020	0.54	0.53	0.65	0.50		
By November 2020	0.55	0.53	0.67	0.57		

This table shows lease up rates per screening of applicants in the evaluation sample for regular and elderly rounds.

TABLE A.7. Regular recipients in W_0 vs. All Regular Recipients in Selected Screenings s_t

	All			Sample			Difference
	N	Mean	SD	N	Mean	SD	(5)-(2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	2,354	0.85	0.35	317	0.91	0.29	0.05
Poor	2,354	0.31	0.46	317	0.22	0.42	-0.09
Tenant	2,354	0.68	0.46	317	0.77	0.42	0.09
Family income (UF)	2,354	14.13	5.28	317	13.19	4.98	-0.93
Previous app. to ownership subsidy	2,354	0.18	0.38	317	0.15	0.36	-0.03
Geocoded location	2,354	0.91	0.29	317	0.92	0.26	0.02
SERVIU county presence	2,354	0.49	0.50	317	0.45	0.50	-0.04
Saving balance (UF)	2,354	15.04	14.18	317	15.77	15.82	0.74
Online Application	2,354	0.34	0.47	317	0.35	0.48	0.01
Multiple screenings within round	2,354	0.14	0.35	317	0.60	0.49	0.45
Age 25-35	2,354	0.58	0.49	317	0.65	0.48	0.07
Chilean	2,354	0.94	0.24	317	0.97	0.18	0.03
Spouse/partner	2,354	0.23	0.42	317	0.12	0.33	-0.10
Household Size	2,354	3.37	1.30	317	2.75	1.13	-0.62
Number of bedrooms	2,354	1.59	0.74	317	1.66	0.82	0.06
Informal Shelter	2,354	0.17	0.37	317	0.06	0.23	-0.11
Overcrowding indicator	2,348	0.41	0.49	317	0.03	0.18	-0.38
Previous app. in neighborhood (500mts)	2,354	0.51	0.50	317	0.47	0.50	-0.04
County poverty rate	2,354	0.11	0.06	317	0.13	0.07	0.02
Santiago	2,354	0.16	0.37	317	0.11	0.31	-0.05
North	2,354	0.07	0.25	317	0.03	0.18	-0.03
Valparaiso	2,354	0.09	0.28	317	0.06	0.24	-0.02
Center South	2,354	0.31	0.46	317	0.23	0.42	-0.08
South	2,354	0.38	0.48	317	0.56	0.50	0.18
High density county	2,354	0.43	0.50	317	0.35	0.48	-0.08
Answered Baseline Survey	2,354	0.69	0.46	317	0.72	0.45	0.03
Previous round applications	2,354	0.25	0.47	317	0.26	0.48	0.01
KM to closest SERVIU	2,137	16.80	21.86	293	21.62	27.24	4.82
Rent burden	2,091	0.54	0.13	239	0.51	0.22	-0.04
Rent (UF)	2,285	5.43	1.61	281	5.33	2.70	-0.10
Desire to stay in place	1,472	0.55	0.50	194	0.56	0.50	0.01
Satisfied with housing	1,515	0.59	0.49	211	0.66	0.48	0.07
Score Components and Total Score							
Family size score	2,354	76.52	35.40	317	50.60	22.70	-25.92
Single parenthood score	2,354	22.20	16.86	317	29.26	12.98	7.06
Number of children under 5 score	2,354	19.87	17.43	317	24.13	11.92	4.26
Number of children 6 to 18 score	2,354	17.21	16.32	317	9.97	11.32	-7.24
Number of people with disability score	2,354	1.75	7.13	317	7.67	13.11	5.92
Number of elderly score	2,354	0.61	4.99	317	0.09	1.68	-0.52
Social vulnerability score	2,354	173.54	18.77	317	172.76	19.08	-0.78
Housing vulnerability score	2,354	49.86	57.03	317	13.63	23.30	-36.23
Previous application score	2,354	4.67	8.99	317	4.98	9.37	0.31
Application score	2,354	364.99	75.78	317	301.55	25.78	-63.44

This table shows summary statistics for all regular recipients in screenings s_t selected into the evaluation sample (Columns 1-3) and for those included in the evaluation sample (Columns 4-6). Column 7 reports the difference in means between the two groups.

TABLE A.8. Elderly recipients in W_0 vs. All Elderly Recipients in Selected Screenings s_t

	All			Sample			Difference
	N	Mean	SD	N	Mean	SD	(2)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	3,035	0.55	0.50	973	0.61	0.49	0.06
Poor	3,035	0.59	0.49	973	0.52	0.50	-0.07
Tenant	3,035	0.48	0.50	973	0.52	0.50	0.03
Family income (UF)	3,035	6.38	3.31	973	6.35	2.88	-0.04
Previous app. to ownership subsidy	3,035	0.06	0.24	973	0.05	0.23	-0.01
Geocoded location	3,035	0.90	0.31	973	0.89	0.32	-0.01
Spouse/partner	3,035	0.41	0.49	973	0.43	0.50	0.02
SERVIU county presence	3,035	0.55	0.50	973	0.56	0.50	0.01
Age 60-75	3,035	0.52	0.50	973	0.41	0.49	-0.12
Chilean	3,035	0.98	0.13	973	0.99	0.12	0.00
Household Size	3,035	1.85	1.39	973	1.50	0.83	-0.36
Number of bedrooms	3,035	1.27	0.71	973	1.30	0.61	0.03
Informal Shelter	3,035	0.33	0.47	973	0.19	0.39	-0.14
Overcrowding indicator	2,872	0.11	0.32	973	0.01	0.11	-0.10
Previous app. in neighborhood (500mts)	3,035	0.60	0.49	973	0.71	0.45	0.11
County poverty rate	3,035	0.09	0.05	973	0.09	0.05	-0.00
Santiago	3,035	0.22	0.42	973	0.26	0.44	0.03
North	3,035	0.14	0.34	973	0.13	0.34	-0.00
Valparaiso	3,035	0.24	0.43	973	0.23	0.42	-0.01
Center South	3,035	0.23	0.42	973	0.21	0.41	-0.01
South	3,035	0.18	0.38	973	0.17	0.38	-0.01
High density county	3,035	0.46	0.50	973	0.50	0.50	0.03
Previous round applications	3,035	0.17	0.43	973	0.05	0.23	-0.12
KM to closest SERVIU	2,719	12.58	18.52	864	12.26	19.03	-0.32
Score Components and Total Score							
Family size score	3,035	45.71	20.14	973	40.95	6.60	-4.76
Single parenthood score	3,035	0.18	2.53	973	0.00	0.00	-0.18
Number of children under 5 score	3,035	0.46	4.09	973	0.00	0.00	-0.46
Number of children 6 to 18 score	3,035	1.46	6.59	973	0.16	2.02	-1.30
Number of people with disability score	3,035	3.64	10.50	973	0.34	3.17	-3.30
Number of elderly score	3,035	57.27	9.66	973	59.45	4.68	2.17
Social vulnerability score	3,035	178.37	9.94	973	179.72	4.07	1.35
Housing vulnerability score	3,035	51.13	56.86	973	14.41	22.99	-36.72
Previous application score	3,035	3.28	8.35	973	0.82	4.27	-2.46
Application score	3,035	419.39	50.76	973	380.02	0.32	-39.37

This table replicates the analysis in Table A.7 using elderly rounds data. See Table A.7 for details.

TABLE A.9. Pre-pandemic Outcomes (OLS, ITT, and LATE estimates) for Regular Rounds

Outcome Variable	N	Control Mean [SD]	Voucher Use OLS	Reduced Form ITT	Reduced Form ITT	IV LATE
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	925	2.85	0.008	0.112	0.119	0.441
		[1.21]	(0.100)	(0.089)	(0.085)	(0.309)
Number of bedrooms	921	1.76	0.420***	0.215***	0.243***	0.895***
		[0.83]	(0.072)	(0.060)	(0.056)	(0.196)
Number of people per bedroom	921	1.80	-0.369***	-0.134***	-0.162***	-0.595***
		[0.69]	(0.053)	(0.047)	(0.042)	(0.145)
Overcrowing indicator	921	0.12	-0.084***	-0.035*	-0.045**	-0.167**
		[0.33]	(0.022)	(0.021)	(0.021)	(0.077)
Female head of household	925	0.73	0.015	-0.021	-0.013	-0.049
		[0.44]	(0.034)	(0.032)	(0.027)	(0.094)
Moved to diff. unit	849	0.43	0.210***	0.080**	0.073*	0.269**
		[0.50]	(0.046)	(0.037)	(0.038)	(0.132)
Stayed in 1km radius	849	0.71	-0.165***	-0.074**	-0.077**	-0.285**
		[0.46]	(0.047)	(0.035)	(0.036)	(0.128)
Moved +10km away	849	0.12	0.107***	0.062**	0.062**	0.231**
		[0.33]	(0.037)	(0.027)	(0.027)	(0.099)
Moved to another county	849	0.07	0.051*	0.055**	0.059***	0.217***
		[0.26]	(0.028)	(0.022)	(0.021)	(0.079)
County level poverty	856	-0.05	-0.024	0.021	-0.028	-0.103
		[1.00]	(0.081)	(0.070)	(0.060)	(0.203)
County crime victims	856	0.02	-0.028	-0.001	0.048	0.179
		[0.83]	(0.058)	(0.060)	(0.045)	(0.162)
School Quality	816	0.02	-0.055	-0.027	-0.028	-0.108
		[0.94]	(0.100)	(0.073)	(0.072)	(0.266)
Distance to school	849	-0.08	0.340**	0.249**	0.248**	0.918**
		[0.69]	(0.172)	(0.102)	(0.103)	(0.386)
Distance to early childhood educ.	849	-0.07	0.352**	0.227**	0.210**	0.777**
		[0.76]	(0.151)	(0.093)	(0.091)	(0.335)
Distance to health care	849	-0.05	0.291*	0.179*	0.162*	0.599*
		[0.78]	(0.157)	(0.097)	(0.098)	(0.361)
Kms to closest municipality	921	0.00	0.075	0.044	0.016	0.058
		[1.01]	(0.094)	(0.067)	(0.064)	(0.232)
Application to Ownership Programs	926	0.31	-0.001	0.016	0.005	0.017
		[0.46]	(0.042)	(0.033)	(0.031)	(0.112)
Application DS1	926	0.23	-0.019	0.007	-0.001	-0.004
		[0.42]	(0.039)	(0.030)	(0.029)	(0.103)
Application DS49	926	0.12	-0.004	0.006	-0.002	-0.009
		[0.32]	(0.027)	(0.022)	(0.022)	(0.076)
Active ownership savings account	926	0.92	0.007	0.014	0.012	0.043
		[0.27]	(0.023)	(0.019)	(0.018)	(0.066)
COVARIATES			YES	NO	YES	YES
SCREENING FE			YES	YES	YES	YES

This table presents different estimators for the effect of the rental voucher on outcomes measured in December 2019, included in Table V. Columns 2 reports the control mean and standard deviation (in brackets). Column 3 presents OLS estimates of the effect of voucher use. Columns 4 and 5 report ITT estimates from the RDD research design with and without covariates used in balance tests. Column 6 shows LATE estimates from a two-stage least squares model using the score discontinuity as an instrument for voucher use. All specifications include applicant screenings fixed effects. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE A.10. Pre-pandemic Outcomes (OLS, ITT, and LATE estimates) for Elderly Rounds

Outcome Variable	N	Control Mean [SD] (2)	Voucher Use OLS (2)	Reduced Form ITT (3)	Reduced Form ITT (4)	IV LATE (5)
Household size	1,717	1.60	-0.113***	-0.151***	-0.156***	-0.289***
		[1.11]	(0.043)	(0.057)	(0.051)	(0.094)
Number of bedrooms	1,604	1.35	0.880***	0.443***	0.439***	0.782***
		[0.74]	(0.044)	(0.046)	(0.045)	(0.075)
Number of people per bedroom	1,604	1.24	-0.490***	-0.296***	-0.300***	-0.535***
		[0.59]	(0.024)	(0.032)	(0.027)	(0.044)
Overcrowing indicator	1,604	0.03	-0.020***	-0.014	-0.014	-0.026
		[0.17]	(0.007)	(0.010)	(0.009)	(0.017)
Female head of household	1,717	0.49	0.017	0.043	0.026	0.049
		[0.50]	(0.016)	(0.027)	(0.016)	(0.030)
Moved to diff. unit	1,549	0.34	0.351***	0.261***	0.257***	0.447***
		[0.47]	(0.026)	(0.028)	(0.028)	(0.047)
Stayed in 1km radius	1,549	0.76	-0.283***	-0.195***	-0.194***	-0.338***
		[0.43]	(0.027)	(0.027)	(0.026)	(0.045)
Moved +10km away	1,549	0.11	0.112***	0.081***	0.084***	0.147***
		[0.31]	(0.022)	(0.020)	(0.020)	(0.034)
Moved to another county	1,549	0.09	0.122***	0.048***	0.055***	0.096***
		[0.29]	(0.020)	(0.018)	(0.018)	(0.030)
County level poverty	1,577	-0.03	-0.006	-0.028	-0.050	-0.086
		[0.98]	(0.046)	(0.058)	(0.047)	(0.081)
County crime victims	1,575	-0.01	-0.057	-0.004	-0.007	-0.013
		[0.80]	(0.040)	(0.047)	(0.039)	(0.067)
School Quality	1,509	-0.02	0.014	-0.006	0.001	0.001
		[0.99]	(0.053)	(0.056)	(0.055)	(0.095)
Distance to school	1,549	0.04	-0.029	-0.070	-0.066	-0.115
		[1.27]	(0.046)	(0.051)	(0.051)	(0.089)
Distance to early childhood educ.	1,549	0.04	-0.038	-0.073	-0.066	-0.116
		[1.24]	(0.047)	(0.051)	(0.051)	(0.088)
Distance to health care	1,549	0.04	-0.024	-0.073	-0.067	-0.117
		[1.24]	(0.047)	(0.053)	(0.053)	(0.092)
Kms to closest municipality	1,624	0.04	-0.110**	-0.083	-0.102**	-0.179**
		[1.11]	(0.048)	(0.056)	(0.052)	(0.090)
Application to Ownership Programs	1,717	0.12	0.059***	0.047***	0.048***	0.088***
		[0.33]	(0.019)	(0.018)	(0.018)	(0.033)
Application DS1	1,717	0.07	0.019	0.022	0.023	0.043
		[0.26]	(0.015)	(0.014)	(0.014)	(0.026)
Application DS49	1,717	0.07	0.048***	0.035**	0.034**	0.063**
		[0.25]	(0.016)	(0.014)	(0.014)	(0.026)
COVARIATES			YES	NO	YES	YES
SCREENING FE			YES	YES	YES	YES

This table replicates the analysis in Table A.9 using data from elderly rounds and outcomes from December 2019 in Table VI. See Tables A.9 and VI for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE A.11. Post-pandemic Outcomes (OLS, ITT, and LATE estimates) for Regular Rounds

Outcome Variable	N	Control Mean [SD]	Voucher Use OLS	Reduced Form ITT	Reduced Form ITT	IV LATE
	(1)	(2)	(3)	(4)	(5)	(6)
Shelter Deprived	464	0.17	-0.160***	-0.028	-0.029	-0.050
		[0.38]	(0.034)	(0.035)	(0.035)	(0.058)
Formal Lease	402	0.60	0.407***	0.099*	0.116**	0.200**
		[0.49]	(0.044)	(0.052)	(0.052)	(0.080)
Total rent (unit)	326	6.80	0.059	-0.094	0.040	0.059
		[2.81]	(0.287)	(0.289)	(0.277)	(0.398)
Rent burden (rent paid)	284	0.48	-0.145***	-0.116***	-0.100***	-0.151***
		[0.27]	(0.033)	(0.030)	(0.031)	(0.043)
Employed	344	0.69	-0.016	-0.027	-0.032	-0.055
		[0.47]	(0.065)	(0.054)	(0.056)	(0.091)
Family Income	340	13.42	-0.275	0.388	0.336	0.573
		[5.71]	(0.659)	(0.593)	(0.618)	(1.009)
Debt overload	342	0.69	-0.134*	-0.120**	-0.123**	-0.213**
		[0.46]	(0.069)	(0.057)	(0.058)	(0.096)
Spouse/Partner	339	0.32	-0.000	0.098*	0.089	0.151*
		[0.47]	(0.065)	(0.057)	(0.055)	(0.090)
Household Size	428	3.28	-0.315**	-0.075	-0.066	-0.110
		[1.40]	(0.133)	(0.137)	(0.141)	(0.225)
Number of people per bedroom	417	1.58	-0.263***	-0.102	-0.099	-0.168
		[0.69]	(0.072)	(0.068)	(0.070)	(0.112)
Overcrowding indicator	418	0.11	-0.058*	-0.034	-0.035	-0.060
		[0.31]	(0.032)	(0.029)	(0.032)	(0.051)
Number of bedrooms	417	2.24	0.066	0.019	0.019	0.033
		[0.88]	(0.085)	(0.080)	(0.081)	(0.132)
Laundry Room	415	0.36	0.040	0.019	0.034	0.058
		[0.48]	(0.059)	(0.050)	(0.049)	(0.080)
Kitchen Room	415	0.75	0.132***	0.138***	0.146***	0.247***
		[0.43]	(0.047)	(0.042)	(0.042)	(0.069)
Heat system	415	0.80	0.075**	0.103***	0.093***	0.157***
		[0.40]	(0.031)	(0.033)	(0.031)	(0.052)
Cable, Wifi	412	0.59	0.028	-0.004	-0.018	-0.030
		[0.35]	(0.045)	(0.037)	(0.038)	(0.061)
Satisfaction current housing unit	459	0.77	0.205***	0.066*	0.070*	0.121*
		[0.42]	(0.035)	(0.039)	(0.039)	(0.064)
2 or more years current house	459	0.47	-0.290***	-0.120**	-0.127**	-0.217***
		[0.50]	(0.050)	(0.049)	(0.050)	(0.078)
Household income loss after COVID-19	343	0.80	-0.070	-0.067	-0.068	-0.118
		[0.40]	(0.064)	(0.051)	(0.054)	(0.088)
Temporary unemployment due to COVID-19	344	0.18	0.049	0.065	0.058	0.100
		[0.39]	(0.056)	(0.047)	(0.050)	(0.080)
COVID-19: Expenses	340	0.69	-0.036	-0.015	-0.019	-0.033
		[0.46]	(0.066)	(0.055)	(0.056)	(0.091)
COVID-19: Debt	340	0.67	-0.067	-0.139**	-0.151**	-0.255**
		[0.47]	(0.069)	(0.059)	(0.060)	(0.101)
COVID-19: New Income Source	340	0.43	-0.114*	-0.043	-0.040	-0.067
		[0.50]	(0.068)	(0.058)	(0.061)	(0.097)
COVID-19: Applied to Emergency Support	340	0.57	-0.127*	-0.061	-0.070	-0.119
		[0.50]	(0.068)	(0.059)	(0.061)	(0.097)
COVID-19: Moved out	340	0.07	-0.013	-0.037	-0.033	-0.055
		[0.25]	(0.030)	(0.023)	(0.025)	(0.041)
COVID-19: Others moved in	340	0.06	-0.000	0.036	0.049	0.083
		[0.23]	(0.035)	(0.033)	(0.032)	(0.054)
COVID-19: Delayed rent payments	340	0.22	-0.170***	-0.108**	-0.108**	-0.184***
		[0.42]	(0.040)	(0.042)	(0.043)	(0.070)
Positive Ammenities	450	-0.02	-0.141	-0.014	-0.043	-0.072
		[1.02]	(0.123)	(0.105)	(0.105)	(0.170)
Negative Ammenities	328	-0.00	-0.207*	0.046	-0.013	-0.021
		[1.01]	(0.123)	(0.115)	(0.115)	(0.184)
Would ask neighbors for childcare	427	0.29	-0.058	-0.100**	-0.100**	-0.163**
		[0.45]	(0.050)	(0.044)	(0.045)	(0.072)
2 or more years current neighborhood	451	0.55	-0.232***	-0.081	-0.084	-0.143*
		[0.50]	(0.055)	(0.051)	(0.051)	(0.081)
Satisfaction current neighborhood	443	0.82	0.082**	-0.042	-0.040	-0.068
		[0.38]	(0.042)	(0.039)	(0.040)	(0.064)
COVARIATES			YES	NO	YES	YES
SCREENING FE			YES	YES	YES	YES

This table replicates the analysis in Table A.9 using survey data from regular rounds and November 2020 outcomes from Table VII. See Table A.9 for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE A.12. Balance in Baseline Characteristics in $W = [-1, 1]$ (Regular Rounds)

		Control		Treated			Balance Test	
	N	Mean	SD	Mean	SD	Diff	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	539	0.97	0.18	0.98	0.15	0.01	0.577	0.594
Poor	539	0.16	0.37	0.20	0.40	0.04	0.283	0.290
Tenant	539	0.76	0.43	0.72	0.45	-0.04	0.592	0.576
Family income (UF)	539	12.39	3.58	12.18	3.89	-0.21	0.321	0.325
Saving balance (UF)	539	16.04	14.37	16.00	15.13	-0.04	0.611	0.612
Previous app. to ownership subsidy	539	0.14	0.35	0.16	0.37	0.01	0.373	0.370
Geocoded location	539	0.88	0.33	0.91	0.29	0.03	0.907	0.974
SERVIU county presence	539	0.54	0.50	0.49	0.50	-0.05	0.748	0.710
Online Application	539	0.42	0.49	0.41	0.49	-0.00	0.519	0.502
Multiple screenings within round	539	0.67	0.47	0.53	0.50	-0.14	0.008***	0.013**
Age 25-35	539	0.67	0.47	0.68	0.47	0.01	0.610	0.615
Chilean	539	0.94	0.23	0.97	0.18	0.02	0.144	0.133
Spouse/partner	539	0.05	0.21	0.04	0.19	-0.01	0.933	0.829
Household Size	539	2.31	0.84	2.52	1.06	0.21	0.480	0.505
Number of bedrooms	539	1.42	0.71	1.51	0.77	0.09	0.826	0.809
Informal Shelter	539	0.13	0.34	0.07	0.25	-0.06	0.777	0.866
Crowding	539	1.77	0.40	1.79	0.37	0.03	0.566	0.569
Previous app. in neighborhood (500mts)	539	0.42	0.49	0.50	0.50	0.08	0.211	0.222
County poverty rate	539	0.11	0.06	0.12	0.06	0.01	0.969	0.963
Santiago	539	0.17	0.37	0.13	0.33	-0.04	0.443	0.429
North	539	0.09	0.29	0.04	0.19	-0.05	0.093*	0.091*
Valparaiso	539	0.10	0.30	0.08	0.27	-0.02	0.615	0.598
Center South	539	0.30	0.46	0.29	0.45	-0.01	0.109	0.112
South	539	0.35	0.48	0.47	0.50	0.12	0.582	0.574
High density county	539	0.39	0.49	0.38	0.49	-0.01	0.928	0.927
Answered Baseline Survey	539	0.75	0.44	0.81	0.40	0.06	0.130	0.128
Previous round applications	539	0.31	0.47	0.19	0.40	-0.11	0.021**	0.018**
KM to closest SERVIU	480	15.34	20.36	17.52	23.53	2.18	0.482	0.468
Rent burden	257	0.48	0.26	0.53	0.28	0.04	0.097*	0.087*
Rent (UF)	355	5.35	3.18	5.38	3.53	0.03	0.952	0.947
Desire to stay in place	355	0.54	0.50	0.54	0.50	0.00	0.869	0.871
Satisfied with housing	380	0.64	0.48	0.65	0.48	0.01	0.835	0.850
SCREENING INDICATORS							Yes	Yes
SCREENING INDICATORSxTREAT							No	No
Joint Significance (p)							0.186	0.389

This table presents summary statistics and balance tests between treatment and control groups in the sample of randomized vouchers within the narrower window $W = [-1, 1]$ from regular rounds. Columns 1-5 report baseline characteristics. Columns 7-8 show results from the first balance from equation 3 using, respectively, large-sample inference (F-test) and Fisherian randomization inference p-values (Randomization-t exact test), computed using 1,000 iterations in the Stata package randcmd (Young, 2019). The bottom panel reports joint significance tests from regressing treatment on baseline covariates using both inference methods. See Section 4 and Table V for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE A.13. Balance in Baseline Characteristics in $W = [-1, 1]$ (Elderly Rounds)

		Control		Treated			Balance Test	
	N	Mean	SD	Mean	SD	Diff	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	1,672	0.61	0.49	0.61	0.49	-0.00	0.540	0.541
Poor	1,672	0.57	0.50	0.52	0.50	-0.05	0.114	0.103
Tenant	1,672	0.55	0.50	0.51	0.50	-0.04	0.885	0.905
Family income (UF)	1,672	6.02	2.47	6.25	2.74	0.23	0.402	0.422
Previous app. to ownership subsidy	1,672	0.06	0.23	0.05	0.22	-0.00	0.779	0.764
Geocoded location	1,672	0.92	0.27	0.89	0.32	-0.04	0.949	0.976
Spouse/partner	1,672	0.39	0.49	0.42	0.49	0.04	0.907	0.884
SERVIU county presence	1,672	0.51	0.50	0.56	0.50	0.05	0.027**	0.029**
Age 60-75	1,672	0.57	0.50	0.40	0.49	-0.18	0.853	0.823
Chilean	1,672	0.98	0.13	0.99	0.12	0.00	0.666	0.696
Household Size	1,672	1.51	0.98	1.45	0.78	-0.06	0.008***	0.011**
Number of bedrooms	1,672	1.33	0.65	1.28	0.60	-0.05	0.018**	0.015**
Informal Shelter	1,672	0.16	0.37	0.19	0.39	0.03	0.320	0.330
Crowding	1,672	1.17	0.46	1.18	0.45	0.01	0.589	0.594
Previous app. in neighborhood (500mts)	1,672	0.60	0.49	0.72	0.45	0.11	0.170	0.187
County poverty rate	1,672	0.08	0.05	0.09	0.05	0.00	0.762	0.771
Santiago	1,672	0.23	0.42	0.26	0.44	0.03	0.087*	0.087*
North	1,672	0.09	0.29	0.13	0.34	0.04	0.208	0.204
Valparaiso	1,672	0.36	0.48	0.22	0.42	-0.14	0.656	0.626
Center South	1,672	0.20	0.40	0.21	0.41	0.01	0.622	0.600
South	1,672	0.12	0.33	0.17	0.38	0.05	0.266	0.226
High density county	1,672	0.51	0.50	0.49	0.50	-0.02	0.442	0.456
Previous round applications	1,672	0.20	0.48	0.04	0.20	-0.15	0.139	0.148
KM to closest SERVIU	1,509	12.78	17.83	12.04	18.86	-0.75	0.194	0.213
SCREENING INDICATORS							Yes	Yes
SCREENING INDICATORSxTREAT							No	No
Joint Significance F-Test (p)							0.293	0.339

This table replicates the analysis in Table A.12 using the sample of randomized vouchers within the narrower window $W = [-1, 1]$ from elderly rounds. See Table A.12 and VI for details.

TABLE A.14. Pre-pandemic Outcomes in $W = [-1, 1]$ (Regular Rounds)

Outcome Variable	N	Control Mean [SD]	Voucher Use OLS	Reduced Form ITT	Reduced Form ITT	IV LATE
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	538	2.65	-0.196	0.067	0.026	0.089
		[1.13]	(0.124)	(0.119)	(0.119)	(0.382)
Number of bedrooms	536	1.58	0.474***	0.297***	0.295***	1.008***
		[0.77]	(0.098)	(0.080)	(0.076)	(0.244)
Number of people per bedroom	536	1.84	-0.527***	-0.247***	-0.264***	-0.902***
		[0.65]	(0.069)	(0.058)	(0.053)	(0.168)
Overcrowing indicator	536	0.10	-0.110***	-0.046*	-0.059**	-0.200**
		[0.29]	(0.024)	(0.025)	(0.026)	(0.087)
Female head of household	538	0.87	-0.028	-0.019	-0.028	-0.096
		[0.34]	(0.042)	(0.036)	(0.032)	(0.097)
Moved to diff. unit	480	0.48	0.209***	0.096*	0.071	0.239
		[0.50]	(0.060)	(0.050)	(0.051)	(0.159)
Stayed in 1km radius	480	0.67	-0.167***	-0.084*	-0.072	-0.243
		[0.47]	(0.061)	(0.047)	(0.048)	(0.156)
Moved +10km away	480	0.14	0.096**	0.043	0.043	0.146
		[0.34]	(0.046)	(0.035)	(0.035)	(0.112)
Moved to another county	480	0.09	0.057	0.039	0.048*	0.162*
		[0.29]	(0.036)	(0.028)	(0.028)	(0.088)
County level poverty	485	-0.26	-0.067	0.013	-0.065	-0.218
		[0.90]	(0.102)	(0.090)	(0.080)	(0.229)
County crime victims	485	0.06	0.038	-0.010	0.068	0.230
		[0.82]	(0.072)	(0.077)	(0.058)	(0.188)
School Quality	467	0.00	-0.009	-0.028	-0.024	-0.081
		[0.93]	(0.125)	(0.091)	(0.093)	(0.304)
Distance to school	480	-0.07	0.395	0.348**	0.345*	1.164*
		[0.80]	(0.269)	(0.165)	(0.183)	(0.620)
Distance to early childhood educ.	480	-0.08	0.426*	0.368**	0.324**	1.091**
		[0.81]	(0.227)	(0.144)	(0.155)	(0.525)
Distance to health care	480	-0.04	0.352	0.311**	0.274	0.924
		[0.88]	(0.243)	(0.156)	(0.173)	(0.580)
Kms to closest municipality	536	0.08	0.089	0.049	0.000	0.001
		[1.17]	(0.135)	(0.102)	(0.100)	(0.330)
Application to Ownership Programs	539	0.34	0.043	0.061	0.031	0.106
		[0.47]	(0.053)	(0.044)	(0.040)	(0.129)
Application DS1	539	0.24	0.031	0.044	0.024	0.081
		[0.43]	(0.048)	(0.041)	(0.037)	(0.116)
Application DS49	539	0.16	-0.011	0.013	-0.010	-0.036
		[0.36]	(0.038)	(0.033)	(0.032)	(0.104)
Active ownership savings account	539	0.92	-0.004	0.018	0.013	0.046
		[0.27]	(0.032)	(0.025)	(0.025)	(0.084)
COVARIATES			YES	NO	YES	YES
SCREENING FE			YES	YES	YES	YES

This table replicates the analysis in Table V for the sample of randomized vouchers within the narrower window $W = [-1, 1]$ from regular rounds. See Table V for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE A.15. Pre-pandemic Outcomes in $W = [-1, 1]$ (Elderly Rounds)

Outcome Variable	N	Control Mean [SD] (2)	Voucher Use OLS (2)	Reduced Form ITT (3)	Reduced Form ITT (4)	IV LATE (5)
Household size	1,672	1.59	-0.118***	-0.207***	-0.195***	-0.359***
		[1.10]	(0.043)	(0.055)	(0.050)	(0.093)
Number of bedrooms	1,562	1.35	0.889***	0.433***	0.432***	0.767***
		[0.74]	(0.045)	(0.048)	(0.047)	(0.077)
Number of people per bedroom	1,562	1.24	-0.494***	-0.317***	-0.312***	-0.555***
		[0.59]	(0.025)	(0.032)	(0.027)	(0.045)
Overcrowing indicator	1,562	0.03	-0.017**	-0.017*	-0.016*	-0.028*
		[0.17]	(0.007)	(0.009)	(0.009)	(0.016)
Female head of household	1,672	0.50	0.015	0.042	0.029*	0.053*
		[0.50]	(0.016)	(0.028)	(0.017)	(0.031)
Moved to diff. unit	1,509	0.33	0.354***	0.269***	0.266***	0.462***
		[0.47]	(0.026)	(0.028)	(0.028)	(0.047)
Stayed in 1km radius	1,509	0.76	-0.286***	-0.201***	-0.201***	-0.350***
		[0.42]	(0.027)	(0.027)	(0.027)	(0.046)
Moved +10km away	1,509	0.10	0.106***	0.073***	0.077***	0.134***
		[0.31]	(0.022)	(0.020)	(0.020)	(0.035)
Moved to another county	1,509	0.09	0.119***	0.044**	0.053***	0.092***
		[0.28]	(0.020)	(0.018)	(0.018)	(0.031)
County level poverty	1,537	-0.03	-0.014	-0.024	-0.049	-0.086
		[0.99]	(0.047)	(0.060)	(0.048)	(0.083)
County crime victims	1,535	-0.00	-0.059	-0.011	-0.009	-0.016
		[0.80]	(0.040)	(0.048)	(0.040)	(0.068)
School Quality	1,471	-0.01	0.001	-0.015	-0.011	-0.018
		[0.98]	(0.054)	(0.058)	(0.056)	(0.097)
Distance to school	1,509	0.04	-0.032	-0.066	-0.065	-0.113
		[1.28]	(0.046)	(0.052)	(0.053)	(0.091)
Distance to early childhood educ.	1,509	0.04	-0.041	-0.072	-0.069	-0.120
		[1.25]	(0.047)	(0.052)	(0.053)	(0.091)
Distance to health care	1,509	0.04	-0.028	-0.065	-0.063	-0.109
		[1.24]	(0.048)	(0.055)	(0.055)	(0.095)
Kms to closest municipality	1,582	0.03	-0.109**	-0.074	-0.096*	-0.166*
		[1.10]	(0.048)	(0.057)	(0.053)	(0.091)
Application to Ownership Programs	1,672	0.12	0.060***	0.045**	0.047**	0.086**
		[0.33]	(0.020)	(0.018)	(0.018)	(0.033)
Application DS1	1,672	0.07	0.015	0.018	0.020	0.036
		[0.26]	(0.015)	(0.015)	(0.015)	(0.027)
Application DS49	1,672	0.07	0.051***	0.035**	0.034**	0.064**
		[0.25]	(0.016)	(0.014)	(0.014)	(0.026)
COVARIATES			YES	NO	YES	YES
SCREENING FE			YES	YES	YES	YES

This table replicates the analysis in Table VI for the sample of randomized vouchers within the narrower window $W = [-1, 1]$ from elderly rounds. See Table VI for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

B Sample Construction

Following Cattaneo, Idrobo and Titiunik (2019), I restrict the sample to screenings with at least 10 observations on each side of the cutoff c_{s_t} within the smallest possible window to ensure sufficient statistical power for balance tests.[24] Column 6 of Appendix Tables A.3 and A.2 reports, respectively for each screening in elderly and regular rounds, the minimum number of observations on either side of the cutoff in the smallest window. This criterion removes 30,301 observations (24,246 applicants) across 61 screenings–47 from regular and 14 from elderly rounds–60% of which occurred in 2019, after the introduction of regional screenings. Figure B.1 presents a sample construction flowchart.

The rolling application system within rounds introduces two types of control units: later-treated applicants (who received a voucher in a subsequent screening) and never-treated applicants (who never received a voucher). Columns 7 of Appendix Tables A.3 and A.2 shows that, with only a few exceptions, the control group in each screening consists exclusively of either later-treated or never-treated, but not both. Of the remaining screenings, nine include later-treated applicants, only one of which occurs in an elderly round. To ensure comparability between estimands for elderly and regular rounds, I restrict the sample to screenings with only never-treated applicants, comparing voucher recipients to individuals who were never treated. This data restriction excludes 26,773 observations (corresponding to 7,071 applicants).

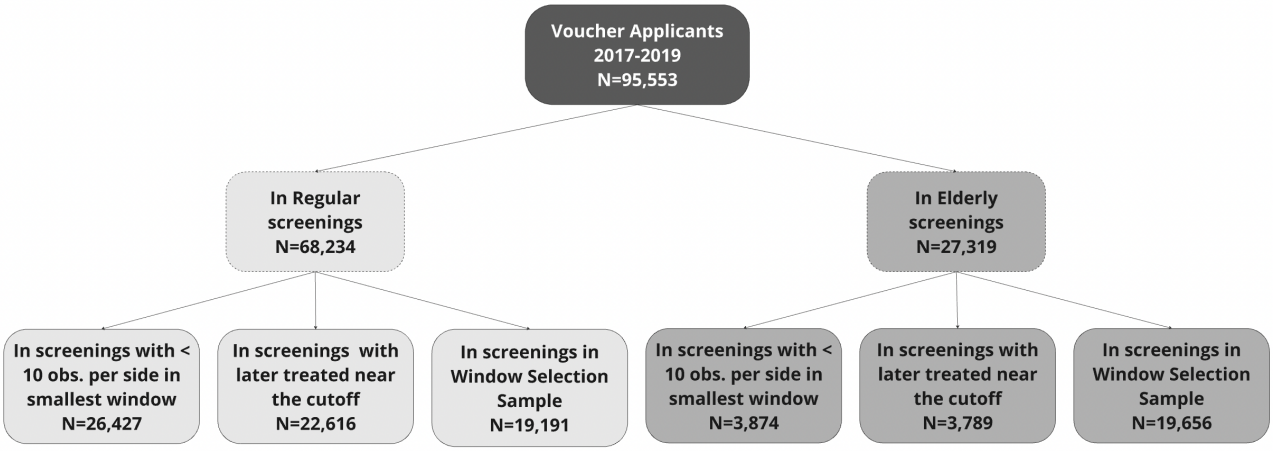


FIGURE B.1. Sample Restrictions

This figure describes the sample construction for both the elderly and regular rounds.

If ties occur at the cutoff, I adjust the running variable based on the program's three-step tie-breaking protocol (see Section 2.1). I assign $X_i = -1$ to applicants randomized out of treatment and $X_i = 1$ to those randomized into treatment; if tie-breaking occurred via non-random score components, I assign $X_i = \pm 2$. This transformation ensures treated and control units lie on opposite sides of the cutoff. Any transformation that preserves this order yields equivalent results under LRRD (Cattaneo, Idrobo and Titiunik, 2019).

[24] Assuming a discrete outcome, a minimum detectable effect of one standard deviation, and significance levels between 0.05 and 0.15, this yields 60-80% power in the smallest window.

C Follow Up Survey Data Attrition

TABLE C.1. Follow Up Sample Attrition in Regular Rounds

	Response Prob.	Rand-t	Response Prob.	Rand-t
	(1)	(2)	(3)	(4)
Treat	0.089	0.3219	0.023	0.8296
	(0.309)		(0.813)	
Treat*December 2018	-0.064	0.0041	0.029	0.9999
	(0.576)		(0.814)	
Treat*October 2019 (O'Higgins)	-0.025	0.8703	0.003	0.9793
	(0.865)		(0.985)	
Treat*October 2019 (Araucania)	-0.032	0.7610	0.042	0.6979
	(0.764)		(0.715)	
Treat*October 2019 (Los Lagos)	-0.098	0.5783	-0.030	0.8563
	(0.563)		(0.866)	
F-Test (p-value)	0.789		0.855	
Rand-t Joint Test (p-value)	0.735		0.885	
Observations	776		776	
COVARIATES	NO		YES	

This table shows the effect of voucher assignment on survey response (R_{i,s_t}), replacing Z_{i,s_t} with R_{i,s_t} in equation 4. Columns 1 and 3 report OLS estimates of δ_{s_t} and standard errors, with and without baseline covariates. Columns 2 and 4 show Fisherian randomization inference p-values (Randomization-t exact test), based on 1,000 iterations using the Stata package randcmd (Young, 2019). The bottom panel presents joint significance test for each $\delta_{s_t} = 0$ using both inference methods. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

We could not offer monetary incentives but encouraged survey response by (i) sending follow-up invitations from the same institutional address used at baseline, (ii) adding a link to MINVU's webpage verifying the ongoing survey, and (iii) launching an FAQ blog where we answered respondent questions submitted after completing the survey. Pandemic policy changes and office closures generated heavy information demand; we received over 10,000 questions during data collection.

TABLE C.2. Balance in Baseline Characteristics in Follow-Up Survey Sample

		Control		Treated			Balance Test	
	N	Mean	SD	Mean	SD	Diff	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	496	0.92	0.28	0.93	0.26	0.01	0.836	0.786
Poor	496	0.20	0.40	0.19	0.39	-0.01	0.729	0.747
Tenant	496	0.85	0.35	0.80	0.40	-0.06	0.683	0.620
Family income (UF)	496	13.47	4.85	13.40	4.77	-0.07	0.693	0.716
Saving balance (UF)	496	15.03	14.11	15.70	16.46	0.67	0.869	0.865
Previous app. to ownership subsidy	496	0.13	0.34	0.14	0.34	0.00	0.878	0.790
Geocoded location	496	0.91	0.28	0.93	0.25	0.02	0.818	0.801
SERVIU county presence	496	0.53	0.50	0.48	0.50	-0.05	0.335	0.327
Online Application	496	0.40	0.49	0.39	0.49	-0.01	0.799	0.764
Multiple screenings within round	496	0.63	0.48	0.60	0.49	-0.03	0.634	0.620
Age 25-35	496	0.62	0.49	0.70	0.46	0.08	0.086*	0.100*
Chilean	496	0.92	0.27	0.98	0.15	0.05	0.017**	0.019**
Spouse/partner	496	0.13	0.34	0.11	0.31	-0.02	0.851	0.845
Household Size	496	2.61	0.99	2.69	1.12	0.08	0.393	0.412
Number of bedrooms	496	1.65	0.78	1.63	0.85	-0.02	0.847	0.799
Informal Shelter	496	0.07	0.26	0.04	0.19	-0.04	0.532	0.607
Crowding	496	1.74	0.50	1.78	0.41	0.04	0.213	0.222
Previous app. in neighborhood (500mts)	496	0.46	0.50	0.49	0.50	0.03	0.541	0.498
County poverty rate	496	0.12	0.06	0.13	0.07	0.01	0.739	0.740
Santiago	496	0.10	0.30	0.08	0.28	-0.02	0.572	0.554
North	496	0.05	0.22	0.04	0.19	-0.01	0.882	0.888
Valparaiso	496	0.09	0.28	0.06	0.24	-0.03	0.623	0.667
Center South	496	0.28	0.45	0.27	0.45	-0.01	0.108	0.100
South	496	0.48	0.50	0.55	0.50	0.07	0.272	0.263
High density county	496	0.42	0.49	0.33	0.47	-0.09	0.060*	0.059*
Answered Baseline Survey	496	0.88	0.32	0.86	0.34	-0.02	0.326	0.328
Previous round applications	496	0.31	0.55	0.26	0.49	-0.06	0.292	0.308
KM to closest SERVIU	457	18.90	25.15	21.46	26.17	2.55	0.701	0.697
Rent burden	305	0.48	0.32	0.49	0.28	0.01	0.842	0.843
Rent (UF)	394	5.58	3.89	5.39	3.50	-0.19	0.615	0.640
Desire to stay in place	377	0.60	0.49	0.58	0.49	-0.02	0.568	0.565
Satisfied with housing	403	0.67	0.47	0.70	0.46	0.03	0.440	0.428
SCREENING INDICATORS							Yes	Yes
SCREENING INDICATORSxTREAT							No	No
Joint Significance (p)							0.903	0.851

This table replicates the analysis in Table III using the subset of regular applicants who responded the follow up survey. It only presents the first balance test, excluding interaction terms from equation 3. See Table III for further details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE C.3. Pre-pandemic Outcomes (OLS, ITT, and LATE estimates) in Survey Data

Outcome Variable	N	Control Mean [SD]	Voucher Use OLS	Reduced Form ITT	Reduced Form ITT	IV LATE
	(1)	(2)	(3)	(4)	(5)	(6)
Household size	496	3.04	-0.200	0.042	0.083	0.258
		[1.24]	(0.141)	(0.124)	(0.125)	(0.383)
Number of bedrooms	495	1.96	0.535***	0.161*	0.188**	0.585**
		[0.88]	(0.114)	(0.082)	(0.081)	(0.242)
Number of people per bedroom	495	1.72	-0.512***	-0.119*	-0.128**	-0.398**
		[0.70]	(0.077)	(0.066)	(0.063)	(0.182)
Overcrowing indicator	495	0.11	-0.086***	-0.019	-0.023	-0.072
		[0.32]	(0.026)	(0.028)	(0.029)	(0.086)
Female head of household	496	0.76	-0.016	-0.022	-0.013	-0.040
		[0.43]	(0.052)	(0.043)	(0.037)	(0.108)
Moved to diff. unit	457	0.44	0.260***	0.072	0.073	0.233
		[0.50]	(0.070)	(0.050)	(0.051)	(0.153)
Stayed in 1km radius	457	0.69	-0.142*	-0.070	-0.077	-0.245*
		[0.46]	(0.073)	(0.047)	(0.047)	(0.147)
Moved +10km away	457	0.12	0.052	0.060*	0.067*	0.213*
		[0.32]	(0.054)	(0.036)	(0.036)	(0.109)
Moved to another county	457	0.08	0.028	0.043	0.056**	0.176**
		[0.27]	(0.041)	(0.029)	(0.028)	(0.087)
County level poverty	462	-0.05	-0.004	0.010	-0.055	-0.174
		[0.95]	(0.141)	(0.092)	(0.079)	(0.225)
County crime victims	462	0.04	0.034	-0.009	0.068	0.216
		[0.82]	(0.093)	(0.079)	(0.060)	(0.189)
School Quality	438	0.06	-0.069	-0.089	-0.077	-0.245
		[0.94]	(0.136)	(0.100)	(0.099)	(0.301)
Distance to school	457	-0.03	-0.110	0.232	0.213	0.677
		[0.84]	(0.128)	(0.165)	(0.142)	(0.450)
Distance to early childhood educ.	457	-0.03	-0.108	0.162	0.145	0.461
		[0.86]	(0.111)	(0.137)	(0.120)	(0.379)
Distance to health care	457	-0.00	-0.174	0.161	0.138	0.436
		[0.89]	(0.114)	(0.153)	(0.134)	(0.421)
Kms to closest municipality	495	0.01	-0.168	0.017	0.004	0.011
		[1.08]	(0.113)	(0.095)	(0.086)	(0.261)
Application to Ownership Programs	496	0.30	0.068	0.006	-0.008	-0.023
		[0.46]	(0.063)	(0.044)	(0.042)	(0.124)
Application DS1	496	0.24	0.032	-0.030	-0.043	-0.135
		[0.43]	(0.057)	(0.040)	(0.037)	(0.112)
Application DS49	496	0.11	0.037	0.024	0.017	0.053
		[0.31]	(0.050)	(0.030)	(0.029)	(0.088)
Active ownership savings account	496	0.91	0.043	0.012	0.011	0.036
		[0.28]	(0.034)	(0.025)	(0.025)	(0.075)
COVARIATES			YES	NO	YES	YES
SCREENING FE			YES	YES	YES	YES

This table replicates the analysis in Table A.9 using the subset of follow up survey respondents. See Table A.9 for details.

D Questionnaire

Baseline Survey Questions

1. **How satisfied are you with the dwelling you currently live in?** (Consider only the dwelling, not the neighborhood)
   (a) Very satisfied
   (b) Satisfied
   (c) Dissatisfied
   (d) Very dissatisfied
2. **If you obtained the Rental Subsidy, which of the following location options would you prefer?**
   (a) I would stay in the same neighborhood (environment) in this municipality
   (b) In another neighborhood (environment) in this municipality
   (c) In another municipality in this region
   (d) In another region
   (e) Another location. Which one?

Follow-up Survey Questions

1. **How satisfied are you with the dwelling you currently live in?** (Consider only the dwelling, not the neighborhood)
   (a) Very satisfied
   (b) Satisfied
   (c) Dissatisfied
   (d) Very dissatisfied
2. **How satisfied are you with the neighborhood (surroundings) where you currently live?** (Consider only the neighborhood, not the dwelling)
   (a) Very satisfied
   (b) Satisfied
   (c) Dissatisfied
   (d) Very dissatisfied

3. **Thinking about the establishments and services within 4 blocks around the dwelling you currently live in, indicate whether there is at least one:** *(Mark all that apply)*

   (a) Nursery or Kindergarten

   (b) School, high school or private school

   (c) Supermarket

   (d) Shopping center or mall

   (e) Corner store/bakery

   (f) Park or plaza

   (g) Pharmacy

   (h) Highway

   (i) Primary health care center

   (j) Hospital/Clinic

   (k) Bus stop, shared taxi stop, or metro/metro train station

4. **To what extent do you agree or disagree with the following statements?** *(Indicate if you are: Strongly disagree / Disagree / Agree / Strongly agree)*

   (a) I identify with the people in this neighborhood

   (b) If I need someone to take care of my children, I can ask my neighbors for help

   (c) In my neighborhood I have close friends

   (d) If I have financial problems, I can ask my neighbors for help

   (e) I prefer to rent in my current neighborhood rather than buy in another one I don't know

   (f) Renting is a waste of money

5. **Including yourself, how many people live in the dwelling you currently live in?** *(Open numeric response)*

6. **How many rooms of each type does the dwelling you currently live in have?** *(Record the number of rooms of each type in the dwelling.)*

   (a) Living-dining room

   (b) Bedrooms (for sleeping only)

   (c) Bathrooms

(d) Terrace/balcony

(e) Laundry room/utility room

(f) Separate kitchen

7. **In the dwelling you currently live in, do you have in use and functioning:** *(Yes / No for each item)*

   (a) Water heater (electric boiler, solar heater, gas water heater)

   (b) Paid television (cable TV/satellite/digital TV)

   (c) Computer (PC, notebook, laptop, tablet)

   (d) Smart TV or television connected to the internet

   (e) Fixed or mobile broadband (WiFi or USB modem)

   (f) Any heating system (gas, paraffin, firewood, electricity, oil, etc.)

8. **Under which of the following situations do you occupy the dwelling you currently live in?**

   (a) You pay rent to a family member

   (b) You pay rent to a non-family member

   (c) You are living as a guest in a family member's dwelling

   (d) You are living as a guest in a non-family member's dwelling

   (e) You are the owner and are still paying for the dwelling

   (f) You are the owner and have finished paying for the dwelling

   (g) Other. Specify.

9. **Do you rent this dwelling with a contract?**

   (a) Yes

   (b) No

10. **What is the total monthly rent of the house, apartment, or other place where you currently live?** *(Open numeric response)*

11. **How much do YOU pay monthly of the total monthly rent? (Do not include common expenses)** *(Open numeric response)*

12. **Which of these situations best describes your main work activity during the last month?**

    (a) Work full-time

(b) Work part-time or do occasional jobs

(c) Not working due to the pandemic but will return to my job

(d) Study and work

(e) Only study

(f) Retired or pensioner

(g) Unemployed, looking for work

(h) Not working and not looking for work

(i) Perform unpaid tasks (household chores, caring for children or other people)

(j) Other. Specify.

13. **As a result of the Coronavirus pandemic, have you or someone in your household experienced a decrease in income?**

(a) Yes, the pandemic caused the total loss of the household's income

(b) Yes, the pandemic caused a partial loss of the household's income

(c) No, the household's income was not affected by the pandemic

14. **Last month, what was your household's total income?**

(a) Less than $280,000

(b) $280,001–$330,000

(c) $330,001–$380,000

(d) $380,001–$450,000

(e) $450,001–$520,000

(f) $520,001–$590,000

(g) $590,001–$660,000

(h) $660,001–$750,000

(i) $750,001–$840,000

(j) $840,001–$930,000

(k) $930,001–$1,100,000

(l) $1,100,001–$1,270,000

(m) $1,270,001–$1,500,000

(n) $1,500,001–$2,000,000

(o) More than $2,000,001

15. **Currently, to what extent do you feel overburdened by your debts?**

(a) Not overburdened at all

(b) Not very overburdened

(c) Quite overburdened

(d) Very overburdened

16. **Since the pandemic began, have you or your household had to adopt any of the following strategies to cover family needs?** *(Mark all that apply)*

(a) Move or change dwelling

(b) Delay paying the rent

(c) Other people have moved in to live with you

(d) Reduce spending on food

(e) Reduce spending on health (medicines, medical consultations, exams, treatments, etc.)

(f) Reduce spending on basic services

(g) Defer (delay) payment of bills

(h) Request a loan from friends, family members, neighbors, acquaintances, or another informal channel

(i) Request a loan, use a line of credit or withdraw money from a credit card from a bank, department store, or other financial entity

(j) Sell valuable goods (e.g., jewelry, vehicle, furniture, etc.)

(k) Sell or rent a property, land, room, work tool, etc.

(l) Use household savings

(m) Do additional activities to generate more income

(n) Lend or give money to a family member

(o) Apply or resort to any of the emergency measures taken due to the Coronavirus (COVID-19) pandemic (loan to self-employed workers, middle-class bonus, Emergency Family Income (IFE), Special Middle-Class Rent Subsidy (July 2020), withdraw pension funds (AFP), etc.)

(p) It has not been necessary to resort to any of these strategies to cover the household's needs

(q) Another strategy. Which one?

17. **What is your marital status?**

(a) Married

(b) Cohabiting or partner

(c) Divorced – Annulled

(d) Separated

(e) Widowed

(f) Single

18. **Who currently lives with you?** Include only permanent residents. *(Mark all that apply)*

(a) Partner (spouse, civil union partner, or boyfriend/girlfriend)

(b) Son(s)/daughter(s)

(c) Father/Mother or Father-/Mother-in-law

(d) Grandfather/Grandmother(s)

(e) Son-in-law / Daughter-in-law

(f) Grandchild(ren)

(g) Brother(s)/Sister(s) or Brother-/Sister-in-law

(h) Other relative(s)

(i) Other non-relative(s)

(j) Live alone

(k) Pet(s) (dog, cat, chicken, etc.)

19. **During the last 6 months, have you witnessed any of the following events in your neighborhood?** *(Yes / No for each item)*

(a) Consumption of alcohol in public spaces

(b) Consumption of illegal drugs in public spaces

(c) Trafficking of illegal drugs

(d) Wall defacement or graffiti

(e) Damage to private property due to disorder or vandalism, not including “wall defacement” (graffiti)

(f) Gang fights

(g) People carrying bladed or firearms

(h) Have heard gunfire

(i) Prostitution/ sex trade