RENTAL VOUCHER PROGRAMS IN MIDDLE INCOME COUNTRIES: QUASI-EXPERIMENTAL EVALUATION OF THE CHILEAN RENTAL SUBSIDY

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Abstract

Many low and middle income countries are transitioning from ownership subsidies towards rental policies for low income families, similar to the US Housing Choice Voucher program. This paper presents the first evaluation of such programs in Chile, a middle-income country. I exploit the voucher assignment protocol to implement a local randomization regression discontinuity approach using applicants between March 2017 and September 2019. Two voucher schemes are evaluated, one offered to young families and one to elder people. Treatment effects are estimated linking baseline administrative data to administrative and public data on a range of housing and neighborhood outcomes in December 2019. I further complement this data with a survey implemented in November 2020, eight months following the COVID-19 outbreak of March 2020. In the period prior to the pandemic, results were similar to the US literature: holding a voucher reduced overcrowding but did little to induce residential mobility to better neighborhoods for low income families. In contrast, results from November 2020 show that rental vouchers had a broader impact on recipient households. Holding a voucher affected how families were coping with the large unexpected shock caused by COVID-19. They experienced less unwanted mobility and were less likely to miss rent payments, cut food expenses or use emergency relief policies during this period. These results point to a previously underappreciated insurance role of rental subsidies in helping poor households cope with negative aggregated shocks. ***JEL Codes:*** I38, O18, R23

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1 Introduction

A large literature shows that rental voucher programs have been effective in reducing rent burden, crowding, and homelessness of low-income households, yet they have not lived up to their promise of providing better environments for children to grow up in (Ellen, 2020; Chyn and Katz, 2021). This literature is based on the US Housing Choice Voucher program, the largest federal housing program in the US (Collinson, Ellen and Ludwig, 2015).

In recent years, several middle income countries in Latin America have started to move away from ownership subsidies towards rental voucher programs. The first of such programs was the *Subsidio de Arriendo* (Rental Subsidy), implemented by the Chilean Ministry of Housing and Urban Planning (MINVU) in December 2013.[1]

The design of the Chilean program was advised by the US Department of Housing and Urban Development (HUD) and inspired in the Housing Choice Voucher program. Despite of the similarities to the US policy, the institutional differences between countries may have large consequences for potential outcomes of voucher recipients, who rely on the private rental market to use their subsidies (Colburn, 2021). However, how these programs do outside of the US is unknown.

This paper presents the first evaluation of a rental voucher program in a middle income country, Chile. Similar to other Latin American countries, Chile is poorer, more unequal, has higher levels of informality and a much smaller rental market than the US. Further, MINVU has offered large demand-side subsidies for decades, strongly encouraging ownership among low income families.[2]

This study exploits the voucher assignment mechanism to evaluate the effect of rental

[1]To date, Argentina, Brazil, Colombia, Peru, among others have followed Chilean steps towards rental voucher programs– although policy design varies across countries.

[2]In Chile, GDP per capita was US$15,091 in 2019, the Gini coefficient was 0.444 in 2017 (www.data.worldbank.org); and informality accounted for 29% of the employment in 2019 (Henriquez, 2019). The size of the rental market is about half of the size of US rental market (Ross and Pelletiere, 2014; Blanco, Cibils and Miranda, 2014). Further, more than 60% of households in the bottom 20% of the income distribution were homeowners in 2017 (CASEN 2017).

vouchers assigned by MINVU between 2017 and 2019. MINVU assigns available vouchers to families above a score cutoff and, when there are ties at the cutoff, implements a three step tie-breaking protocol, including randomization. This research leverages the exogenous variation in treatment probability at the score cutoff to estimate treatment effects using the Local Randomization approach to Regression Discontinuity Designs (LRRD), developed by Cattaneo, Frandsen and Titiunik (2015).

This paper analyzes two different short-term rental voucher schemes in Chile: a modest monthly voucher offered to young families in regular rounds and a more generous monthly voucher offered to 60 or older individuals in elderly rounds. The evaluation sample includes 1,131 and 1,328 applicants just above and below the application score cutoff in regular and elderly rounds, respectively.

This research evaluates the effect of the voucher on individual and neighborhood outcomes obtained from different administrative and public data sources in December 2019. I supplement this data with a survey implemented in partnership with MINVU between September and November 2020. Survey data is used to further investigate whether rental vouchers affected how families in regular rounds were coping with the large aggregated shock that came with the COVID-19 pandemic.

Pre-pandemic data yielded results similar to the evidence from the US Housing Choice Voucher program. While the voucher reduced overcrowding (6.1 pp (46%) in regular rounds and 2 pp (59%) in elderly rounds) neighborhood characteristics did not change for treated families. If anything, younger families in regular rounds ended up farther away from their initial location, and farther away from schools. In addition, data from December 2019 shows that applications to homeownership programs and private savings to buy a house of families in regular rounds were unaffected by the voucher, and actually increased among elderly voucher holders.

Eight months after the COVID-19 outbreak in March 2020, treatment effects around the cutoff show that the voucher had an important positive effect on housing and income stability, pointing to a previously underappreciated insurance role of rental vouchers in times of unexpected economic shocks. More specifically, treated families were less likely to miss rent payments, experience unwanted mobility, cut food expenses and use emergency relief policies to adapt to the new economic circumstances.

This paper contributes to the large literature that evaluates rental voucher programs based on the US Housing Choice Voucher.[3] To the best of my knowledge, this paper is the first evaluation of a rental voucher program outside of the US.[4] This research further contributes to the literature by presenting treatment effects of rental vouchers separately for the elderly, a population that has been understudied despite of holding a large (and increasing) share of housing subsidies in the US (Collinson, Ellen and Ludwig, 2015; Reina and Aiken, 2022).

In addition, this research contributes to the small economic literature on housing security and housing policy. Previous evidence shows that rental vouchers can be effective at reducing the risk of homelessness and doubled up of low-income families participating in welfare programs (Mills et al., 2006). However, whether these effects hold when low-income families experience large unexpected shocks, such as unemployment, illness or death, is unknown. This study contributes to close this gap in the literature by estimating the effect of rental vouchers on families response to the large unexpected income shock that came with the COVID-19 pandemic.

The rest of the paper is organized as follows. Section 2 explains the policy context and design of the Chilean rental voucher program. Section 3 describes the available data for this evaluation and Section 4 explains the research design. Section 5 shows how the local randomization approach to regression discontinuity designs is applied to create the evaluation sample. Then, Section 6 presents the econometric model used to estimate average treatment effects and the results of the evaluation. Section 7 concludes.

[3] Mills et al. (2006); Kling, Liebman and Katz (2007); Jacob and Ludwig (2012); Andersson et al. (2016); Chetty, Hendren and Katz (2016).

[4] The closest work is the evaluation of a rental policy similar to public housing by Barnhardt, Field and Pande (2017) in Ahmedabad, India.

2 Policy Context and Design

In December 2013, the Chilean Ministry of Housing and Planning (MINVU) launched the program *Subsidio de Arriendo* (Rental Subsidy). Between 2014 and 2019, MINVU spent US$325 million in the program, received about ninety thousand applications and assigned fifty thousand rental vouchers (Table B.1 in the Online Appendix).[5]

The program offers two voucher schemes in regular and elderly rounds of vouchers. Regular rounds are the largest program component: 88% of all assigned vouchers between 2014 and 2019 were regular vouchers (Table B.1 in the Online Appendix)).

Regular rounds target 18 or older-headed families with monthly income from US$250 to US$900[6], who are in the four (out of seven) most vulnerable groups according to the national Household Social Registry (RSH).[7] Also, applicants must have US$180 or more in private savings to buy a house.[8]

Elderly rounds, on the other hand, target individuals 60 or older, with monthly income above $140, who are also in the first four vulnerability groups in the RSH. Savings to buy a house are not required in these rounds.

Voucher holders in regular rounds receive US$6,200 in fixed monthly installments of US$180 to pay monthly rents up to the maximum payment standard. Regular voucher holders may space out the use of their total subsidy over an eight year period— although if used continuously, the subsidy lasts for 36 months. The same rent payment standard is set nationally for regular and elderly rounds, at US$402.[9]

[5]Just for context, only in 2020, the two largest homeownership programs delivered forty thousand subsidies.

[6]Families with 3 or more members have higher income upper bounds.

[7]The RSH is administered by the Ministry of Social Development and used to target most social assistance in Chile. It uses a vulnerability score calculated using survey and administrative data on educational achievement, income, expenses, health, food security and living arrangements to classify families in seven groups: below 40th, 41th-50th, 51-60th and 61-70th, 71-80th, 80-90th and 90-100th percentiles in the score distribution.

[8]MINVU asks proof of savings to apply to homeownership programs since the 1990s. The amount asked in the rental voucher programs is about 40% of the amount asked in ownership programs for most vulnerable families.

[9]Except for 30 out of 346 counties where payment standard is US$475.

In elderly rounds, total subsidy and rent coverage slightly vary across the four RSH groups. Specifically, less vulnerable voucher holders (fourth group in the RSH) get US$7,380 to cover up to 90 percent of monthly rents. Most vulnerable voucher holders (first group in the RSH) receive US$7,780 to cover up to 95 percent of monthly rents.[10] Elderly households receive assistance for 24 months.[11]

Rounds are opened for two to nine months. During this time, MINVU assigns 1,000 to 3,000 rental vouchers every one or two months. To apply to the Chilean program, families can go online or in person to any of the fifty local housing authorities across the country, the Housing and Urban Planning Service (SERVIU).[12]

MINVU uses a score to screen applicants and assign vouchers to the most vulnerable families. A detailed description of the assignment mechanism is provided in Section 4.1. Once voucher recipients are announced, they have two years to find a landlord willing to participate in the program.[13] Family members cannot be landlords and eligible units need at least three separated spaces, a residential use certificate from the municipality and a tax registration number. Families that are initially renting can stay in the same house, while those who are doubled up must move. Homeowners cannot apply to the program.

Some important differences between the US and Chilean policies are worth noting. Chile offers a short term rental voucher, while most families never exit the program in the US (Collinson, Ellen and Ludwig, 2015). Also, the US Housing Choice program is more generous than the Chilean voucher, specially than regular vouchers. The US voucher fixes rent burden at 30% and sets city level payment standards, according to local rental market prices.[14]

There are administrative differences as well. In Chile, the central government (MINVU)

[10] Only 4% of voucher recipients in the evaluation sample are not in the most vulnerable group.

[11] In 2019, when the first group of vouchers was about to expire, MINVU extended the benefits for two more years, which was not publicly announced or explained to voucher recipients.

[12] Municipalities may help in application process.

[13] In the US, voucher recipients spend an average of two years on a waiting list to receive a voucher. Once they get a voucher, they have two to four months to lease-up (Collinson and Ganong, 2018).

[14] In 2020, monthly voucher per family was US$810 and average rent paid by voucher holders was US$355. See https://www.huduser.gov/portal/datasets/assthsg.html.

makes all the design and implementation decisions, assigns vouchers and pays rent to the landlords participating in the program. SERVIUs only provide information about the program, help in-person application and lease validation, and coordinate housing inspections.

Finally, in the first five years of the program, four out of ten voucher recipients have used their vouchers in Chile (Column 4 in Table B.1 in the Online Appendix), almost two thirds of the average lease-up rate in the US (69%) (Finkel and Buron, 2001).

The next section presents the data used in the evaluation of the Chilean rental voucher.

3 Data

This paper uses a unique data set including administrative, survey and public data at three different moments in time: baseline data gathered at application; outcome data collected in December 2019, before the pandemic; and outcome data collected from September to November 2020, six to eight months after the COVID-19 outbreak in March 2020.

This paper uses four different sources of baseline data. First, data that MINVU collected to determine applicants eligibility and calculate application score, including socioeconomic and demographic characteristics, location and some housing characteristics. To replicate voucher assignments, this data was linked to public records to verify individual scores, assignment dates and cutoffs.[15]

The second data source is a survey implemented in partnership with MINVU and applied to all applicants in regular rounds between March 2017 and October 2019. Surveys were collected before voucher recipients were announced and asked questions about housing and neighborhood experience, preferences and beliefs about housing and residential mobility. On average, response rate in the period of analysis was 78%.

Third, geocoded administrative data[16] was linked to public geocoded location of munici-

[15]Several meeting with policy makers involved in voucher assignment were held to fix inconsistencies.

[16]This project uses a unique geocoded data of all applicants to the program collected from multiple data sources provided by MINVU and complemented with survey data to analyze its quality.

palities and SERVIUs and county level information including poverty rates from CASEN 2017, density from the 2012 Census data and total crime from 2013 administrative data. Finally, MINVU provided administrative data on household application to the two largest homeownership programs - *Fondo Solidario de Vivienda (DS49)* and *Subsidio Clase Media (DS1)* since 2011, and before application to the program.[17]

Outcome data for December 2019 is collected from three data sources. First, unit characteristics, household composition and location were obtained from both RSH records and MINVU's administrative data from December 2019. Second, neighborhood variables were created linking geocoded location in December 2019 to several public data sources including geocoded schools, geocoded health care centers, and county level poverty, assault, robbery and theft rates.[18] Third, MINVU provided administrative data on household application to the two largest homeownership programs between voucher assignment and December 2019. Finally, for regular rounds only, MINVU provided access to the total amount in private savings account to buy a house.[19]

Finally, I partnered MINVU to implement a follow up survey between September and November 2020. The survey included questions to measure crowding, residential mobility, neighborhood characteristics, housing and neighborhood satisfaction, subjective well-being, health, income, employment, and behavioral responses during the first eight months following the COVID-19 outbreak in March 2020.

[17]The DS49 provides fully funded housing (no mortgage) for very low income families, who are only required US$300 in savings. The DS1 provides partial funding to low and middle income families. It gives a down payment that decreases with the price of the house and income of the family, available for low and middle income households who can finance the rest of the house with a mortgage loan or savings.

[18]2019 data except for poverty rates since CASEN 2017 was the last poverty measurement by December 2019.

[19]Savings accounts are required to apply to homeownership programs but they can be used to buy any house in the private market.

4 Research Design

This section describes the assignment mechanism of the program and how it is used to identify causal treatment effects of the Chilean rental voucher program.

4.1 Voucher Assignment Mechanism

MINVU calculates an application score for each applicant using a complex formula. Each time that MINVU screens applicants using this score, families with the highest score values get a voucher. Table I describes the variables that are considered in the score formula.[20]

MINVU assigns rental vouchers several times within each round. More formally, in each screening $s_t \in S$ in assignment period t of round r, applicants are sorted over their score X_{i,s_t} and those above the score cutoff ($X_{i,s_t} > c_{s_t}$) receive a voucher.[21] Applicants who are not offered a voucher ($X_{i,s_t} < c_{s_t}$) are screened again with all new applicants in following assignment periods until they get a voucher or the round closes. Families need to apply again to be considered for the next round, yet few families apply more than once to the program.

The cutoff c_{s_t} is the value of the score of the applicant who was offered the last available voucher. Each assignment period had a unique national cutoff until 2019, when MINVU switched to regional screenings of applicants. Currently, each assignment period has different cutoffs, depending on the score distribution and number of available vouchers per region.[22]

The number of available vouchers and number of assignments periods is set by decree before the beginning of each round of applications. Sometimes these quantities change

[20]See Section 2 for a general description of the program.

[21]Recall that the number of screenings and assignment periods differ since 2019, when regional screenings were implemented. Since then, 16 screenings take place at each assignment period. Each assignment period is unique to a round, therefore, I do not use the sub-index r to simplify notation.

[22]The change was made in response to a request made by two local housing authorities from two small regions in the extreme south of the country who complained about getting too few vouchers.

following administrative or political decisions made outside of the rental policy team at MINVU. These changes are not announced to the public.

In 2017, a reform by the Ministry of Social Development to the Social Registry of Households (RSH) transformed the social vulnerability score that MINVU used in the application score formula.[23] As a result, the total application score to assign rental vouchers became a discrete variable including multiples of 5. Confronted with ties at the score cutoff, MINVU had to establish a tie-breaking protocol to assign left standing available vouchers.

A three-step protocol was implemented. First, families with the same total score would be re-ranked using their family size score. Families with the highest score would get a voucher. Second, applicants with the same total and family size score would be re-ranked using their social vulnerability score. Again, families with the highest score would get a voucher. Finally, left standing available vouchers would be randomized among applicants with the same total, family size and social vulnerability score.[24]

4.2 Identification Strategy

This research exploits the described voucher assignment mechanism to evaluate the Chilean rental voucher program using a Regression Discontinuity Design (RDD). In particular, this paper leverages the discontinuity in the probability of treatment at the score cutoff in each screening of applicant s_t to estimate treatment effects using a Sharp Multi-cutoff Regression Discontinuity Design.

The RDD is one of the most credible research designs in the absence of experimental treatment assignment. Identification is based in a simple and intuitive idea: when there is a discontinuous change in the probability of treatment by just surpassing a threshold, observations in a small window around that cutoff can be considered ”as good as randomly

[23] Previous continuous social vulnerability index is replaced by the current index taking four values, one for each group of the RSH. See Section 2 for more details.

[24] This research does not use this randomized sample of vouchers exclusively given the small number of randomized vouchers in regular rounds. However, this sample is included in the evaluation sample and analyzed separately as a robustness check in Section 6.3.

assigned" to treatment and control groups (Lee and Card, 2008).

Figure I shows the application score distribution and score cutoffs in the Chilean rental voucher program. Figure II illustrates the sharp discontinuity in treatment status at the cutoff. As it is common in RDD applications, the running variable X_{i,s_t} is normalized to have a score cutoff centered at zero.

The support of the running variable in the Chilean rental voucher is finite and includes only a small number of mass points (131 unique values in regular rounds and 109 unique values in elderly rounds). In this case, the standard continuity approach fails to provide unbiased coefficients and confidence intervals in the smallest window possible around the cutoff (Cattaneo, Idrobo and Titiunik, 2019).[25]

To estimate treatment effects, this research uses the Local Randomization Approach to Regression Discontinuity Design (LRRD), first introduced by Cattaneo, Frandsen and Titiunik (2015).[26]

The LRRD makes stronger assumptions about the assignment mechanism than the continuity approach. Specifically, the LRRD assumes that there exists a small window around the cutoff, $W = [c - e, c + e]$, in which the distribution of the score is known and the same for all units, as in experimental data.[27]

More formally, Let $Y_i(1)$ and $Y_i(0)$ be the pair of potential outcomes under treatment and control and $D_i = D_i(X_i) = I(X_i \geq c^*) \in \{0, 1\}$ the treatment indicator. Then, $Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0)$ is the observed outcome for individual i (Rubin, 1974).

[25] In practice, the continuity approach will consider each mass points as a bin and local polynomial methods would extrapolate from the closest mass point on either side of the cutoff. More formally, the continuity assumption implies that the 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 above the cutoff would have had in the absence of treatment (Lee and Lemieux, 2010). The average treatment effect at the cutoff, τ_{Cont}, is $\tau_{Cont} = \mathbb{E}\{Y_i(1) - Y_i(0)|X_i = 0\} = \lim_{x \downarrow c} \mathbb{E}\{Y_i(1)|X_i = 0\} - \lim_{x \uparrow c} \mathbb{E}\{Y_i(0)|X_i = 0\}$. When the running variable is discrete, 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.

[26] In settings with large number of mass points, it is common practice to use the continuity approach and estimate standard errors clustered by the discrete running variable (Lee and Card, 2008; Kolesár and Rothe, 2018). See Branson and Mealli (2018) for a review of alternative estimation methods in RDD settings.

[27] There are no modelling assumptions, as in the standard continuity approach.

The LRRD assumes that in $W = [c-e, c+e]$, potential outcomes depend on the score only through treatment indicators and there is no interference between potential outcomes of different units. This is known as the stable unit treatment value assumption or SUTVA.[28] Under these assumptions, score ignorability $Y_i(X_i, D_i) = Y_i(D_i)$ is guaranteed inside W. Then, as in experimental settings, causal treatment effects, τ_{LRRD}, are the difference between the average outcome in the treated and control groups in W:

$$\tau_{LRRD} = \bar{Y}_{i \in W}(1) - \bar{Y}_{i \in W}(0) \approx \mathbb{E}\left\{Y_i(1) - Y_i(0) | X_i \in W\right\} \tag{1}$$

Since normally there are very few observations close to the cutoff, LRRD uses randomization inference, robust in small finite samples.[29]

When there are ties at the cutoff, the running variable requires a transformation to have treatment and control units in different sides of the cutoff. Importantly, any transformation that keeps the same order between mass points produces the same results in the LRRD (Cattaneo, Idrobo and Titiunik, 2019).

This research uses the three-step tie breaking protocol of the program (See Section 4.1) to transform the running variable. Specifically, the score $X_{i,s_t} = 0$ of applicants who were untied using randomization was transformed to $X_{i,s_t} = -1$ if they did not get the voucher and to $X_{i,s_t} = 1$ if they got a randomized voucher. The score $X_{i,s_t} = 0$ of those who were untied using family size or social vulnerability score was replaced with $X_{i,s_t} = -2$ and $X_{i,s_t} = 2$ for controls and treatment units, respectively.

Similar to the problem of bandwidth selection in the standard continuity approach, window selection is the most important step in LRRD.

[28] In a rental voucher program, interference could happen through neighbors direct interaction or through rental market. I argue that this is unlikely in the Chilean program, specially considering the sample in a small window around the cutoff since vouchers are assigned across applicants from large geographical units. General equilibrium effects in local rental markets are very unlikely given the small size of the program and low lease up rate. Also, it is unlikely to live nearby others who have won the voucher at the same time; descriptive data on applicants supports these ideas. Baseline survey data shows that only 3% of applicants between 2017 and 2019 know a neighbor that won the voucher in the past.

[29] Randomization inference assumes fixed potential outcomes but random assignment mechanism.

In this paper, I use the data driven procedure developed by Cattaneo, Idrobo and Titiunik (2019) that selects the largest window around the cutoff in which LRRD assumptions hold. This method identifies the largest window such that the minimum p-value obtained in balance tests in pre-treatment covariates is above a pre-determined significance threshold, α.[30]

When the running variable is discrete, treated and controls must be balanced in the window that contains the two mass points that are immediately above and below the cutoff. When this is satisfied, balance is tested in increasing windows adding mass points at each side of the cutoff.

In this research, balance is evaluated at each screening of applicants s_t to select the largest window W_{s_t} around c_{s_t} in which LRRD assumptions hold. In each s_t, balance is analyzed in four increasing windows around the cutoff using $\alpha = 0.10$.[31]

Once windows W_{s_t} are selected, they are stacked together in the evaluation sample W_0. In W_0, treatment effects are estimated using a fixed effect model, averaging $\tau_{LRRD_{s_t}}$ across all s_t.[32]

Note that balance tests in the LRRD are similar to testing for no discontinuities in pre-treatment covariates around the cutoff in the standard continuity approach. To further validate the RDD design, the running variable cannot be not manipulated. In the LRRD, this is tested using binomial test of the probability of treatment in a small window around the cutoff (Cattaneo, Idrobo and Titiunik, 2019).[33] Table II shows that the observed treatment probability in the data is not statistically different from complete randomization ($q = 0.5$). This result is consistent with the high cost that manipulation of the application

[30]LRRD uses exact hypothesis tests to analyze balance. The Fisher sharp null hypothesis of zero (additive) treatment effect ($H_0 : Y_i(0) = Y_i(1)$) is exact in that it uses observed outcomes to impute potential outcomes under treatment and control, such that $Y_i(0) = Y_i(1) = Y_i$. To be conservative, p-values in balance tests for window selection do not adjust for multiple testing.

[31]I use the package rdwinselect in Stata (Cattaneo, Idrobo and Titiunik, 2019).

[32]This research design mimics a sequential stratified experimental design (Pocock and Simon, 1975) in which each assignment s is a strata or block of applicants that are independently assigned to treatment and control groups.

[33]For intuition, if applicants cannot precisely control the value of their score, the probability of success (treatment) q is expected to be consistent with the assumed assignment mechanism in a small window around the cutoff.

score would have for prospective applicants in the Rental Voucher program.[34]

The next section explains how the data driven window selection procedure is implemented to build the evaluation sample. Then, Section 6 presents the fixed effect model used to estimate treatment effects of the Chilean rental voucher program.

5 Window Selection and Evaluation Sample

This section describes the data used to implement the window selection procedure, and presents the selected windows W_{s_t} in which LRRD assumptions hold and the characteristics of the applicants in the evaluation sample W_0.

5.1 Window Selection Data

The initial data set to select windows W_{s_t} includes all screenings of applicants s_t that took place between March 2017 and September 2019. During this time, there were 82 screenings in 22 assignment periods in 8 rounds of the program. Table III shows the number of participants, maximum and minimum application score, available vouchers, and the score cutoff for each assignment period in regular and elderly rounds of the program, respectively. In total, this data has 95,910 observations from 56,705 unique applicants.[35]

Two main data restrictions were applied to this data. First, I analyzed the number of observations close to the cutoff in each screening s_t. Following Cattaneo, Frandsen and Titiunik (2015), screenings of applicants in which the minimum window around the cutoff had less than ten observations at each side of the cutoff c_{s_t} were excluded.[36] Doing this dropped 30,294 observations (14,504 unique applicants) from 61 screenings of applicants

[34]It would require them to anticipate voucher availability, their own score and the entire score distribution.

[35]Recall that the rolling application system implies that the same applicant can participate in multiple screenings until the round closes.

[36]This is done to have enough statistical power to test for balance in each assignment. Assuming a discrete outcome, a minimum detectable effect of one standard deviation and significance levels of 0.05-0.15, the randomization-based test of the sharp null of no treatment effect in the minimum window would have 60-80 percent of statistical power.

from the data.[37]

Second, I analyzed the control group close to the cutoff. The rolling application system generates two different controls units: i) later treated or applicants that received the voucher at a later assignment period during round r and ii) never treated or applicants that did not receive the voucher in any assignment period in round r. Comparing later treated to voucher holders measures the effect of holding a voucher for a few more months (treatment timing), not the effect of just holding a voucher. Due to the lack of statistical power to estimate these effects separately, 9 screenings s_t that had only later treated in the control group were dropped from the study (26,773 observations from 7,071 unique applicants).[38]

The final data set to implement the window selection procedure has 35,848 observations from 30,610 unique applicants that participated in 12 screenings (7 in regular and 5 in elderly rounds) in 9 voucher assignment periods (5 in regular and 4 in elderly rounds).[39]

Two sets of pre-treatment covariates are used in the window selection procedure. One for balance tests within screenings s_t and another one for further falsification tests in the evaluation sample W_0, that stacks all selected windows W_{s_t} together.

The first set of covariates includes family income, and indicator variables for tenant, previous application to homeownership programs, having geocoded location, living in high density counties and in counties where there is a SERVIUs.[40] Baseline savings to buy a

[37] 60% were in 2019 elderly and regular rounds, after regional screenings were implemented. Only regular assignments in October in the Los Lagos, Araucania and O'Higgins regions (in the south), and the elderly assignments in July in Santiago and Valparaiso regions (in the center) had enough units in each side of the cutoff.

[38] Screenings with just later treated in the control group had a particularly small number of units around the cutoff and others did not meet LRRD assumptions. For this reason, screenings of April, May, July, August, September of 2017, September and November of 2018 and August 2019, and elderly screening of June 2018 were excluded from the analysis.

[39] Two additional minor data restriction that had no implications in the window selection procedure were implemented. First, 2,992 observations from 2,174 applications before June 30th were dropped from the assignment period of September 2017 to have common support in application dates between treated and controls. Second, three applicants far from the cutoff who were mistakenly assigned to the control group are dropped from the sample.

[40] I create a dummy indicator for whether the county is one of the 53 counties (out of 343) that has a SERVIUs. This is a proxy for location characteristic and access to formal information about the rental voucher program and other housing policy options.

house and online application are also available for regular rounds. In elderly rounds, an indicator variable for validating income documents in person at the closest SERVIU is also included.[41]

The second set of covariates comprises distance (in kilometers) to the closest SERVIU and dummy variables for female, married, age between 25 and 35 (70 and 79) for younger (elder) rounds, Chilean nationality, family poverty status[42], living in Santiago, in high poverty counties (above the national poverty rate), and having a valid email address. For regular rounds only, rent amount and rent burden are included in assignment periods after September 2018. Also, several dummy variables were created using baseline survey data: survey response, strong preferences to stay in baseline neighborhood, high housing satisfaction, knowledge of other applicants to the program, access to a car and having high social class neighbors.[43]

5.2 Window Selection Results

Nine windows W_{s_t} were selected with the window selection procedure using the data and covariates described above. Columns 1 to 3 of Table IV show the assignment period, region and cutoff of each selected W_{s_t}.

In these windows, treated and control groups were balanced in both the first and the second set of covariates.[44] Columns 4 to 9 in Table IV show the minimum p-value of

[41] Online application was not available for elderly rounds in the period of analysis. In regular rounds income validation is not reported in the data for online applications.

[42] Age is strongly correlated with application score, specially in elderly rounds and the number of children and family size enter the formula directly. To include control with a weaker correlation with application score, I created a dummy indicator for the 25 and 75 percentiles of the age distribution per round type. Also, I included family adjusted poverty status that, for similar income level, varies across families of different sizes. In 2017 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 percent, varying from 2.1 percent in Magallanes to 17.2 percent in the Araucania region. Female and married are also strongly correlated with application score, specially in regular rounds.

[43] Survey data is not available for the entire sample yet having a valid email and response to baseline survey are balanced between treated and control units. See Section 5.3

[44] Only one adjustment was made to the windows W_{s_t} selected using the first set of covariates to use a narrower window in the regular screening of applicants of December 2018. Initially, the selected regular window $W_{Dec2018}$ had 80 treated and 749 control units, with all treated units at $X_{i,s_t} = 1$. Two (instead of four) increasing windows around the cutoff were kept for this assignment period, excluding 454 observations with a normalized score below $X_{i,s_t} < -5$ from the control group.

balance tests, the number of units to the right of the cutoff (treated), the number of units to the left of the cutoff (controls), and the minimum and maximum values of the normalized score included in each selected W_{s_t}. The maximum window length in regular rounds is $W_{s_t} = [-15, 10]$ and $W_{s_t} = [-5, 5]$ in elderly rounds.

In total, the evaluation sample W_0 including all selected W_{s_t} has 2,459 observations (2,425 unique applicants): 1,131 observations (1,107 unique applicants) from 5 regular screenings in 3 assignment periods and 1,328 observations (1,318 unique applicants) from 4 elderly screenings in 3 assignment periods.[45]

Columns 8 and 9 of Tables V and VI present the results of balance tests in regular and elderly rounds using the following fully interacted fixed effect model:

$$Z_{i,s_t} = \alpha + \tau_{1,s_t} D_{i,s_t} + \gamma_{s_t} * S_{s_t} + \beta_{s_t} D_{i,s_t} * S_{s_t} + \epsilon_{i,s} \tag{2}$$

Where Z_{i,s_t} is the vector including both sets of baseline covariates, D_{i,s_t} is the treatment indicator variable $(X_{i,s_t} > c_{s_t})$, γ_{s_t} are screenings of applicants fixed effects, and $D_{i,s_t} * S_{s_t}$ is the interaction between treatment and screening of applicants S_{s_t}. Testing the null (H_0) of no treatment effect in each screening of applicants s_t is equivalent to test for $\tau_{1,s_t} = 0$ and $\beta_{s_t} = 0$ in equation 2.

Some covariates in Z_{i,s_t} do not vary across groups in some screenings of applicants.[46] A modified version of equation 2 that assumes $\beta_{s_t} = 0$ is estimated for these covariates. Then, τ_{1,s_t} tests a different and weaker null hypothesis (H_0'): the weighted average effect across all screening of applicants together in the pooled data equals zero.[47]

Results show that treated and controls are balanced in baseline characteristics analyzed separately and using a joint significance test.[48] In other words, LRRD assumptions hold

[45] Randomized vouchers $W_0 = [-1, 1]$ represent 47.7% and 89.4% of the sample in regular and elderly rounds.

[46] Baseline survey response, geocoded location, female, married, Chilean, Santiago MSA, rent and rent burden.

[47] This is a commonly used yet weaker balance test in that H_0' could be zero if a specific linear combination of the effects in each s_t is zero, while H_0 is false (Young, 2019; Firpo, Foguel and Jales, 2020).

[48] I run a regression using treatment status as the dependent variables and all covariates that are available

in the selected windows W_{s_t} and causal treatment effects can be identified comparing treated and controls in the evaluation sample W_0.[49]

5.3 Descriptive Statistics of the Evaluation Sample

Columns 1 to 7 of Tables V and VI show summary statistics of the evaluation sample W_0. Columns 1 to 3 describes the pooled sample, columns 4 and 5 the treatment group and columns 6 and 7 the control groups in W_0.

The evaluation sample in regular rounds includes mostly Chilean families headed by young single mothers.[50] One fifth of the families are under the poverty line and three fourths are tenants at application, paying almost half of their household income (US$530) towards rent (US$224). Also, 67% live in high poverty counties.

In elderly rounds, 61% of elder applicants in the evaluation sample are female, 39% have a partner, and 54% are initially renting. Compared to the regular sample, the elderly have lower family income (average income is US$243) and are more likely to be under the poverty line. However, they live in denser, less poor counties, and are located closer to a SERVIU than those in regular rounds.

To assess the external validity of treatment effects presented in Section 6, Tables B.2 and B.3 in the Online Appendix show descriptive statistics for the full sample of voucher recipients, separately for regular and elderly rounds. An advantage of the multi-cutoff RDD is that the evaluation sample has treated and control units around different cutoffs, which may contribute to reducing the local nature of single cutoff RDD estimates (Cattaneo et al.,

for the full sample as the independent variables. I replace missing values of distance to the closest SERVIU with the observed average distance in each screening and add a dummy to control for missing geocoded data.

[49]Covariates used in the window selection procedure did not enter the application score formula directly. Instead, most pre-treatment covariates used in balance tests were created using administrative data from other government agencies or divisions inside MINVU, or were obtained from survey and geocoded data, not observed by policy makers at MINVU. To further understand identification, Tables B.6 and B.7 in the Online Appendix analyze differences in score components and total score between the evaluation sample and the randomized sample of vouchers across regular and elderly rounds. There are very small differences, specially in elderly rounds. Further, looking at the application score formula (Table I), these differences do not have an economic meaning to the extent that they do not translate in significant household differences.

[50]Average household income in Chile was US$1,302 in the last National Socioeconomic Survey (CASEN); in the first four income deciles was, respectively, US$140, US$400, US$540 and US$655 (CASEN 2017).

2016).

Indeed, the data shows few and small differences between all voucher recipients in the period of analysis and the subset of observations in the evaluation sample, specially in elderly rounds. In regular rounds, there is larger fraction of families living in poor counties (67% vs 50%), although the average proportion of families under the poverty line is similar between all voucher recipients and the evaluation sample (21% vs 25%).

This seems to be explained by the exclusion of the screening of applicants that took place in Santiago in October 2019, that did not have enough observations in the smallest window around the cutoff, from the sample.

The next section presents the fixed effect model estimated using this sample and the results of the evaluation of the Chilean rental Voucher program.

6 Results

This section presents the results of the evaluation of the Chilean rental voucher program using the following equation for outcome Y_{i,s_t} of applicant i screened by MINVU in screening s_t :

$$Y_{i,s_t} = \alpha + \tau_{LRRD} D_{i,s_t} + \beta Z_{i,s_t} + \gamma_{s_t} + \epsilon_{i,s_t} \tag{3}$$

D_{i,s_t} is an indicator variable for having an application score above the cutoff ($X_{i,s_t} > 0$); γ_{s_t} are screenings of applicants fixed effects; and Z_{i,s_t} is a set of baseline covariates used to test for balance in the evaluation sample W_0 in Section 5.2.[51]

For the period before the pandemic, Y_{i,s_t} includes overcrowding, residential mobility, savings to buy a house (holding an account and total balance), application to the main two

[51] The subset of covariates with fewer missing values for most of the sample: tenancy, savings, income, online application, previous applications to homeownership programs, non missing geocoded data, SERVIU in the county, high poverty county, high density county, female, chilean, family poverty status, age, distance to the closest SERVIU, married and baseline survey response. Online application, savings and baseline survey response are not available for elderly rounds.

homeownership programs in Chile and several neighborhood characteristics: access to school and healthcare services, school quality, economic activity, safety and income composition.[52]

In November 2020, eight months after the COVID-19 outbreak, Y_{i,s_t} consists of overcrowding, residential mobility, tenure, rent burden, housing and neighborhood satisfaction, and consumption of other housing services (Wifi, heating system, Cable TV, etc.). Neighborhood characteristics are measured by access to childcare, schools, health care, public transportation, and parks in a 4 blocks radius; commute times; social support; and several safety indicators. Survey data is also used to measure employment, income, health, and families' response to the economic hardship that came with the pandemic.

Equation 3 is estimated separately for regular and elderly rounds. The parameter of interest, τ_{LRRD}, is the LRRD estimate of the effect of being assigned a voucher, or Intention to Treatment Effect (ITT). In this research, τ_{LRRD} recovers a double average: the weighted average of the average ITT effect within screenings s_t.

The effects of using the rental voucher or Local Average Treatment Effects (LATE), are not reported in the paper due to the small sample size per window W_{s_t} in W_0 and the low lease-up rate (compliance) among voucher recipients.[53] Importantly, ITTs are a conservative measure of the effect of the program[54] and are of interest from a policy perspective, since lease-up cannot be enforced.

Note that since each s_t takes place in a specific moment in time, the available data cannot disentangled the heterogeneity across different cutoffs from the heterogeneity from

[52] Neighborhood outcomes in December 2019 comprises access to schools and health care services (primary care and hospitals) measured by the distance to the closest service and availability in one or two kilometers (kms); neighborhood school quality measured by average standardized math and language sixth grade tests scores and the fraction of private, public and subsidized schools in one km; commercial activity approximated by the distance to the closest municipality, that are normally located in denser areas that have higher business activity; safety assessed by assault, robbery and theft county rates (as a fraction of people 18 years or older) during 2019; and neighborhood income composition measured by county poverty rate and the fraction of schools in 2km in which the majority of students are from low income families.

[53] Average voucher use among recipients in W_0 is 38% and it varies between 11% and 57% across W_{s_t}. See Table B.9 in the Online Appendix.

[54] In a one-side compliance setting (the control group cannot get the voucher), LATE is τ_{LRRD} adjusted by the estimated compliance rate (Angrist and Pischke, 2008).

having a voucher for different amounts of time.

Sections 6.1 and 6.2 below present the results of the evaluation of the Chilean rental voucher program before and after the COVID-19 outbreak in March 2020.

6.1 Treatment Effects in December 2019: Before the COVID-19 Pandemic

Tables VII and VIII present estimates of τ_{LRRD} in equation 3 for outcomes measured in December 2019, separately for regular and elderly rounds.

Four set of outcomes are presented in these tables. Panels A, B and C show treatment effects on housing characteristics, residential mobility and neighborhood characteristics, respectively. Panel D presents the effects of voucher assignment on applications to homeownership policies and private savings to buy a house.

Columns 2 and 3 in these tables show the counterfactual mean and standard deviation. Columns 4 to 6 present results of specification 1 of equation 3, including screening of applicants fixed effects γ_{s_t}. Columns 7 to 9 show the results of specification 2 of equation 3, controlling for γ_{s_t} and baseline covariates ($Z_{i,s}$). Columns 5 and 8 report large-sample inference (F-test) and columns 6 and 9 present Fisherian randomization inference, robust in small samples. The bottom panel in these tables shows the Westfall-Young multiple-testing test of overall treatment irrelevance.

Otherwise noted, this section discusses the results of specification 2 (column 7) and randomization inference (column 9).[55]

6.1.1 ***Housing, residential mobility and neighborhood characteristics***

Tables VII and VIII show important differences in residential mobility, household, housing and neighborhood characteristics between regular and elderly rounds.

[55]Including covariates in $Z_{i,s}$ has efficiency gains and only little impact on the coefficients. I use the package randcmd in Stata to estimate Randomization-t exact test developed in Young (2019)). I use 1000 iterations, re-randomizing the data by screening of applicants, as in a stratified experimental design.

The control group mean in Column 2 in Panel A shows that elder households were smaller and less crowded than younger households in regular rounds. In December 2019, 58% and 68% of families in regular and elderly rounds had not moved since application. However, elder households in the control group had moved longer distances than younger households in regular rounds.

Compared to the counterfactual, holding a voucher reduced overcrowding in 6.1 pp (46%) in regular rounds and 2 pp (59%) in elderly rounds.[56] In regular rounds, these results were driven by an increase in the number of bedrooms and not by a change in household size. In contrast, in elderly rounds the effect can be attributed to both smaller household size and larger number of bedrooms.

Voucher assignment affected residential mobility in regular and elderly rounds differently. The overall effect of regular vouchers on residential mobility was 7.6 pp (12%), almost one third of the observed 20 pp (29.4%) increase among elder household.

The voucher did not affect the distance moved by elder recipients, although it increased cross-county residential mobility in 3.9 pp (45%). In regular rounds, on the other hand, voucher holders moved 15.7 km further away from their initial location and were 4.8 pp (74%) more likely to move to a different county.

Importantly, voucher assignment did not improve neighborhood characteristics for regular or elderly recipients. Moreover, younger families in regular rounds, ended up about 0.5 km farther away from schools; this is a 50% increase with respect to the control group.

6.1.2 ***Homeownership***

Panel D in Tables VII and VIII shows that holding a voucher did not reduce application to homeownership programs.

[56] Overcrowding is defined as more than 2 family members sleeping together in one bedroom. This is one of the variables that MINVU uses to measure applicants' housing vulnerability. This is a more severe measure of overcrowding than the most commonly used in Chile. Three indicators are more broadly used: mild (between 2.5 and 3.5 individuals per bedroom), high (3.5-5 individuals per bedroom) and critical (above 5) (Casen 2017).

In regular rounds (Table VII), coefficients for application to these programs are positive but small and non significant. In addition, the data shows that treated and controls were equally likely to keep their savings account opened and had similar amounts, enough to apply to a homeownership program.

In elderly rounds (Table VIII), the rental voucher assignment actually increased applications to ownership subsidies in 3.2 pp (25.2%). This effect was driven by an increase in applications to the fully funded program, the "Fondo Solidario" (DS49), that provides housing at the periphery and has contributed to increase income segregation in Chile (Blanco, Cibils and Miranda, 2014).

The evidence from the period before the pandemic suggests that, similar to previous literature focused in the US Housing Choice program, the Chilean rental voucher program has improved housing related-outcomes but has not provided better environments for low income families to live in. In addition, the data for this period shows that in contrast to MINVU's expectations, the short-term rental policy may increase, not decrease, application to ownership subsidies.

6.2 Treatment Effects During the COVID-19 Pandemic

Equation 3 in this section is estimated using a subset of individuals in the evaluation sample who responded the online survey implemented between September and November 2020.

Given the few survey responses from elderly rounds, the analysis presented in this section focuses on regular rounds only.[57] In particular, causal effects are estimated using 619 individuals, corresponding to 638 observations in regular rounds in the evaluation sample W_0.

Online Appendix C analyses selective attrition and balance in pre-treatment covariates in this sample. Results show that treatment did not affect response probability and local

[57]The survey was sent to the 88% of the evaluation sample in regular rounds who had a valid email address. The response rate was 65%. On the other hand, only 37% of elder applicants in W_0 had a valid email and the response rate was 38.4%.

randomization assumptions still hold in this subset of W_0. [58]

Table IX shows causal effects of holding a voucher six to eight months following the COVID-19 pandemic outbreak. Three sets of outcomes are analyzed in this period. First, housing and household characteristics (Panel A), residential mobility (Panel B), neighborhood characteristics (Panel C) and housing and neighborhood satisfaction (Panel D). Second, health and subjective well being (Panel E). Third, employment, income (Panel F) and how families were coping with the large aggregated shock that came with the COVID-19 pandemic (Panel G).

6.2.1 *Residential mobility, housing, household, and neighborhood characteristics*

Panel A in Table IX shows that eight months into the pandemic, 86% of the control group was renting; one out of four tenants did not have a lease and the average rent was US$261 (column 2).

Column 7 shows that voucher assignment had no significant effect on tenancy, although it increased the probability of having a lease in 12.6 pp (17%). While average rent and income were not affected by the policy, monthly out of the pocket rent payment decreased in US$48.5. This translated in an average rent burden decrease of 12.6 pp (25%).

The program affected living arrangements: the fraction of couples living together increased in 7.8 pp (24.5%) in the treatment group. Similar to December 2019, the voucher reduced overcrowding in 6.4 pp (49.5%). In addition, compared to the control group, voucher recipients were about 8 pp (10%) more likely to have an independent room for the kitchen[59] and 10 pp (13%) more likely to have heat at home.[60] Consistent with these positive effects, housing satisfaction increased in 8.4 pp (11%),

Similar to December 2019, Panel B shows that holding a voucher increased residential

[58] In addition, Table B.8 in the Online Appendix shows treatment effects in December 2019 for the subset of applicants who responded the survey. While some coefficients are slightly smaller and others have larger p-values, overall the results are very similar to the estimates using the full sample of regular rounds in W_0 presented above.

[59] Which is one of the requirements to use the voucher in a certain unit.

[60] Other housing expenses like cable TV, Wifi or computer were unaffected by the voucher.

mobility in 9.4 pp (16%), and Panel C shows that voucher holders did not access neighborhoods with better characteristics.

Despite being 7.5 pp (12%) more likely to live close to a park, the voucher had no statistically significant effect on access to childcare, schools, public transportation and primary care centers.[61] Also, distance to work, family and friends did not change because of the voucher.

However, the data shows that voucher holders were 7.7 pp (47%) more likely to have been recently exposed to gang fights and 7.3 pp (25%) less likely to have a neighbor they could ask childcare support from, suggesting that the voucher may isolate families from their social networks.[62] These results are consistent with the small and non statistical differences between treated and controls in neighborhood satisfaction and safety perception.

The coefficient for distance in this subset of observations is positive but smaller than before the pandemic, and not statistically significant. This difference could be driven by families with stronger location preferences moving nearby after a longer search or by a change in location preferences after the pandemic outbreak. Unfortunately, these mechanisms cannot be disentangled with this data.

In November 2020, results confirm findings from the period before the pandemic: the voucher improved housing related outcomes but did not induced mobility to better neighborhoods. While positive effects on housing did not fade between periods, with this data I cannot disentangle the effect of the pandemic from the long term effects of the voucher.

6.2.2 ***Health and Subjective Well Being***

Panel E of Table IX shows that the voucher did not affect overall physical health and happiness of voucher recipients, and had mixed effects on mental health.

[61] While not statistically significant, consistent with the results for December 2019 the coefficient for the indicator variable taking the value of one if the family lived close to a school is negative (-5.1 pp).

[62] Estimates imply that voucher holders were 4.2 pp (17%) less likely to have a neighbor they could ask for economic help if they needed to. But this effect was not statistically significant (p-value 0.249). Isolation in rental policies that do not rely on the private market in low income countries have been documented by (Barnhardt, Field and Pande, 2017).

The survey included the Patient Health Questionnaire-4 (PHQ4) test, a four-questions screening for anxiety and depression. Column 2 shows that 17%, 40% and 31% of the control group were evaluated as normal, anxious and depressed using this test, respectively.

Column 7 shows that voucher holders were 8.1 pp (11.8%) less likely to feel worried (pvalue 0.125) but were 9.9 pp (24.6%) more likely to feel anxious according to the PHQ4 test.

The mechanisms behind these results and how they interact with the pandemic are unknown. Location may play a role in these findings: moving away from social ties may increase anxiety, specially in times of uncertainty. Future research could further explore the link between rental vouchers and mental health.

6.2.3 *Household responses during COVID-19 pandemic*

Column 2 in Panel G in Table IX gives us a sense of the size of the unexpected economic shock for young low income families in Chile. Roughly 90% of the control group suffered partial or total income loss after the COVID-19 outbreak in March 2020.

Also, 95% of the families had to turn to some strategy to generate new income, cut spending or increase debt to cope with the economic shock that came with the pandemic. Among the fifteen strategies included in the survey, the two most common were to resort to government emergency assistance (58%) and reduce food expenses (59%). In addition, about half of the sample had to cut monthly bills (including utilities) and used family savings to adapt to the new economic circumstances.

The rental voucher did not prevent the decrease in household income generated by the pandemic or the need to adapt to the new economic circumstances. Also, the rental voucher had no effect employment in November 2020.[63]

[63] This result is different from previous literature showing negative effects of rental policies on employment in normal economic times (Jacob and Ludwig, 2012). Regardless of the economic circumstances, however, the fixed (and smaller) amount of the subsidy in Chile does not change the marginal tax rate. Hence, is expected that employment is not affected by the policy.

Voucher assignment did reduce debt overload of treated families in 12.5 pp (18%) and had an important positive effect on the way in which families were coping with the consequences of the large unexpected shock. Holding a rental voucher reduced housing instability: unwanted or emergency moves decreased in 5.6 pp (72%) and rent payment delays occurred 11 pp (45%) less often because of the voucher. The voucher seemed to reduce income instability as well: voucher holders were 12.6 pp (21.5%) less likely to have reduced their food budget and 8.5 pp (15%) less likely to have applied to emergency relief policies. These results point to a previously underappreciated insurance role of rental subsidies in helping poor households cope with negative aggregated shocks.

Interestingly, the voucher also increased temporary unemployment in the beginning of the pandemic, mostly from suspended contracts of dependent workers or independent workers who could not go out to work during strict quarantines. Further research could explore whether the voucher allowed more single mothers —main voucher recipients in regular rounds— to be at home with their kids when the pandemic first hit and schools shut down.

Evidence from the first eight months of the COVID-19 pandemic shows broader impacts of the rental voucher program. The voucher had an important insurance role, providing housing and income stability to low income families in times of large unexpected income shocks.

6.3 Robustness Checks

This section uses 1,187 elderly and 539 regular randomly assigned vouchers to analyze the robustness of the results presented in the previous section.[64] These randomized applicants are included in the smallest window possible around the cutoff in the evaluation sample. Hence, this exercise is equivalent to analyze robustness to the length of the window considered in the evaluation sample.

[64] Between March and September 2019, 2,400 elderly and 1,315 regular vouchers were randomly assigned. However, screenings s_t in which randomization failed to provide a balanced sample, s_t with very few units around the cutoff, and s_t in which the control group had only later treated units were not be used in this analysis.

Tables B.4 and B.5 in the Appendix show balance tests in the sub-sample of randomized vouchers in regular and elderly rounds. In both cases, there is no evidence of statistically significant differences between treated and controls.

Tables A.1 and A.2 in the Appendix show treatment effects in December 2019 using randomized regular and elderly vouchers, respectively. Results from the period before the pandemic show that despite some small differences, coefficients in Section 6.1 are robust to window length using the sample of randomized vouchers.

Given the smaller sample in regular rounds, treatment effects in November 2020 are not reported, but they can be asked directly from the author.

7 Discussion

Similar to previous empirical work studying the US Housing Choice Voucher, the Chilean rental voucher improved housing related outcomes but it did not provide low-income families with access to better neighborhoods. These findings suggest that vouchers alone do not eliminate the barriers that low-income families face in the rental market to use their subsidies to move to better areas in both high- and middle-income countries (Aliprantis, Martin and Tauber, 2020; Bergman et al., 2019).

The pandemic exposed a global housing crisis. High and increasing rents and low and stagnated wages had left low income families with no residual income to overcome unexpected income shocks, susceptible to the long-term consequences of evictions (Ellen, 2020; Collinson and Reed, 2018). Importantly, the pandemic was just an example of an unexpected income shocks that low-income families may experience over the years, specially in poorer countries with high levels of informality and income inequality. Other examples are job loss, illness or death of a family member.

This research coincided with the COVID-19 pandemic, and offered an unexpected opportunity not just to explore the effects of voucher programs in lower-income countries, but also to explore the effects of voucher programs when families are confronted with large economic shocks.

In November 2020, this evaluation showed that the Chilean rental voucher had a positive effect on how families were coping with the COVID-19 pandemic. The voucher reduced housing instability, the need to cut food expenses and apply to emergency relief policies, pointing to a previously underappreciated insurance role of rental vouchers in times of economic struggle.

The experience of the Chilean rental voucher program can inform the ongoing housing policy debate in the US about how to expand the Housing Choice Voucher program. Some policymakers and academics have suggested the implementation of a shorter term voucher to provide assistance to a larger number of families (Ellen, 2020).

This research suggests that a modest short-term rental voucher to young families with children can improve their housing related outcomes and have important effects on housing security in times of economic shocks. Further, starting in 2022, families will exit the program in Chile and future research will be able to assess whether the estimated effects are persistent or fade over time, after families no longer receive direct rental assistance.

As the Chilean program increases, future research could also overcome some of the limitations of this evaluation and answer other important research questions. For instance, evaluations using more data after the regional screening protocol was implemented in 2019, could analyze heterogeneity of treatment effects across local rental markets, specially between Santiago and the rest of the country. Also, future research could exploit changes to subsidy amounts in certain counties over time to estimate the elasticity of treatment effects with respect to voucher generosity within rounds.

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Figures and Tables

TABLE I. 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 (max 3)	20 per prev application	=
11	Social Vulnerability (RSH Index)[3]	0 (81-100th), 45 (71-80th), 90 (61-70th)	=
		135 (51-60th), 180 (40-50th)	=
12	Housing Vulnerability (sum of multiple scores)[4]	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

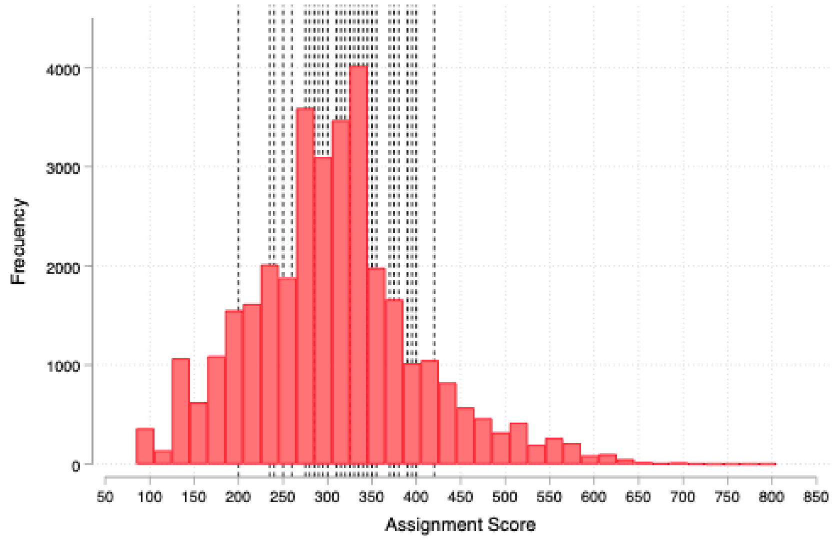
This table presents all score components. Notes: (1) Applicants are excluded in regular rounds; (2) Age by the end of the application year; (3) Includes crowding, housing quality, access to reliable water and basic sanitation; (4) Before the reform the formula was (13484-Family's FPS Score)/100, using the Social Vulnerability Card (FPS) instead of the RSH Index.

TABLE II. Density Test

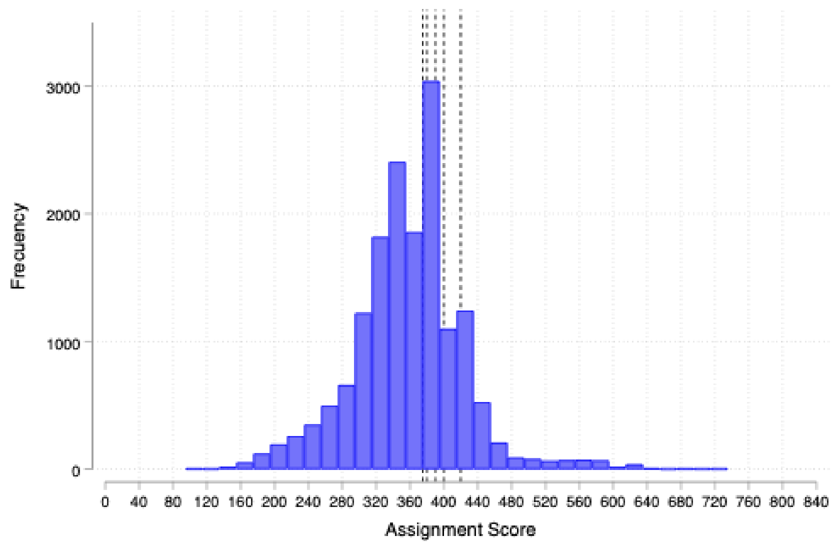
	Binomial Test (q=0.5)				
Screenings	N	Observed T	Expected T	Observed q	p-value
	(1)	(2)	(3)	(4)	(5)
Window Selection	5,043	2,485	2,522	0.49	0.311
Evaluation Sample	2,801	1,405	1,400	0.50	0.880

This table presents the results of a binomial tests to evaluate the presence of manipulation in the running variable. The assumed probability of success q is 50%. See Section 4.2 for more details.

FIGURE I. Multiple Cutoff Regression Discontinuity Design



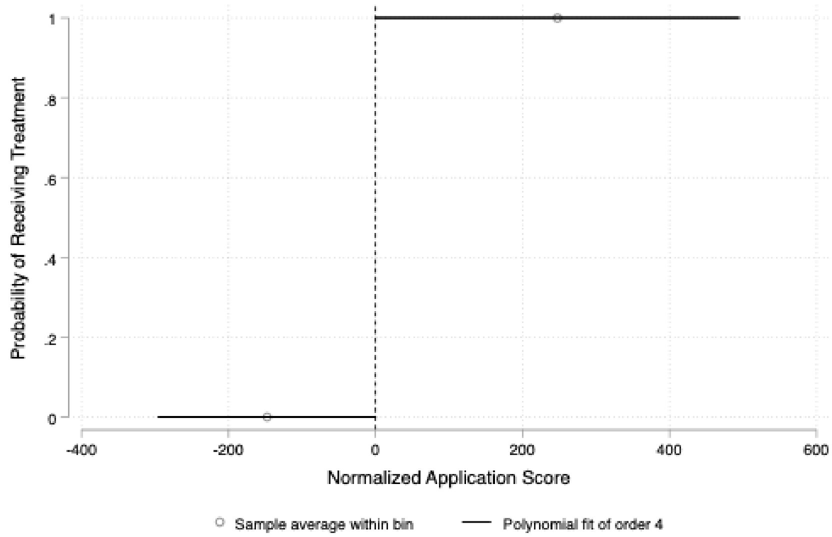
(a) Regular Rounds



(b) Elderly Rounds

The figure presents the distribution of the application score in (a) regular and (b) elderly rounds in the pooled data. Vertical lines indicate multiple values of cutoff in the program.

FIGURE II. Sharp RD Design



This figure presents the treatment probability for all values of the normalized score c.

TABLE III. Assignments in Regular and Elderly Rounds

Assignment Date	N (1)	Min Xi (2)	Max Xi (3)	Vouchers (4)	Cutoff (5)
Regular Rounds					
26apr2017	2,090	85	665	956	300
17may2017	2,214	85	720	996	275
21jun2017	2,373	85	720	1,000	275
24jul2017	2,343	85	705	999	240
24aug2017	2,495	85	685	1,000	240
27sep2017	2,714	85	650	999	235
19oct2017	3,085	85	695	1,933	200
13dec2017	5,751	85	790	900	395
11apr2018	2,591	85	695	1,500	285
01jun2018	6,848	85	755	1,500	370
21sep2018	3,399	125	700	1,000	355
26oct2018	4,162	125	800	1,000	375
20nov2018	7,174	125	800	2,157	350
28dec2018	5,017	125	345	80	345
03jun2019	4,657	85	700	1,985	331
19aug2019	5,076	85	680	1,990	297
10oct2019	6,607	85	740	3,559	273
Total	68,596	85	800	23,554	317
Elderly Rounds					
04sep2017	6,280	135	730	1,859	380
11apr2018	2,063	175	645	1,000	380
25jun2018	3,789	175	860	999	420
19oct2018	8,084	145	710	997	420
05jul2019	7,098	105	740	1,033	394
Total	27,314	105	860	5,888	401

This table shows descriptive statistics for each assignment period that occurred between April 2017 and October 2019. Column 1 shows the total number of applicants that were screened. Column 2 and 3 present the maximum and minimum score among all applicants. Column 4 indicates the number of available vouchers and Column 5 the value of the cutoff. Panel A presents assignment periods in regular rounds and Panel B in elderly rounds. Columns 1 to 4 in June, July, August and October 2019 aggregate all 16 regional screening of applicants and Column 5 shows the average cutoff across all regions. Total cutoff in Column 5 presents the average cutoff.

TABLE IV. Window Selection Results

Assignment Period	Screening (1)	Region (2)	Cutoff (3)	Controls (4)	Treated (5)	Length (6)	Min pvalue (7)	Left (8)	Right (9)
Regular Rounds									
11apr2018	2		285	151	117	10	.12	-5	5
28dec2018	4		345	295	80	7	.21	-5	2
10oct2019	5	6	285	97	49	20	.29	-10	10
10oct2019	6	9	285	153	122	30	.4	-15	15
10oct2019	7	10	275	48	19	4	.25	-2	2
Elderly Rounds									
04sep2017	1		380	377	279	15	.23	-10	5
11apr2018	2		380	275	110	10	.14	-5	5
05jul2019	4	5	380	159	30	10	.18	-5	5
05jul2019	5	13	400	19	79	7	.28	-5	2

This table shows descriptive statistics of each screening of applicants in the evaluation sample. Columns 2 describes the region where the assignment takes place after switching to regional screenings in 2019. Column 3 shows the cutoff. Columns 4 and 5 show the number of individuals below (control) and above (treated) the cutoff. Columns 6 to 6 describe the window selected in each assignment: the length of the window, the minimum p-value of all balance tests using covariates explained in Section 5.2, the minimum and maximum value of the running variable inside the window.

TABLE V. Balance in Baseline Characteristics in Regular Rounds

	Summary Statistics							Balance	
		Pooled		Control		Treated		Test	
	N	Mean	SD	Mean	SD	Mean	SD	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenant in baseline	1,131	0.75	0.43	0.75	0.43	0.74	0.44	0.978	0.978
Saving balance on application day (UF)	1,131	16.60	29.44	16.75	34.31	16.31	16.47	0.388	0.402
Family income (UF)	1,131	13.33	4.80	13.24	4.61	13.50	5.13	0.686	0.688
Online application	1,131	0.36	0.48	0.37	0.48	0.35	0.48	0.512	0.486
High density county	1,131	0.39	0.49	0.40	0.49	0.37	0.48	0.906	0.919
County above national poverty	1,131	0.67	0.47	0.65	0.48	0.71	0.46	0.648	0.672
PHA in county of residence	1,131	0.47	0.50	0.48	0.50	0.47	0.50	0.740	0.747
Previous app. to ownership subsidy	1,131	0.15	0.36	0.14	0.35	0.17	0.37	0.747	0.733
Age 25-35	1,131	0.60	0.49	0.58	0.49	0.64	0.48	0.103	0.128
Below family adjusted PL	1,131	0.21	0.41	0.20	0.40	0.22	0.42	0.733	0.744
KM to closest PHA	1,131	18.03	22.99	17.52	22.20	19.01	24.43	0.486	0.497
Valid email address	1,131	0.88	0.33	0.88	0.33	0.88	0.33	0.810	0.823
Want to stay same neighborhood	677	0.56	0.50	0.57	0.50	0.55	0.50	0.713	0.737
Satisfaction with housing unit	723	0.66	0.47	0.66	0.47	0.65	0.48	0.156	0.196
Does not know other applicants	659	0.53	0.50	0.51	0.50	0.57	0.50	0.095*	0.118
Access to car	655	0.34	0.47	0.35	0.48	0.31	0.47	0.537	0.562
(Perceived) High social class neighbors	702	0.49	0.50	0.49	0.50	0.49	0.50	0.627	0.667
Baseline Survey response	995	0.82	0.38	0.82	0.39	0.82	0.38	0.764	0.941
Geocoded location	1,131	0.89	0.31	0.90	0.30	0.88	0.32	0.146	0.890
Female	1,131	0.89	0.31	0.89	0.31	0.89	0.31	0.611	0.233
Spouse/partner	1,131	0.17	0.38	0.18	0.38	0.15	0.36	0.158	0.751
Chilean	1,131	0.94	0.24	0.93	0.26	0.97	0.18	0.007***	0.557
Santiago MSA	1,131	0.11	0.31	0.11	0.32	0.10	0.30	0.887	0.821
Rent	772	5.65	3.03	5.65	3.12	5.66	2.81	0.622	0.943
Rent burden	772	0.47	0.28	0.47	0.29	0.48	0.24	0.654	0.235
SCREENING FE								Yes	Yes
Joint Significance F-Test (p)								0.245	0.373

This table presents summary statistics and balance tests between treatment and control groups in the evaluation sample in regular rounds. Columns 1 to 7 show summary statistics of baseline characteristics. Columns 8 and 9 show balance results from testing the fully interacted model in equation 2 (H_0) or the the weaker null hypothesis (H_0') excluding interaction terms from 2. Column 8 presents inference using large-sample based inference (F-test) and column 9 present Fisherian randomization inference p-values (Randomization-t exact test). I use the package randcmd (1000 iterations) to calculate randomization inference p-values in Stata (Young, 2019). The bottom panel presents the F-test of joint significance from regressing the treatment indicator on baseline covariates. See Section 5.2 for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE VI. Balance in Baseline Characteristics in Elderly Rounds

		Summary Statistics						Balance Test	
		Pooled		Control		Treated			
	N	Mean	SD	Mean	SD	Mean	SD	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenant in baseline	1,328	0.54	0.50	0.55	0.50	0.53	0.50	0.451	0.471
Family income (UF)	1,328	6.22	2.81	6.19	2.74	6.29	2.92	0.611	0.633
PHA in county of residence	1,328	0.47	0.50	0.47	0.50	0.47	0.50	0.426	0.474
County above national poverty	1,328	0.32	0.46	0.34	0.47	0.28	0.45	0.262	0.398
High density county	1,328	0.54	0.50	0.52	0.50	0.58	0.49	0.877	0.875
Female	1,328	0.61	0.49	0.59	0.49	0.63	0.48	0.115	0.141
Age 70-79	1,328	0.56	0.50	0.57	0.49	0.54	0.50	0.300	0.324
Below family adjusted PL	1,328	0.56	0.50	0.57	0.50	0.55	0.50	0.864	0.872
KM to closest PHA	1,328	12.03	16.62	12.42	16.83	11.39	16.26	0.195	0.263
Valid email address	1,328	0.37	0.48	0.39	0.49	0.34	0.47	0.222	0.235
Spouse/partner	1,328	0.39	0.49	0.39	0.49	0.40	0.49	0.697	0.701
Chilean	1,328	0.98	0.13	0.98	0.14	0.99	0.12	0.078*	0.649
Previous app. to ownership subsidy	1,328	0.05	0.22	0.06	0.23	0.04	0.20	0.452	0.312
Income documents to PHA	1,328	0.99	0.12	0.99	0.11	0.98	0.13	0.948	0.492
Santiago MSA	1,328	0.27	0.44	0.23	0.42	0.34	0.47	0.847	0.066*
Geocoded location	1,328	0.96	0.20	0.95	0.21	0.97	0.18	0.324	0.483
SCREENING FE								Yes	Yes
Joint Significance F-Test (p)								0.120	0.170

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

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

				Specification 1			Specification 2		
		Control		Treatment	OLS	Rand-t	Treatment	OLS	Rand-t
	N	Mean	SD	Effect	p-value	p-value	Effect	p-value	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Housing Conditions									
Household size Dec 2019	1,131	2.847	1.204	0.052	0.494	0.491	0.058	0.434	0.441
Number of bedrooms	1,121	1.750	0.820	0.194	0.000***	0.000***	0.203	0.000***	0.000***
Number of people per bedroom	1,121	1.816	0.770	-0.175	0.000***	0.000***	-0.182	0.000***	0.000***
Overcrowing indicator	1,121	0.133	0.340	-0.061	0.001***	0.001***	-0.061	0.001***	0.001***
B. Residential Mobility									
Stayed in same unit	1,003	0.587	0.493	-0.089	0.008***	0.008***	-0.076	0.021**	0.020**
Distance (km)	1,003	7.392	45.429	16.781	0.039**	0.022**	15.711	0.049**	0.036**
Stayed in 1km radius	1,003	0.724	0.447	-0.084	0.007***	0.004***	-0.077	0.014**	0.012**
Moved to another county	1,003	0.062	0.241	0.048	0.008***	0.015**	0.046	0.010***	0.016**
C. Neighborhood Characteristics									
Distance to closest municipality	1,003	3.273	4.627	0.394	0.245	0.247	0.387	0.249	0.266
Distance to closest School (1km)	1,003	0.896	1.797	0.441	0.027**	0.033**	0.446	0.032**	0.043**
Distance to closest Pre-Shcool (km)	1,003	0.976	2.286	0.489	0.028**	0.034**	0.493	0.028**	0.040**
Distance to closest Primary Care (km)	930	1.545	2.440	0.348	0.158	0.169	0.331	0.195	0.218
Number of Schools in 1Km	1,003	4.851	4.265	-0.297	0.330	0.343	-0.256	0.384	0.389
Number of Preschool in 1Km	1,003	3.008	2.535	-0.070	0.691	0.682	-0.045	0.790	0.796
Number of Health Care in 2km	1,003	4.959	4.567	-0.326	0.252	0.263	-0.250	0.308	0.334
Fraction of Public Schools 1Km	827	0.445	0.288	-0.008	0.712	0.684	-0.006	0.785	0.774
Fraction of Subsidized Schools 1Km	827	0.521	0.281	-0.000	0.984	0.980	-0.003	0.894	0.884
Fraction of Private Schools 1Km	827	0.034	0.105	0.008	0.262	0.267	0.009	0.241	0.253
Lang. SIMCE, 3 Closest Schools 2km	878	263.786	17.432	0.293	0.818	0.817	-0.090	0.943	0.948
Mat. SIMCE, 3 Closest School 2km	878	249.516	18.520	0.246	0.858	0.855	0.070	0.959	0.961
Fraction of Low Income Schools 2km	886	0.597	0.266	0.002	0.909	0.909	0.000	0.995	0.994
County poverty rate	1,003	0.115	0.064	-0.000	0.950	0.952	-0.002	0.548	0.528
Assault rate (people 18 or over)	1,002	0.003	0.003	-0.000	0.429	0.416	-0.000	0.649	0.632
Robbery rate (people 18 or over)	1,002	0.011	0.006	0.000	0.861	0.868	0.000	0.707	0.698
Theft rate (people 18 or over)	1,002	0.010	0.006	0.000	0.445	0.437	0.000	0.357	0.378
D. Homeownership									
Application to Ownership Programs	1,131	0.313	0.464	0.027	0.343	0.293	0.012	0.583	0.552
Application DS1	1,131	0.222	0.416	0.029	0.273	0.244	0.017	0.428	0.419
Application DS49	1,131	0.124	0.329	0.014	0.470	0.433	0.010	0.599	0.602
Active ownership savings account	1,131	0.911	0.285	0.010	0.565	0.523	0.008	0.644	0.631
Total savings (UF)	1,033	24.132	31.862	1.071	0.597	0.612	0.365	0.838	0.845
SCREENING FE				YES	YES	YES	YES	YES	YES
CONTROLS (Z)				NO	NO	NO	YES	YES	YES
Westfall-Young Multiple Testing (p-value)						0.003***			0.003***

This table presents estimates of equation 3 using outcomes measured in December 2019. Columns 2 and 3 show the average and standard deviation of the outcome in the control group. Specifications 1 (Columns 4 to 6) includes screening of applicants fixed effects. Specification 2 (Columns 7 to 9) includes screening of applicants fixed effects and baseline covariates explained in Section 6. Large-sample based inference (OLS p-values) are presented in Columns 5 and 8, and Fisherian randomization inference (Randomization-t p-values from Young (2019) are presented in Columns 6 and 9. The bottom panel shows the Westfall-Young multiple-testing test of overall treatment irrelevance considering all outcomes together. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

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

		Control		Specification 1			Specification 2		
	N	Mean	SD	Treatment Effect	OLS p-value	Rand-t p-value	Treatment Effect	OLS p-value	Rand-t p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Housing Conditions									
Household size Dec 2019	1,328	1.600	1.091	-0.144	0.012**	0.014**	-0.175	0.001***	0.002***
Number of bedrooms	1,252	1.358	0.735	0.443	0.000***	0.001***	0.443	0.000***	0.001***
Number of people per bedroom	1,247	1.243	0.597	-0.298	0.000***	0.001***	-0.317	0.000***	0.001***
Overcrowing indicator	1,314	0.034	0.182	-0.017	0.097*	0.108	-0.020	0.046**	0.061*
B. Residential Mobility									
Stayed in same unit	1,198	0.680	0.467	-0.201	0.000***	0.001***	-0.199	0.000***	0.001***
Distance (km)	1,198	16.123	116.539	1.389	0.838	0.859	-0.520	0.938	0.950
Stayed in 1km radius	1,198	0.776	0.417	-0.144	0.000***	0.001***	-0.142	0.000***	0.001***
Moved to another county	1,200	0.086	0.280	0.042	0.031**	0.023**	0.039	0.041**	0.027**
C. Neighborhood Characteristics									
Distance to closest municipality	1,198	3.777	7.220	-0.554	0.138	0.140	-0.481	0.189	0.195
Distance to closest School (1km)	1,198	1.117	4.007	-0.130	0.473	0.499	-0.099	0.612	0.645
Distance to closest Pre-Shcool (km)	1,198	1.129	4.269	-0.155	0.451	0.455	-0.111	0.612	0.629
Distance to closest Primary Care (km)	1,137	1.614	4.103	-0.120	0.561	0.580	-0.081	0.704	0.699
Number of Schools in 1Km	1,198	7.056	5.731	-0.315	0.353	0.349	-0.536	0.097*	0.098*
Number of Preschool in 1Km	1,198	3.731	2.925	-0.136	0.470	0.479	-0.202	0.267	0.270
Number of Health Care in 2km	1,198	6.546	5.648	-0.145	0.675	0.653	-0.364	0.238	0.250
Fraction of Public Schools 1Km	1,050	0.405	0.241	-0.010	0.537	0.550	-0.004	0.796	0.808
Fraction of Subsidized Schools 1Km	1,050	0.529	0.244	0.007	0.660	0.651	0.004	0.823	0.814
Fraction of Private Schools 1Km	1,050	0.066	0.137	0.003	0.747	0.755	0.000	0.957	0.957
Lang. SIMCE, 3 Closest Schools 2km	1,087	264.174	17.522	-0.758	0.507	0.493	-0.874	0.455	0.442
Mat. SIMCE, 3 Closest School 2km	1,088	251.717	18.091	-0.129	0.914	0.917	-0.240	0.843	0.848
Fraction of Low Income Schools 2km	1,092	0.438	0.266	-0.023	0.198	0.197	-0.008	0.639	0.630
County poverty rate	1,200	0.084	0.048	-0.003	0.389	0.400	0.002	0.467	0.457
Assault rate (people 18 or over)	1,199	0.005	0.004	0.000	0.731	0.738	-0.000	0.798	0.786
Robbery rate (people 18 or over)	1,199	0.015	0.007	0.000	0.795	0.795	-0.000	0.241	0.233
Theft rate (people 18 or over)	1,199	0.011	0.005	0.000	0.269	0.259	0.000	0.906	0.907
D. Homeownership									
Application to Ownership Programs	1,328	0.123	0.329	0.021	0.292	0.294	0.032	0.052*	0.043**
Application DS1	1,328	0.077	0.267	-0.002	0.891	0.864	0.005	0.687	0.686
Application DS49	1,328	0.061	0.240	0.027	0.095*	0.097*	0.030	0.044**	0.039**
SCREENING FE				YES	YES	YES	YES	YES	YES
CONTROLS (Z)				NO	NO	NO	YES	YES	YES
Westfall-Young Multiple Testing (p-value)						0.008***			0.009***

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

TABLE IX. Effect of Regular Voucher During the COVID-19 Pandemic (2020)

		Control		Specification 1			Specification 2		
	N	Mean	SD	Treatment Effect	OLS p-value	Rand-t p-value	Treatment Effect	OLS p-value	Rand-t p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Housing and Household Characteristics									
Tenancy	480	0.862	0.345	0.014	0.676	0.680	0.026	0.421	0.415
Formal Lease	394	0.733	0.444	0.119	0.007***	0.006***	0.126	0.007***	0.004***
Total rent (unit)	387	261.322	94.026	-3.780	0.705	0.705	-0.294	0.974	0.972
Rent paid	376	241.706	106.387	-51.372	0.000***	0.001***	-48.538	0.000***	0.001***
Rent burden (rent paid)	334	0.509	0.271	-0.137	0.000***	0.000***	-0.126	0.000***	0.000***
Rent burden (rent amount)	344	0.553	0.252	-0.041	0.108	0.096*	-0.032	0.204	0.183
Lives with Parents/Grand parents	410	0.143	0.351	-0.001	0.970	0.969	-0.010	0.785	0.768
Living with grandchild	410	0.023	0.151	0.004	0.832	0.873	0.012	0.508	0.523
Spouse/Partner	409	0.319	0.467	0.071	0.166	0.156	0.078	0.102	0.100*
Child borned since application	380	0.133	0.340	0.050	0.238	0.237	0.045	0.289	0.290
Household Size	512	3.331	1.461	-0.161	0.201	0.201	-0.118	0.341	0.357
Number of bedrooms	496	2.223	0.897	0.028	0.705	0.729	0.037	0.618	0.622
Number of people per bedroom	496	1.653	0.843	-0.145	0.038**	0.034**	-0.147	0.035**	0.039**
Overcrowding indicator	498	0.129	0.336	-0.064	0.021**	0.026**	-0.064	0.030**	0.041**
Pet Owner	410	0.016	0.124	-0.012	0.278	0.250	-0.009	0.400	0.449
Laundry Room	428	0.416	0.494	-0.003	0.955	0.953	0.005	0.924	0.917
Kitchen Room	480	0.796	0.404	0.075	0.042**	0.045**	0.080	0.034**	0.030**
Hot water	496	0.850	0.357	-0.006	0.868	0.868	-0.023	0.508	0.497
Heat system	496	0.775	0.418	0.129	0.000***	0.001***	0.103	0.001***	0.003***
Cable TV	495	0.634	0.483	-0.016	0.718	0.733	-0.042	0.366	0.354
Wifi	493	0.564	0.497	0.021	0.648	0.641	0.004	0.935	0.937
Smart Phone Lease	491	0.641	0.480	0.052	0.250	0.262	0.038	0.406	0.405
Computer	495	0.497	0.501	0.053	0.260	0.260	0.041	0.383	0.397
B. Residential Mobility									
Stayed in same unit	441	0.591	0.493	-0.094	0.059*	0.052*	-0.094	0.065*	0.057*
Distance (km)	358	7.779	44.523	9.971	0.326	0.370	8.550	0.301	0.344
Number of moves from application	441	0.737	1.137	-0.001	0.992	0.995	0.009	0.930	0.930
2 or more years current house	546	0.499	0.501	-0.130	0.003***	0.004***	-0.134	0.003***	0.003***
2 or more years current neighborhood	538	0.586	0.493	-0.093	0.036**	0.043**	-0.085	0.057*	0.064*
C. Neighborhood Characteristics									
Close to childcare/pre-school (4 blocks)	538	0.580	0.494	0.009	0.837	0.848	0.014	0.766	0.779
Close to schools (4 blocks)	538	0.586	0.493	-0.065	0.149	0.152	-0.051	0.259	0.235
Close to subway/bus (4 blocks)	538	0.642	0.480	0.013	0.760	0.776	0.038	0.394	0.419
Close to park (4 blocks)	538	0.612	0.488	0.063	0.146	0.147	0.075	0.080*	0.086*
Close to health care (4 blocks)	538	0.470	0.500	-0.021	0.641	0.642	0.001	0.974	0.974
Less than 15 min commute time to family	370	0.439	0.497	0.009	0.867	0.847	-0.005	0.937	0.933
Less than 15 min commute time to friends	325	0.458	0.499	0.031	0.604	0.577	0.045	0.459	0.424
Less than 15 min commute time to school	347	0.519	0.501	0.017	0.768	0.768	0.003	0.960	0.963
Less than 30 min commute time to work	310	0.713	0.454	-0.029	0.611	0.601	-0.025	0.670	0.642
Street alcohol Consumption	397	0.544	0.499	0.027	0.606	0.606	0.021	0.694	0.700
Street Drug Consumers	397	0.435	0.497	-0.027	0.596	0.600	-0.034	0.515	0.527
Street Drug Trafficking	397	0.274	0.447	-0.026	0.579	0.579	-0.024	0.605	0.613
Destroyed property	397	0.327	0.470	-0.029	0.558	0.563	-0.028	0.564	0.585
Graffiti	397	0.210	0.408	-0.029	0.468	0.468	-0.039	0.362	0.355
Gang Fights	397	0.165	0.372	0.064	0.133	0.133	0.077	0.076*	0.075*
People carrying guns	397	0.190	0.393	0.015	0.723	0.740	0.015	0.716	0.736
Shooting	397	0.387	0.488	0.043	0.413	0.395	0.047	0.368	0.356
Prostitution	397	0.060	0.239	0.005	0.842	0.843	0.012	0.629	0.636
Feels safe walking at night	398	0.550	0.498	-0.034	0.529	0.532	-0.033	0.545	0.540
Feels safe inside the house at night	394	0.765	0.425	0.031	0.496	0.461	0.025	0.573	0.524
Victim of violence (physical)	391	0.119	0.324	-0.023	0.449	0.425	-0.016	0.625	0.609
Victim of robbery	370	0.298	0.458	0.005	0.912	0.888	0.010	0.833	0.832
D. Housing and Neighborhood Satisfaction									
Satisfaction current housing unit	547	0.754	0.431	0.078	0.029**	0.025**	0.084	0.019**	0.015**
Satisfaction current neighborhood	526	0.802	0.399	-0.023	0.524	0.539	-0.031	0.378	0.391
Would ask neighbors for childcare	510	0.297	0.458	-0.081	0.046**	0.051*	-0.073	0.082*	0.092*
Has close friends in the neighborhood	513	0.436	0.497	-0.034	0.464	0.471	-0.019	0.688	0.697
Would ask neighbors for economic help	507	0.243	0.429	-0.036	0.348	0.323	-0.042	0.282	0.249

TABLE IX. *(Continuation)* Effect of Regular Voucher During the COVID-19 Pandemic (2020)

				Specification 1			Specification 2		
		Control		Treatment	OLS	Rand-t	Treatment	OLS	Rand-t
	N	Mean	SD	Effect	p-value	p-value	Effect	p-value	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
E. Health and Subjective Well Being									
Covid-19 case at Home	388	0.041	0.199	0.025	0.309	0.601	0.019	0.473	0.642
Do not know any COVID-19 case	388	0.307	0.462	-0.056	0.244	0.245	-0.037	0.441	0.428
Good health	397	0.586	0.494	0.063	0.225	0.199	0.057	0.277	0.252
Happy	382	0.702	0.458	0.046	0.339	0.326	0.029	0.566	0.569
Feel depressed	393	0.794	0.405	-0.069	0.130	0.122	-0.050	0.280	0.278
Feel worried	393	0.685	0.465	-0.094	0.067*	0.076*	-0.081	0.122	0.125
PHQ4 Test: Normal	393	0.169	0.376	-0.031	0.436	0.438	-0.034	0.423	0.451
PHQ4 Test: Anxiety	393	0.403	0.492	0.111	0.038**	0.051*	0.099	0.067*	0.066*
PHQ4 Test: Depression	393	0.310	0.464	0.049	0.332	0.336	0.028	0.583	0.579
F. Employment and Income									
Work	406	0.700	0.459	-0.018	0.710	0.710	-0.036	0.465	0.461
Covid-19 unemployment	406	0.170	0.376	0.056	0.172	0.152	0.068	0.100*	0.090*
Debt overload	414	0.696	0.461	-0.124	0.016**	0.015**	-0.125	0.017**	0.017**
Income (UF)	410	13.367	5.604	0.712	0.185	0.211	0.503	0.351	0.384
G. Household Response During in Covid-19 Crisis									
Covid-19: moved out	411	0.077	0.267	-0.052	0.017**	0.023**	-0.056	0.014**	0.018**
Covid-19 response: delayed rent payments	364	0.241	0.429	-0.117	0.006***	0.007***	-0.108	0.012**	0.016**
Covid-19 response: others moved in	411	0.066	0.248	0.011	0.702	0.718	0.024	0.418	0.416
Covid-19 response: reduced food budget	411	0.587	0.493	-0.109	0.038**	0.039**	-0.126	0.018**	0.018**
Covid-19 response: reduced health expenses	411	0.363	0.482	-0.060	0.217	0.239	-0.067	0.180	0.200
Covid-19: reduced utilities expenses	411	0.467	0.500	-0.033	0.528	0.529	-0.030	0.574	0.575
Covid-19 response: delayed monthly billings	411	0.444	0.498	-0.076	0.137	0.143	-0.085	0.110	0.118
Covid-19 response: informal loan (family/friends)	411	0.405	0.492	-0.054	0.283	0.265	-0.051	0.325	0.314
Covid-19 response: formal loan or credit	411	0.224	0.418	-0.054	0.192	0.197	-0.048	0.255	0.248
Covid-19: sold belongings (vehicle, jewelry, etc.)	411	0.158	0.366	0.011	0.758	0.739	0.023	0.527	0.530
Covid-19: sold or rented real state/land	411	0.004	0.062	0.015	0.238	0.240	0.017	0.174	0.185
Covid-19: used family savings	411	0.494	0.501	-0.013	0.808	0.809	-0.028	0.596	0.592
Covid-19: new income activities	411	0.347	0.477	-0.037	0.448	0.457	-0.046	0.363	0.389
Covid-19: gave or lent money to family	411	0.116	0.321	-0.030	0.362	0.349	-0.029	0.399	0.384
Covid-19: applied to emergency relief	411	0.583	0.494	-0.083	0.110	0.095*	-0.085	0.111	0.100
Covid-19: none	411	0.058	0.234	-0.003	0.895	0.898	0.002	0.926	0.923
Covid-19: other	411	0.050	0.219	-0.028	0.105	0.120	-0.013	0.437	0.432
SCREENING FE				YES	YES	YES	YES	YES	YES
CONTROLS (Z)				NO	NO	NO	YES	YES	YES
Westfall-Young Multiple Testing (p-value)						0.025**			0.026**

This table presents estimates of equation 3 using outcomes measured in the follow-up sample implemented in September-November 2020. Columns 2 and 3 show the average and standard deviation of the outcome in the control group. Specifications 1 (Columns 4 to 6) includes screening of applicants fixed effects. Specification 2 (Columns 7 to 9) includes screening of applicants fixed effects and baseline covariates explained in Section 6. Large-sample based inference (OLS p-values) are presented in Columns 5 and 8, and Fisherian randomization inference (Randomization-t p-values from Young (2019) are presented in Columns 6 and 9. The bottom panel shows the Westfall-Young multiple-testing test of overall treatment irrelevance considering all outcomes together. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

A Appendix

TABLE A.1. Effect of Regular Voucher Before the COVID-19 Pandemic (2019): Randomization

				Specification 1			Specification 2		
		Control		Treatment	OLS	Rand-t	Treatment	OLS	Rand-t
	N	Mean	SD	Effect	p-value	p-value	Effect	p-value	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Housing Conditions									
Household size Dec 2019	539	2.623	1.127	-0.016	0.884	0.894	-0.021	0.847	0.859
Number of bedrooms	536	1.571	0.764	0.262	0.001***	0.000***	0.266	0.001***	0.000***
Number of people per bedroom	536	1.852	0.740	-0.269	0.000***	0.000***	-0.279	0.000***	0.000***
Overcrowing indicator	536	0.092	0.290	-0.047	0.033**	0.026**	-0.053	0.020**	0.016**
B. Residential Mobility									
Stayed in same unit	472	0.522	0.500	-0.071	0.144	0.147	-0.060	0.214	0.225
Distance (km)	472	6.291	24.988	19.916	0.073*	0.024**	18.607	0.071*	0.021**
Stayed in 1km radius	472	0.665	0.473	-0.053	0.249	0.244	-0.045	0.335	0.324
Moved to another county	472	0.086	0.281	0.033	0.211	0.207	0.030	0.237	0.232
C. Neighborhood Characteristics									
Distance to closest municipality	472	3.491	5.211	0.690	0.229	0.237	0.738	0.215	0.213
Distance to closest School (1km)	472	0.953	2.099	0.619	0.097*	0.084*	0.668	0.096*	0.091*
Distance to closest Pre-Shcool (km)	472	1.033	2.580	0.767	0.048**	0.043**	0.784	0.051*	0.047**
Distance to closest Primary Care (km)	440	1.630	2.780	0.623	0.162	0.156	0.632	0.189	0.185
Number of Schools in 1Km	472	5.097	4.496	-0.481	0.293	0.272	-0.449	0.318	0.293
Number of Preschool in 1Km	472	3.201	2.615	-0.120	0.650	0.630	-0.103	0.687	0.674
Number of Health Care in 2km	472	5.047	4.359	-0.550	0.146	0.129	-0.632	0.064*	0.064*
Fraction of Public Schools 1Km	386	0.457	0.286	0.021	0.515	0.514	0.032	0.329	0.333
Fraction of Subsidized Schools 1Km	386	0.517	0.277	-0.043	0.177	0.182	-0.053	0.103	0.104
Fraction of Private Schools 1Km	386	0.025	0.087	0.022	0.041**	0.040**	0.021	0.044**	0.040**
Lang. SIMCE, 3 Closest Schools 2km	412	261.867	17.804	1.630	0.356	0.340	1.119	0.525	0.512
Mat. SIMCE, 3 Closest School 2km	412	248.423	19.461	0.531	0.786	0.755	-0.014	0.994	0.990
Fraction of Low Income Schools 2km	415	0.573	0.274	0.031	0.264	0.276	0.025	0.335	0.354
County poverty rate	472	0.105	0.060	0.001	0.786	0.798	-0.001	0.820	0.831
Assault rate (people 18 or over)	472	0.003	0.003	-0.000	0.732	0.739	-0.000	0.484	0.495
Robbery rate (people 18 or over)	472	0.011	0.006	0.000	0.715	0.726	0.000	0.503	0.510
Theft rate (people 18 or over)	472	0.010	0.005	0.000	0.526	0.534	0.000	0.318	0.335
D. Homeownership									
Application to Ownership Programs	539	0.336	0.473	0.061	0.156	0.140	0.028	0.409	0.391
Application DS1	539	0.236	0.425	0.044	0.265	0.240	0.018	0.564	0.521
Application DS49	539	0.157	0.365	0.013	0.690	0.689	-0.002	0.944	0.941
Active ownership savings account	539	0.918	0.274	0.018	0.486	0.539	0.015	0.568	0.587
Total savings (UF)	498	24.278	32.152	4.000	0.167	0.171	2.526	0.316	0.331
SCREENING FE				YES	YES	YES	YES	YES	YES
CONTROLS (Z)				NO	NO	NO	YES	YES	YES
Westfall-Young Multiple Testing (p-value)						0.021**			0.021**

This table replicates the analysis in Table VII for the sample of randomized vouchers in regular rounds. See Table VII for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

TABLE A.2. Effect of Elderly Voucher Before the COVID-19 Pandemic (2019): Randomization

				Specification 1			Specification 2		
		Control		Treatment	OLS	Rand-t	Treatment	OLS	Rand-t
	N	Mean	SD	Effect	p-value	p-value	Effect	p-value	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Housing Conditions									
Household size Dec 2019	1,187	1.565	1.059	-0.234	0.000***	0.000***	-0.250	0.000***	0.000***
Number of bedrooms	1,122	1.351	0.736	0.436	0.000***	0.000***	0.445	0.000***	0.000***
Number of people per bedroom	1,118	1.223	0.564	-0.328	0.000***	0.000***	-0.341	0.000***	0.000***
Overcrowing indicator	1,176	0.029	0.169	-0.019	0.041**	0.041**	-0.020	0.030**	0.025**
B. Residential Mobility									
Stayed in same unit	1,073	0.681	0.466	-0.209	0.000***	0.001***	-0.208	0.000***	0.001***
Distance (km)	1,073	16.445	122.110	-5.232	0.378	0.406	-6.618	0.303	0.323
Stayed in 1km radius	1,073	0.773	0.419	-0.143	0.000***	0.001***	-0.143	0.000***	0.001***
Moved to another county	1,075	0.086	0.281	0.033	0.106	0.116	0.030	0.133	0.138
C. Neighborhood Characteristics									
Distance to closest municipality	1,073	3.905	7.503	-0.832	0.040**	0.036**	-0.701	0.069*	0.061*
Distance to closest School (1km)	1,073	1.163	4.251	-0.183	0.374	0.405	-0.138	0.524	0.555
Distance to closest Pre-Shcool (km)	1,073	1.186	4.522	-0.237	0.309	0.327	-0.176	0.468	0.473
Distance to closest Primary Care (km)	1,022	1.663	4.327	-0.174	0.452	0.475	-0.116	0.624	0.636
Number of Schools in 1Km	1,073	7.114	5.818	-0.504	0.159	0.150	-0.727	0.035**	0.027**
Number of Preschool in 1Km	1,073	3.755	2.975	-0.227	0.255	0.223	-0.301	0.121	0.108
Number of Health Care in 2km	1,073	6.547	5.699	-0.200	0.584	0.592	-0.413	0.207	0.187
Fraction of Public Schools 1Km	938	0.397	0.237	0.004	0.801	0.826	0.009	0.615	0.625
Fraction of Subsidized Schools 1Km	938	0.534	0.238	-0.004	0.806	0.802	-0.007	0.692	0.673
Fraction of Private Schools 1Km	938	0.069	0.139	-0.000	0.993	0.989	-0.002	0.845	0.855
Lang. SIMCE, 3 Closest Schools 2km	974	264.493	17.587	-1.203	0.324	0.331	-1.203	0.336	0.346
Mat. SIMCE, 3 Closest School 2km	975	251.926	18.012	-0.451	0.718	0.716	-0.476	0.707	0.701
Fraction of Low Income Schools 2km	978	0.437	0.267	-0.019	0.313	0.316	-0.008	0.648	0.646
County poverty rate	1,075	0.083	0.047	-0.003	0.408	0.418	0.001	0.542	0.515
Assault rate (people 18 or over)	1,074	0.005	0.004	0.000	0.777	0.787	-0.000	0.787	0.789
Robbery rate (people 18 or over)	1,074	0.015	0.007	-0.000	0.885	0.894	-0.001	0.166	0.149
Theft rate (people 18 or over)	1,074	0.011	0.005	0.000	0.504	0.483	-0.000	0.853	0.839
D. Homeownership									
Application to Ownership Programs	1,187	0.118	0.323	0.021	0.315	0.303	0.031	0.085*	0.089*
Application DS1	1,187	0.067	0.250	0.006	0.694	0.671	0.012	0.404	0.420
Application DS49	1,187	0.068	0.252	0.015	0.374	0.388	0.020	0.217	0.241
SCREENING FE				YES	YES	YES	YES	YES	YES
CONTROLS (Z)				NO	NO	NO	YES	YES	YES
Westfall-Young Multiple Testing (p-value)						0.001***			0.001***

This table replicates the analysis in Table VII for the sample of randomized vouchers in elderly rounds. See Table VII for details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

B Online Appendix: Additional Figures and Tables

TABLE B.1. Program Summary Statistics

Round	Applicants (1)	Voucher Recipients (2)	Lease-up (N) May-20 (3)	Lease-up (%) May-20 (4)
1-2014 Regular	5023	5004	1994	40%
2-2014 Regular	2045	2045	906	44%
2015 Regular	3525	3001	1391	46%
2016 Regular	11892	10576	4676	44%
2017 Regular	13634	8785	3809	43%
1-2018 Regular	8350	3002	1345	45%
2-2018 Regular	9175	4238	1816	43%
2019 Regular	10584	7536	2775	37%
Total Regular Rounds	64228	44187	18712	42%
2016 Elderly (Pilot)	630	630	326	52%
2017 Elderly	6292	1871	945	51%
1-2018 Elderly	5858	2068	1110	54%
2-2018 Elderly	4526	939	440	47%
2019 Elderly	7118	1049	471	45%
Total Elderly Rounds	24424	6557	3292	50%
Total Program	88652	50744	22004	43%

This table presents descriptive statistics for each round of the program between 2014 and 2019. Columns 1 and 2 show the total number of applicants and number of voucher offers in each round. Column 3 presents the total number of voucher recipients that ever used their vouchers and Column 4 presents the lease up rate (Column 3 divided by Column 2). Columns 3 and 4 use data on all leases that voucher recipients activated between April 2014 and May 2020.

TABLE B.2. Summary Statistics of Voucher Recipients and Non Recipients in Regular Rounds

	All Applicants			Recipients		Non-Recipients		Difference
	N	Mean	SD	Mean	SD	Mean	SD	(7)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenant in baseline	41,738	0.70	0.46	0.68	0.47	0.72	0.45	0.04
Saving balance on application day (UF)	41,738	14.47	16.64	14.18	16.18	14.84	17.21	0.65
Family income (UF)	41,738	14.80	5.47	14.56	5.56	15.12	5.32	0.57
Online application	41,738	0.34	0.47	0.34	0.47	0.34	0.47	0.00
High density county	41,738	0.45	0.50	0.43	0.50	0.47	0.50	0.03
County above national poverty	41,738	0.50	0.50	0.50	0.50	0.50	0.50	-0.01
PHA in county of residence	41,738	0.49	0.50	0.49	0.50	0.50	0.50	0.01
Previous app. to ownership subsidy	41,738	0.14	0.35	0.14	0.35	0.14	0.34	-0.01
Age at application	41,738	34.71	10.46	34.02	9.57	35.60	11.46	1.57
Below family adjusted PL	41,737	0.25	0.43	0.32	0.47	0.16	0.37	-0.16
KM to closest PHA	41,738	14.61	19.04	15.08	19.46	14.00	18.47	-1.08
Valid email address	41,738	0.86	0.35	0.85	0.36	0.87	0.33	0.02
Want to stay same neighborhood	24,771	0.54	0.50	0.54	0.50	0.53	0.50	-0.00
Satisfaction with housing unit	25,983	0.59	0.49	0.58	0.49	0.60	0.49	0.02
Does not know other applicants	24,250	0.62	0.49	0.61	0.49	0.62	0.49	0.01
Access to car	21,943	0.33	0.47	0.33	0.47	0.33	0.47	-0.01
(Perceived) High social class neighbors	25,541	0.51	0.50	0.51	0.50	0.51	0.50	-0.00
Baseline Survey response	36,342	0.79	0.41	0.78	0.41	0.80	0.40	0.02
Geocoded location	41,738	0.90	0.29	0.90	0.30	0.91	0.29	0.01
Female	41,713	0.83	0.38	0.83	0.37	0.83	0.38	-0.00
Spouse/partner	41,738	0.25	0.43	0.25	0.44	0.24	0.42	-0.02
Chilean	41,713	0.92	0.28	0.91	0.29	0.93	0.26	0.02
Santiago MSA	41,738	0.20	0.40	0.20	0.40	0.20	0.40	-0.00
Rent	17,877	6.12	2.74	6.17	2.78	6.04	2.69	-0.13
Rent burden	17,872	0.46	0.26	0.47	0.26	0.44	0.26	-0.03
Score Components and Total Score								
Family size score	41,738	68.03	34.87	81.11	37.42	51.10	21.65	-30.01
Single parenthood score	41,738	19.79	17.35	20.85	17.18	18.41	17.48	-2.44
Number of children under 5 score	41,738	14.38	17.37	18.32	18.51	9.28	14.22	-9.04
Number of children 6 to 18 score	41,738	14.73	15.60	18.48	17.09	9.87	11.77	-8.61
Social vulnerability score	41,738	158.42	38.19	170.86	23.55	142.31	46.57	-28.55
Housing vulnerability score	41,738	36.50	54.16	55.48	61.94	11.92	26.34	-43.55
Application score	41,738	324.46	100.62	375.41	91.90	258.47	67.69	-116.95

This table shows summary statistics for the entire population of applicants. Columns 1 to 3 show statistics for all applicants during the period of analysis, Columns 4 and 5 for voucher recipients and Columns 6 and 7 for non voucher recipients. Columns 7 shows the difference in means between treatment and control group.

TABLE B.3. Summary Statistics of Voucher Recipients and Non Recipients in Elderly Rounds

	All Applicants			Recipients		Non-Recipients		Difference
	N	Mean	SD	Mean	SD	Mean	SD	(7)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tenant in baseline	23,462	0.61	0.49	0.54	0.50	0.64	0.48	0.10
Family income (UF)	23,462	6.74	3.82	6.26	3.17	6.90	4.01	0.63
High density county	23,462	0.49	0.50	0.46	0.50	0.51	0.50	0.04
County above national poverty	23,462	0.39	0.49	0.40	0.49	0.38	0.49	-0.02
PHA in county of residence	23,462	0.49	0.50	0.51	0.50	0.49	0.50	-0.02
Previous app. to ownership subsidy	23,462	0.07	0.25	0.06	0.23	0.07	0.25	0.01
Age at application	23,462	70.46	6.65	75.29	6.89	68.85	5.72	-6.44
Below family adjusted PL	23,462	0.60	0.49	0.60	0.49	0.60	0.49	-0.00
KM to closest PHA	22,175	13.53	19.42	14.04	20.16	13.35	19.16	-0.69
Valid email address	23,462	0.41	0.49	0.34	0.48	0.43	0.50	0.09
Geocoded location	23,462	0.95	0.23	0.94	0.23	0.95	0.23	0.00
Female	23,371	0.61	0.49	0.55	0.50	0.63	0.48	0.08
Spouse/partner	23,462	0.38	0.49	0.37	0.48	0.38	0.49	0.01
Chilean	23,371	0.98	0.15	0.98	0.14	0.98	0.15	-0.00
Santiago MSA	23,462	0.25	0.43	0.22	0.42	0.25	0.44	0.03
Income documents to PHA	23,462	0.95	0.22	0.97	0.17	0.94	0.23	-0.03
Score Components and Total Score								
Family size score	23,462	43.06	14.46	47.42	23.97	41.60	8.84	-5.82
Single parenthood score	23,462	0.18	2.48	0.18	2.53	0.17	2.46	-0.01
Number of children under 5 score	23,462	0.25	2.96	0.76	5.26	0.08	1.52	-0.68
Number of children 6 to 18 score	23,462	0.85	4.90	1.84	7.72	0.51	3.41	-1.33
Social vulnerability score	23,462	165.06	33.71	178.49	9.54	160.56	37.50	-17.93
Housing vulnerability score	23,462	15.99	37.49	40.99	61.77	7.61	17.85	-33.38

This table replicates the analysis in Table B.2 using elderly rounds data. See Table B.2 for details

TABLE B.4. Balance in Baseline Characteristics in Sample of Randomized Vouchers in Regular Rounds

		Summary Statistics						Balance	
		Pooled		Control		Treated		Test	
	N	Mean	SD	Mean	SD	Mean	SD	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenant in baseline	539	0.70	0.46	0.70	0.46	0.69	0.46	0.965	0.967
Saving balance on application day (UF)	539	16.03	14.67	16.04	14.37	16.00	15.13	0.425	0.469
Family income (UF)	539	12.31	3.71	12.39	3.58	12.18	3.89	0.227	0.259
Online application	539	0.41	0.49	0.42	0.49	0.41	0.49	0.204	0.225
High density county	539	0.39	0.49	0.40	0.49	0.38	0.49	0.883	0.889
County above national poverty	539	0.60	0.49	0.55	0.50	0.67	0.47	0.328	0.340
PHA in county of residence	539	0.51	0.50	0.53	0.50	0.48	0.50	0.671	0.710
Previous app. to ownership subsidy	539	0.15	0.36	0.14	0.35	0.16	0.37	0.899	0.909
Age 25-35	539	0.67	0.47	0.67	0.47	0.68	0.47	0.337	0.360
Below family adjusted PL	539	0.18	0.38	0.16	0.37	0.20	0.40	0.286	0.327
KM to closest PHA	539	15.74	20.35	14.90	19.02	16.96	22.10	0.415	0.461
Valid email address	539	0.90	0.30	0.90	0.30	0.90	0.30	0.619	0.657
Want to stay same neighborhood	349	0.54	0.50	0.53	0.50	0.54	0.50	0.791	0.818
Satisfaction with housing unit	373	0.65	0.48	0.65	0.48	0.65	0.48	0.601	0.655
Does not know other applicants	341	0.55	0.50	0.50	0.50	0.60	0.49	0.043**	0.110
Access to car	339	0.31	0.46	0.33	0.47	0.27	0.45	0.251	0.321
(Perceived) High social class neighbors	361	0.48	0.50	0.48	0.50	0.49	0.50	0.800	0.803
Baseline Survey response	490	0.86	0.35	0.84	0.37	0.88	0.33	0.517	0.674
Geocoded location	539	0.88	0.33	0.88	0.32	0.88	0.33	0.576	0.602
Female	539	0.97	0.17	0.97	0.18	0.98	0.15	0.577	0.334
Spouse/partner	539	0.04	0.20	0.05	0.21	0.04	0.19	0.933	0.496
Chilean	539	0.95	0.21	0.94	0.23	0.97	0.18	0.144	0.910
Santiago MSA	539	0.13	0.33	0.14	0.34	0.12	0.32	0.888	0.266
Rent	341	5.65	3.08	5.63	3.00	5.70	3.27	0.445	0.633
Rent burden	341	0.50	0.28	0.49	0.28	0.52	0.26	0.057*	0.362
SCREENING FE								Yes	Yes
Joint Significance F-Test (p)								0.749	0.811

This table replicates the analysis in Table V using the sample of randomized vouchers assigned by MINVU in regular rounds. See Table V for details.

TABLE B.5. Balance in Baseline Characteristics in Sample of Randomized Vouchers in Elderly Rounds

	Summary Statistics							Balance Test	
		Pooled		Control		Treated			
	N	Mean	SD	Mean	SD	Mean	SD	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenant in baseline	1,187	0.54	0.50	0.55	0.50	0.52	0.50	0.574	0.578
Family income (UF)	1,187	6.03	2.51	6.01	2.46	6.07	2.59	0.622	0.657
PHA in county of residence	1,187	0.47	0.50	0.47	0.50	0.46	0.50	0.264	0.314
County above national poverty	1,187	0.31	0.46	0.33	0.47	0.28	0.45	0.555	0.668
High density county	1,187	0.55	0.50	0.52	0.50	0.59	0.49	0.815	0.835
Female	1,187	0.62	0.49	0.61	0.49	0.64	0.48	0.439	0.450
Age 70-79	1,187	0.57	0.49	0.58	0.49	0.55	0.50	0.428	0.456
Below family adjusted PL	1,187	0.56	0.50	0.57	0.50	0.55	0.50	0.746	0.780
KM to closest PHA	1,187	12.02	16.67	12.66	17.23	11.05	15.75	0.241	0.357
Valid email address	1,187	0.36	0.48	0.38	0.49	0.32	0.47	0.038**	0.072*
Spouse/partner	1,187	0.39	0.49	0.39	0.49	0.39	0.49	0.971	0.984
Chilean	1,187	0.98	0.14	0.98	0.15	0.99	0.12	0.063*	0.373
Previous app. to ownership subsidy	1,187	0.05	0.21	0.05	0.22	0.04	0.19	0.516	0.574
Santiago MSA	1,187	0.27	0.44	0.22	0.41	0.35	0.48	0.905	0.565
Geocoded location	1,187	0.96	0.20	0.95	0.22	0.97	0.18	0.464	0.127
SCREENING FE								Yes	Yes
Joint Significance F-Test (p)								0.094	0.137

This table replicates the analysis in Table VI using the sample of randomized vouchers assigned by MINVU in regular rounds. See Table VI for details.

TABLE B.6. Total Score and Score Components by Group in Sample of Randomized Vouchers

		Pooled		Treated		Controls		Difference
	N	Mean	SD	Mean	SD	Mean	SD	(7)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Regular Rounds								
Family size score	539	40.00	0.00	40.00	0.00	40.00	0.00	0.00
Single parenthood score	539	35.00	0.00	35.00	0.00	35.00	0.00	0.00
Number of children under 5 score	539	23.67	13.25	24.00	13.42	23.56	13.21	0.44
Number of children 6 to 18 score	539	5.23	8.68	8.00	10.95	4.29	8.80	3.71
Number of elderly score	539	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of people with disability score	539	1.85	4.13	6.00	13.42	0.44	0.98	5.56
Social vulnerability score	539	180.00	0.00	180.00	0.00	180.00	0.00	0.00
Housing vulnerability score	539	2.64	5.91	2.71	6.07	2.62	5.85	0.10
Application score	539	295.00	28.28	295.00	28.28	295.00	28.28	0.00
Elderly Rounds								
Family size score	1,187	40.00	0.00	40.00	0.00	40.00	0.00	0.00
Single parenthood score	1,187	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of children under 5 score	1,187	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of children 6 to 18 score	1,187	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of elderly score	1,187	58.52	2.26	59.80	0.28	58.04	3.19	1.76
Number of people with disability score	1,187	0.51	0.49	0.20	0.28	0.57	0.57	-0.37
Social vulnerability score	1,187	180.00	0.00	180.00	0.00	180.00	0.00	0.00
Housing vulnerability score	1,187	11.95	7.78	11.21	7.62	13.65	11.45	-2.44
Application score	1,187	385.00	10.00	385.00	10.00	385.00	10.00	0.00

This table shows summary statistics of total application score and score components in the sample of randomized vouchers included in the evaluation sample. It includes first the sample in regular rounds and then in elderly rounds. Columns 1 to 3 show statistics for the pooled sample, Columns 4 and 5 for the control group and Columns 6 and 7 for the treatment groups. Columns 7 shows the difference in means between treatment and control group.

TABLE B.7. Total Score and Score Components by Group in the Evaluation Sample

		Pooled		Treated		Controls		Difference
	N	Mean	SD	Mean	SD	Mean	SD	(7)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Regular Rounds								
Family size score	1,131	48.65	6.15	51.27	6.98	47.50	6.88	3.77
Single parenthood score	1,131	27.53	4.84	28.40	2.93	27.03	6.36	1.37
Number of children under 5 score	1,131	12.96	8.74	17.80	11.49	10.20	8.20	7.60
Number of children 6 to 18 score	1,131	11.81	5.22	13.03	7.46	12.05	5.84	0.98
Number of elderly score	1,131	0.85	0.49	0.20	0.33	1.18	0.72	-0.98
Number of people with disability score	1,131	1.63	3.34	6.15	13.33	0.38	0.66	5.77
Social vulnerability score	1,131	173.90	3.42	171.78	4.81	174.51	4.21	-2.73
Housing vulnerability score	1,131	6.60	6.61	5.19	5.25	7.46	7.37	-2.27
Application score	1,131	293.51	28.04	297.37	27.34	291.06	29.05	6.31
Elderly Rounds								
Family size score	1,328	41.19	0.53	42.76	1.74	40.87	1.05	1.89
Single parenthood score	1,328	0.06	0.09	0.19	0.30	0.00	0.00	0.19
Number of children under 5 score	1,328	0.01	0.02	0.00	0.00	0.02	0.04	-0.02
Number of children 6 to 18 score	1,328	0.39	0.23	1.19	1.45	0.08	0.16	1.11
Number of elderly score	1,328	57.35	2.10	57.01	3.39	56.85	2.86	0.16
Number of people with disability score	1,328	1.06	0.76	0.81	0.86	1.31	1.11	-0.49
Social vulnerability score	1,328	177.56	1.11	178.19	2.85	174.46	5.92	3.73
Housing vulnerability score	1,328	13.28	8.11	13.14	6.60	15.87	13.36	-2.73
Application score	1,328	384.65	10.03	385.21	9.87	384.11	9.55	1.09

This table replicates the analysis in Table B.6 using the entire evaluation sample. See Table B.6 for details.

TABLE B.8. Effect of Regular Voucher Before the COVID-19 Pandemic (2019): Follow Up Sample

				Specification 1			Specification 2		
		Control		Treatment	OLS	Rand-t	Treatment	OLS	Rand-t
	N	Mean	SD	Effect	p-value	p-value	Effect	p-value	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Housing Conditions									
Household size Dec 2019	634	3.005	1.256	-0.009	0.936	0.954	0.024	0.821	0.842
Number of bedrooms	632	1.905	0.868	0.144	0.040**	0.043**	0.164	0.019**	0.020**
Number of people per bedroom	632	1.771	0.817	-0.164	0.009***	0.003***	-0.167	0.006***	0.002***
Overcrowing indicator	632	0.119	0.325	-0.043	0.077*	0.077*	-0.039	0.110	0.113
B. Residential Mobility									
Stayed in same unit	560	0.581	0.494	-0.117	0.009***	0.006***	-0.098	0.026**	0.029**
Distance (km)	560	5.060	23.019	13.129	0.053*	0.045**	12.650	0.057*	0.045**
Stayed in 1km radius	560	0.721	0.449	-0.111	0.008***	0.005***	-0.095	0.027**	0.027**
Moved to another county	560	0.056	0.230	0.053	0.021**	0.017**	0.049	0.032**	0.032**
C. Neighborhood Characteristics									
Distance to closest municipality	560	3.201	4.264	0.080	0.850	0.855	0.107	0.805	0.802
Distance to closest School (1km)	560	0.905	1.505	0.491	0.111	0.122	0.445	0.157	0.167
Distance to closest Pre-Shcool (km)	560	0.974	2.028	0.398	0.198	0.202	0.358	0.255	0.268
Distance to closest Primary Care (km)	520	1.540	2.155	0.335	0.356	0.406	0.293	0.435	0.478
Number of Schools in 1Km	560	4.696	4.330	-0.418	0.298	0.303	-0.221	0.581	0.550
Number of Preschool in 1Km	560	2.939	2.596	-0.187	0.416	0.419	-0.067	0.761	0.773
Number of Health Care in 2km	560	4.763	4.466	-0.187	0.609	0.609	0.076	0.813	0.823
Fraction of Public Schools 1Km	460	0.445	0.298	-0.012	0.687	0.718	-0.014	0.647	0.654
Fraction of Subsidized Schools 1Km	460	0.512	0.287	0.007	0.804	0.832	0.010	0.731	0.777
Fraction of Private Schools 1Km	460	0.044	0.117	0.005	0.671	0.684	0.004	0.753	0.787
Lang. SIMCE, 3 Closest Schools 2km	487	265.540	17.532	-1.719	0.317	0.309	-1.986	0.228	0.226
Mat. SIMCE, 3 Closest School 2km	487	250.861	18.475	-1.343	0.463	0.473	-1.175	0.507	0.513
Fraction of Low Income Schools 2km	491	0.573	0.268	0.029	0.257	0.283	0.023	0.328	0.369
County poverty rate	560	0.115	0.061	-0.001	0.759	0.752	-0.003	0.437	0.475
Assault rate (people 18 or over)	559	0.003	0.003	-0.000	0.528	0.536	0.000	0.571	0.556
Robbery rate (people 18 or over)	559	0.011	0.007	0.000	0.916	0.923	0.000	0.245	0.250
Theft rate (people 18 or over)	559	0.011	0.006	0.000	0.915	0.917	0.000	0.421	0.436
D. Homeownership									
Application to Ownership Programs	634	0.322	0.468	0.002	0.968	0.952	-0.005	0.870	0.888
Application DS1	634	0.240	0.428	-0.014	0.679	0.608	-0.019	0.489	0.495
Application DS49	634	0.124	0.330	0.013	0.635	0.646	0.005	0.839	0.849
Active ownership savings account	634	0.911	0.285	0.001	0.981	0.908	-0.003	0.887	0.890
Total savings (UF)	578	24.478	34.813	-1.314	0.614	0.630	-1.687	0.438	0.465
SCREENING FE				YES	YES	YES	YES	YES	YES
CONTROLS (Z)				NO	NO	NO	YES	YES	YES
Westfall-Young Multiple Testing (p-value)						0.086*			0.061*

This table replicates the analysis in Table VII including only individuals that responded the follow up sample. See Table VII for details.

TABLE B.9. Lease-up rate by screening of applicants in the Evaluation Sample

	All	Apr 2018	Dec 2018	Oct 2019 O'Higgins	Oct 2019 Araucania	Oct 2019 Los Lagos
Regular	0.29	0.42	0.29	0.24	0.21	0.11

	All	Sept 2017	Apr 2018	Jul 2019 Valparaiso	Jul 2019 Santiago
Elderly	0.44	0.45	0.57	0.43	0.24

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

C Selective Attrition in Follow up Survey Sample

This section analyzes the presence of selective attrition in the Follow-up survey. The survey was sent by email to 31,366 valid email addresses from applicants in regular rounds between 2017 and 2019. The response rate among individuals in the evaluation sample was 65%; 619 responses were collected from applicants in W_0.

Figure C.1 shows the response rate by treatment group in each selected window W_{s_t} in the evaluation sample. In general, treated and controls show similar response rates.

To analyze selective attrition more formally, I estimate the following linear probability model:

$$R_{i,s_t} = \alpha + \tau_{s_t} D_{i,s_t} + \gamma_{s_t} S_{s_t} + \beta_{s_t} D_{i,s_t} * S_{s_t} + \epsilon_{i,s_t} \tag{4}$$

This is a variation of the fully interacted FE model in equation 2 used to analyze balance in Section 5.2. Here, the dependent variable is a dummy variable taking the value of one if individual i in screening of applicants s_t responded the survey, and zero otherwise.

Table C.1 shows that all individual coefficients, τ_s and β_s, are not statistically significant. Furthermore, joint significance of these coefficients is rejected.[65]

LRRD assumptions are checked again in this subset of the evaluation sample in regular rounds.[66] Table C.2 replicates balance analysis in Table V using the follow up sample.

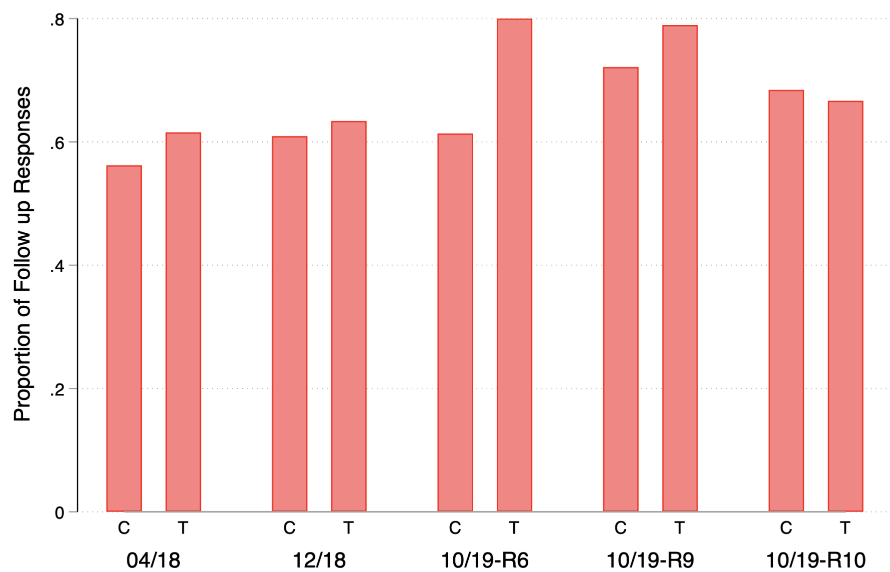
The sample of treated and controls who responded the survey is balanced. Specifically, only few small statistically significant differences are observed between treated and controls —only one of them significant at the 99% of confidence [67]— and balance is confirmed by the joint significance test at the bottom of the table.

[65]To increase response rate in both groups were implemented, the email was sent from the same institutional email address used for sending the baseline survey. Also, the email included a link to MINVU's Web site and we created a blog with short and simple answers to frequently asked questions. Applicants could leave a question at the end of the survey only. We received more than 10,000 inquiries during the data collection period— a period of high demand for information since SERVIUs closed due to the pandemic.

[66]In the continuity approach, it would be hard to study non-linearities generated by attrition in the follow-up survey given that outcomes are analyzed using different bandwidth. In contrast, the LRRD uses a fixed sample, therefore, doing this is straightforward.

[67]There is a larger fraction of Chileans (p-value 0.003) among the treated but the entire sample has only 43 people from other nationalities; between 1 and 17 per screening of applicants.

FIGURE C.1. Follow up Sample Attrition



This Figure shows response rate of the follow up survey in each screening of applicants. C is the control group (below the cutoff) and T is the treatment group (above the cutoff).

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

	Response Prob. (1)	Response Prob. (2)
Treat*April 2018	0.053	0.054
	(0.406)	(0.388)
Treat*December 2018	-0.029	-0.037
	(0.759)	(0.689)
Treat*October 2019 (O'Higgins)	0.133	0.120
	(0.193)	(0.251)
Treat*October 2019 (Araucania)	0.015	0.021
	(0.865)	(0.800)
Treat*October 2019 (Los Lagos)	-0.071	-0.102
	(0.653)	(0.527)
F-Test (p-value)	0.172	0.214
Rand-t Joint Test (p-value)	0.110	0.124
Observations	976	976
SCREENING FE	YES	YES
COVARIATES	NO	YES

This table shows the effect of treatment on survey response using equation 4. Baseline covariates include income, savings, distance to the closest SERVIUs and dummy variables for female, age, married, tenant, Chilean, baseline application to homeownership programs, poor, online application, baseline survey response, living in a high density county, high poverty county, and a county that has a SERVIU. Fisherian randomization inference (Randomization-t p-values from Young (2019)) presented in parenthesis. Bottom panel presents p-values for F-Test and Randomization-t Joint significance test. Significance levels: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

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

		Summary Statistics						Balance	
		Pooled		Control		Treated		Test	
	N	Mean	SD	Mean	SD	Mean	SD	F-test (p)	Rand-t (p)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenant in baseline	1,328	0.76	0.43	0.76	0.43	0.74	0.44	0.681	0.644
Saving balance on application day (UF)	634	15.77	15.27	15.46	14.05	16.32	17.22	0.716	0.740
Family income (UF)	634	13.55	4.83	13.41	4.76	13.79	4.94	0.213	0.220
Online application	634	0.40	0.49	0.40	0.49	0.40	0.49	0.526	0.474
High density county	634	0.40	0.49	0.43	0.50	0.35	0.48	0.041**	0.035**
County above national poverty	634	0.69	0.46	0.68	0.47	0.71	0.45	0.469	0.455
PHA in county of residence	634	0.50	0.50	0.50	0.50	0.49	0.50	0.709	0.647
Previous app. to ownership subsidy	634	0.16	0.36	0.15	0.36	0.17	0.38	0.520	0.489
Age 25-35	634	0.65	0.48	0.62	0.49	0.69	0.46	0.069*	0.061*
Below family adjusted PL	634	0.20	0.40	0.20	0.40	0.19	0.39	0.841	0.856
KM to closest PHA	634	18.02	23.31	17.58	23.16	18.80	23.59	0.883	0.879
Baseline Survey response	634	0.88	0.33	0.88	0.32	0.88	0.33	0.958	0.940
Want to stay same neighborhood	634	0.59	0.49	0.59	0.49	0.59	0.49	0.652	0.661
Satisfaction with housing unit	478	0.68	0.47	0.67	0.47	0.69	0.46	0.575	0.583
Does not know other applicants	506	0.55	0.50	0.53	0.50	0.58	0.50	0.262	0.285
Access to car	467	0.34	0.47	0.35	0.48	0.33	0.47	0.706	0.700
(Perceived) High social class neighbors	465	0.50	0.50	0.50	0.50	0.50	0.50	0.787	0.792
Geocoded location	495	0.89	0.32	0.89	0.31	0.88	0.33	0.494	0.505
Female	634	0.91	0.28	0.91	0.29	0.91	0.28	0.957	0.973
Spouse/partner	634	0.16	0.36	0.17	0.37	0.14	0.35	0.303	0.332
Chilean	634	0.93	0.25	0.91	0.29	0.97	0.17	0.003***	0.003***
Santiago MSA	634	0.09	0.29	0.10	0.30	0.09	0.28	0.943	0.883
Rent	634	5.91	3.53	5.97	3.69	5.78	3.18	0.735	0.744
Rent burden	442	0.49	0.31	0.49	0.34	0.47	0.26	0.544	0.538
SCREENING FE								Yes	Yes
Joint Significance F-Test (p)								0.159	0.242

This table replicates the analysis in Table V using only individuals in regular rounds that responded the follow up sample. Given the smaller sample sizes, this table presents the weaker balance test of the null H_0'. See Table V for further details. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.