Neighborhood spillovers in rental voucher program participation: Evidence from Chile

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Abstract

We study neighborhood spillovers on participation in the Chilean rental voucher program. We estimate the effect on participation of previous voucher holders in the same and neighboring census tracts between 2014 and 2019. We combine census data and geocode location of all applicants and voucher recipients to build a longitudinal data set at the census tract level. We use a neighborhood fixed effect model and exploit the voucher assignment protocol to assume conditional exogeneity of the number of previous voucher recipients in the neighborhood. We find large negative spillovers on participation from nearby previous voucher holders and positive spillovers from farther away past recipients. Spillovers increase with density and proximity between voucher holders. Also, negative spillovers within census tracts are larger in areas with lower historical lease-up rates and areas farther away from local housing authorities. These effects are non-linear on the number of previous voucher recipients. These results hold in a subset of eligible census tracts based on the probability of individual application. We conclude that social interactions in programs that rely in the private market to deliver social benefits need to be taken into account by policy makers to increase participation and reduce disparities in the access to social assistance. We use a theoretical model to develop intuition.

Keywords: neighborhood spillovers; rental vouchers; program participation.

JEL Classification: C23; C31; R23.

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1 Introduction

The problem of imperfect take-up of social benefits has been documented for welfare policies such as conditional and unconditional cash transfers, tax credits, social security and health insurance policies (Currie, 2006; Moffitt, 1983).

Forgo financial aid has severe consequences for poor families (Bhargava & Manoli, 2015; Carneiro, Galasso, & Ginja, 2019). For instance, in the Earned Income Tax Credit program in the US, non-claimant families forgo an amount equivalent to an additional month of income (Bhargava & Manoli, 2015). In Chile, in the child and family allowance program *Subsidio Único Familiar*, non-claimant families forgo about one sixth of their family income per capita (Carneiro et al., 2019).

The literature recognizes three main barriers to take-up in welfare programs: information frictions, perceived stigma and costly application procedures (Bhargava & Manoli, 2015; Chareyron, Domingues, & Lieno-Gaillardon, 2021; Currie, 2006). In addition, recent evidence suggests that social interactions that naturally occur between neighbors have large positive spillover effects on welfare participation (Dahl, 2020). Social interactions may reduce some of the above mentioned barriers through information spreading (Durlauf, 2004), inspiration, identity (Akerlof & Kranton, 2000) or imitation among neighbors (Dahl, Løken, & Mogstad, 2014).

This paper focuses on neighborhood spillovers on participation in a different type of policy: rental voucher programs that provide housing assistance to pay for monthly rents of units that low-income families find in the private market.

In these policies, families decide whether to participate and consider the amount of search effort needed to find a unit meeting program requirements and a landlord willing to accept a rental voucher. Recent literature shows high housing search costs for rental voucher recipients, specially in better neighborhoods (Aliprantis, Martin, & Phillips, 2018; Phillips, 2017).

Furthermore, in these policies neighborhood spillovers may arise from direct social interaction between neighbors, as in welfare programs, but also from the indirect interaction of individual constraints in the private rental market. Depending on the level of competition and the information in the market, neighborhood spillovers on participation in rental voucher policies could be negative (Manski, 2000).

In this paper, we ask whether exposure to previous voucher holders in the same and neighboring tracts impacts application decision of eligible families in a rental voucher program. We use data on the Chilean *Subsidio de Arriendo*, the first rental voucher program in Latin America, which design was advised by the US Department of Housing and Urban Development and based on the Housing Choice Voucher program.

The Chilean program is an interesting case of study. Barriers to lease-up seems to be high. The average lease-up rate has been as low as 42%, and while it has not increased over time, it does vary across rental markets. Also, after decades of subsidizing ownership to low-income families, there is a strong homeonership bias in Chile.[1] Indeed, survey data shows that the rental voucher programs is unpopular even among applicants. Most of them think that paying rent is a waste of money and are already applying or expect to apply soon to a homeonwership program (Selman, 2020).

In addition, application to the Chilean program has been lower than expected. By 2019, roughly nine hundred thousand families were eligible for a rental voucher (DIPRES, 2018). However, the Ministry received only nineteen thousand applications for the ten thousand vouchers available for that year.

To estimate neighborhood spillovers, we first build a unique longitudinal data set at the census tract level. We combine individual administrative geocoded data on applicants between 2014 and 2019 to census tract data from the Chilean 2017 Census.

We use a neighborhood fixed effect model to estimate neighborhood spillovers from previous voucher holders in the same and neighboring census tracts. We exploit voucher assignment rules to assume exogeneity of the number of previous recipients conditional on the number of previous applicants in the neighborhood (List, Momeni, & Zenou, 2020). Also, we select a subset of eligible census tracts based on individual probability of application.

We leverage the variation in density, lease-up rates, access to subsidized homeownership

[1] Two thirds of the families in the bottom tenth percent of the income distribution own their houses (Casen 2017).

and distance to local housing authorities throughout the country to study different mechanisms driving neighborhood spillovers. To develop intuition, we also derive a theoretical model of discrete choice with spillovers that emerge from past society behavior (Brock & Durlauf, 2001). Our model allows current individual application to depend on constraints faced by previous cohorts of voucher recipients to use their vouchers. We assume two types of barriers: transaction costs, such as paperwork, information, and housing search costs; and costs that emerge from cultural factors or social norms, such as homeownership bias. The model predicts positive or negative spillovers, depending on the the number of closest and distant neighbors.

We find that being exposed to previous voucher recipients affects current application to the Chilean rental voucher program. We estimate large negative spillovers within census tracts: an additional past voucher recipient in the same tract reduces the number of applicants in 0.373. In contrast, an additional past voucher recipient in neighboring census tracts has a small positive effect on current application, increasing the number of applicants in 0.024.

The effects are non-linear in the number of previous voucher recipients in the neighborhood. As exposure increases, positive and negative spillovers increase at decreasing rates. Further, treatment effects increase with density and the distance to local housing authorities, and negative spillovers are larger in areas with lower historical lease-up rates.

These findings suggests that policy makers need to take into account neighborhood spillovers from previous rental voucher recipients facing large barriers to use their vouchers. Reducing these barriers, specially of most vulnerable families, is key to reduce geographical disparities in the access to social assistance (Flores, 2021a).

This paper contributes to the literature on neighborhood spillovers in social program participation (Carneiro et al., 2016; Chetty, Friedman, & Saez, 2012; Dahl et al., 2018; Giné & Mansuri, 2018; List et al., 2020; Miguel & Kremer, 2004). To the best of our knowledge, this is the first paper studying spillovers in voucher program participation, in which the government relies on the private market to deliver social benefits.

We also contribute to the small literature studying spillovers in rental voucher programs, focused on the effect of nearby voucher holders on voucher use. Previous work by Chyn, Hyman, and Kapustin (2019) and Ellen, Suher, and Torrats-espinosa (2019) show that exposure to voucher holders increase voucher use in the neighborhood and that nearby voucher holders relocate to the same neighborhood. Our paper focuses on a different relevant outcome, application to the program. Also, we provide the first empirical evidence on spillovers in rental voucher programs outside of the US, contributing to the very small literature on rental voucher programs in middle income countries (Barnhardt, Field, & Pande, 2017; Selman, 2022).

Finally, we contribute to the literature of discrete choice models with spillovers that emerge from past society behavior that predicted constant spillovers in participation (Flores, 2021a, 2021b). Our model extend the proportional spillovers model in Brock and Durlauf (2001) to participation decision in rental voucher programs and obtain neighborhood spillovers that are a function of specific barriers to voucher use that vary with exposure to previous voucher recipients.

The rest of the paper is organized as follows. Section 2 describes the Chilean rental voucher program. Section 3 discusses our analytical framework and presents the theoretical model. Section 4 describes the empirical strategy to estimate neighborhood spillovers. Section 5 presents the data and Section 6 shows the results. Finally, Section 7 concludes.

2 The Chilean Rental Voucher Program

The Chilean government, through the MINVU, launched the rental voucher program in December 2013.[2] The program provides US$6,200 in fixed monthly installments of $180, which are meant to cover 30 (and up to 80) percent of monthly rents. Between 2014 and 2019, MINVU received 90k applications and had spent US$325 million dollars on the assignment of 50k rental vouchers.[3]

Application to the program may be online or in-person at a local housing authority (SERVIU) or at some municipalities that provide this assistance.[4] To use the voucher, however, fam-

[2]This section presents a general description of the program and the dimensions that are relevant for the analysis of this research. See Selman (2022) for more details on the history, benefits and assignment rules of the Chilean rental voucher program.

[3]The Rental voucher program includes two voucher schemes. This paper is focused on regular rounds. See Selman (2022) for more details on the history, voucher schemes, assignment rules of the Chilean rental voucher program and a comparison to the US rental voucher program Section 8.

[4]Online application has increased over time but before the pandemic was still as low as 30%. Some munic-

ilies have to visit any SERVIU and bring all the paperwork and the lease signed by the landlord.[5]

Each round has multiple assignment. Specifically, rounds are opened for two to nine months and MINVU make one or multiple assignments during this period (normally monthly or bi-monthly assignments). The program follows a rolling application system. Within the same round, applicants who are not previously selected are ranked again with all new applicants for the next assignment. To be considered for the next round, non-voucher recipients need to apply again to the program.

A family must meet minimum eligibility requirements. The program is targeted at 18 or older-headed families with family monthly income between US$250 and US$900, who have US$180 in a private savings account for homeownership, and are within the bottom 70 percent of the National Vulnerability Index, a national targeting instrument administered by the Ministry of Social Development in Chile.

The selection of voucher recipients relies on an application score calculated by MINVU from multiple administrative and self reported data. In particular, applicants are evaluated in twelve dimensions including social vulnerability, presence of children in the household, single-headed household, and physical disability, among others. Between 2014 and 2019, the application score has taken values between 572 and 800 points.[6]

Applicants are ranked by their score. All families above a certain cutoff are selected to receive a voucher. The cutoff is set by the number of available vouchers for each assignment in each round[7], which is set by decree before the round begins.[8]

A three steps tie-breaking protocol is implemented for families with the same score at the cutoff, including random assignment of vouchers for families at the cutoff that had the same vulnerability and family size scores.

ipalities have voluntarily decided to provide assistance in application. Nevertheless, MINVU does not know exactly which municipalities offer this service.

[5]Some people may visit a local housing authority several times during the application period, or later to find out about voucher acceptance, get information about paperwork or even ask for places to look for rental housing, although SERVIUs in Chile do not provide assistance in housing search.

[6]See Table A1 in the Appendix for the full list of dimensions included in application score.

[7]In 2019, the program moved from national to regional voucher assignment. Therefore, applicants are currently being ranked by their score separately in each region.

[8]This is not publicly announced and sometimes may change for administrative or political decisions made by people outside of the Rental Policy team at MINVU. Figure A1 in the Appendix shows the application score distribution and cutoff in every round of the program.

Families who get the voucher have two years to find a landlord willing to sign a lease and accept the voucher. Landlords and tenants cannot be family. Furthermore, rental units cannot exceed the national rent cap of US$402 per month[9] and they are required to have minimum three separated spaces and meet certain legal requirements.[10] SERVIUs are supposed to do inspections of all rental units in the program. However, the data shows that while most of the inspections happens in the first three months after the lease is signed, half of the units were never inspected.

The total subsidy covers monthly rents for approximately three years, yet they can use the total amount of the subsidy over an eight year period.[11] Voucher recipients that are initially renting can stay in the same house, while those doubling up with other people have to rent a different unit.[12] Indeed, about forty percent of recipients that were tenants in baseline and used their vouchers to rent the same unit they were initially living in.

Table 1 presents summary statistics of all participants (applicants, recipients, leased-up) in regular rounds between 2014 and 2019 using administrative and survey data. We observe that applicants and voucher recipients are similar in many baseline characteristics such as income, savings, age, sex, nationality, online application, rent and rent burden, employment, education, and preferences and beliefs about renting. Main differences are found on characteristics that have a larger weight in the application score formula: vulnerability index, number of children and overcrowding.

Success rate or lease-up rate in Chile is 42%, and has not increased between 2014 and 2019 (see Table 2). Also, Table 1 shows that compared to the average voucher recipient, families who leased-up have some differences. The latter have higher baseline savings, are less likely to live in Santiago or apply online, and more likely to have a formal lease at the time of application, and importantly, to know other applicants.

Supply side barriers seems to have an important role on voucher use: based on follow-up administrative data, we observe that 53% of those who had not used their entire subsidy

[9]Only 30 out of 346 counties in Chile, at the very north and south, have a higher allowable rental cap of US$475.

[10]Have a certificate of occupancy and a registration number at the IRS.

[11]Landlords are paid directly by MINVU. Specifically, the government collects the copay from the family in the first five working days of the month and pay total rent amount to the landlord in the first ten working days of the month.

[12]Families who own their houses cannot apply to the program.

amount declared difficulties to find a unit meeting all the requirements or a landlord willing to accept a voucher. This is consistent with previous data analysis suggesting the presence of important demand and supply barriers to lease-up in the country. In particular, lack of information, strong preferences for homeownership and residential immobility appeared as main demand side barriers and lack of affordable housing, landlords' lack of information, perceived high transaction costs and discrimination, as main supply side barriers (Selman, 2019).

Therefore, larger neighborhood spillovers may arise as lack of information about the program is still important and perceptions about the merits of a rental voucher, -likely affected by social norms favoring homeownership-, are still in formative stages (Dahl, 2020).[13]

3 Analytical framework

In this section we discuss how barriers to voucher use may shape neighborhood spillovers in a rental voucher program. In particular, in the Chilean rental voucher program. We formalize the discussion in a theoretical model. We use the model to develop intuition about the direction and magnitude of neighborhood spillovers in a program that relies on the private rental market to provide social benefits. Furthermore, we use the model to guide our empirical analysis and provide evidence to discuss key takeaways of the model.

3.1 Neighborhood spillovers in rental voucher programs

Neighborhood spillovers in program participation may be driven by social interaction that naturally occur within a neighborhood. Individual participation may be affected by information spreading across neighbors (Durlauf, 2004). In other words, neighbors may constitute an informal channel of information to other eligible neighbors by sharing program information such as application procedures, benefits, etc. In addition, neighbors' behavior may influence individual participation through psychological factors such as inspiration, identity (Akerlof & Kranton, 2000) and imitation (Dahl et al., 2014).

We study neighborhoods because the social policy is targeted at vulnerable families that

[13] 2.5% of Chilean families doubling up with other families had applied to the program. This figure is 3.3% in the bottom income quintile (CASEN, 2017). Consistently, the number of applicants exceeding voucher availability (excess of demand) has been low and has not increased in recent years. See Table 2.

are commonly segregated in specific geographical areas (Flores, 2021b; Forrest, 2008), facilitating interaction between eligible population. The Chilean rental voucher program is no exception. Figure 1 shows a map with the distribution of applicants to the program in 2016 across census tracts[14]. We observe clusters of applicants and variation in the number of applicants in neighboring census tracts. We show applicant distribution in Santiago and Concepcion[15]. Nevertheless, this pattern is the same throughout urban areas in Chile. In addition, Table 1 shows that on average 40% of new applicants know someone who previously applied to the program. This fraction increases in ten to twenty percentage points in regions with higher poverty rates in the south of the country. Consequently, we can infer that social interactions take place at the neighborhood level.

However, there are some important differences between traditional welfare programs and rental voucher programs that may affect neighborhood spillovers. First, neighborhood spillovers in a rental voucher program may be the result of direct and indirect interactions among eligible neighbors, as families compete for affordable units in the private rental market.

Second, families may have higher expected participation costs in a rental voucher program. On the one hand, the literature describes three main costs involved with the take-up decision in welfare programs: stigma, information acquisition costs and transaction costs (Chareyron et al., 2021; Currie, 2006). On the other hand, in a voucher program, take-up includes two non-independent and consecutive decisions: application and voucher use. In this context, prospective applicants may perceive higher participation costs from barriers to voucher use e.g. additional paperwork, specific lease-up rules and requirements, and housing search costs in the private rental market.[16]

In this context, social interaction might not always have positive consequences over take-up decision of prospective applicants. Spillovers could be negative if expected transaction costs increase as more people get the voucher or if previous voucher recipients may share their negative experiences in the program with others. Note that voucher recipients have

[14]Current eligibility to the program follows a large reform made in 2016. Previously, only people younger than 35 years old could apply to the program.

[15]The capital city and the third largest city located in the south of the country.

[16]Search costs may be increased by the difficulties of finding a landlord that it is willing to participate in the program. See Schwartz, Mihaly, and Gala (2017) for a review of the literature on demand and supply barriers to rental voucher programs.

two years to lease-up with their vouchers. Therefore, voucher recipients from different rounds of the program are searching for a unit at the same time (Selman, 2019).[17]

Descriptive data suggests that applicants compete for affordable housing in very small local rental markets. Baseline survey data shows that 54% of all applicants would like to remain in the same neighborhood and 87% would prefer to stay in the same county, if they were to get the voucher (Table 1). These preferences have increased over time. Furthermore, 25% of leased-up families stayed in the same unit they were initially living in. This fraction is higher among tenants in baseline: one out of three do not move with the voucher. Administrative data shows that 42% of leased-up families moved less than 1 kilometers,[18] suggesting that the housing search occurs at a very local scale.

Conversely, positive spillovers may be driven by the spread of general information about the program and lease-up process[19], information about housing search methods or housing availability. Indeed, Table 1 shows that those who leased-up with their vouchers were more likely to knew other applicants to the program in baseline.

In addition, social norms that arise from cultural factors such as negative beliefs about renting or strong preferences for homeownership may rule prospective applicants behavior. In this context, there would be a positive spillover if perceived costs of deviating from peer behavior (Bénabou & Tirole, 2016) decrease as more nearby families are looking for rental housing. We may expect this effect to decrease as the relatively new program reaches certain size and social norms change.[20]

Descriptive data shows that cultural factors may affect the behavior of applicants and voucher recipients in the Chilean rental voucher program. Survey data in Table 1 shows that one out of four applicants applied to the program to save for homeownership and that most individuals (56%) believe that renting is a waste of money. Administrative data on application to the two largest ownership programs implemented by MINVU also reveals

[17]The average time to lease is seven months.

[18]The average length of a census tract in Chile is 0.7 km.

[19]There is anecdotal evidence suggesting that many families do not know that they got a voucher since they are not aware about the time and the way in which results are revealed.

[20]Social norms could could also respond to more people applying to the program. However, application to the program may be less salient. Therefore, we may expect the strongest effect on attitudes towards renting coming from an increase in the number of people renting or searching for a rental unit, which is more likely to happen after voucher assignment. Survey data shows that only twenty percent of applicants had search for a unit and reached out to the landlord at the time of application.

preferences for homeonwership. While 14% of applicants to the rental voucher program had previously applied to a ownership program, 36% of applicants, 39% of voucher recipients and 44% of families who leased-up with their vouchers applied to such program afterwards.

In the following, We formalize this discussion by developing a theoretical model of neighborhood spillovers in rental voucher programs.

3.2 Theoretical model

Following Brock and Durlauf (2001), we formulate the problem of individual discrete choice with spillovers that emerge from past society behavior. Formally, consider a population of I individuals indexed by $i = 1, 2, ..., I$. Each agent i belongs to one of the N neighborhoods that are indexed by $g = 1, 2, ..., N$, and must choose a binary action at time $t = 1, 2, ..., T$. In particular, an individual i in a neighborhood g at time t chooses whether to apply or not to a voucher program. This choice (application) is denoted by y_{igt} with support $Y = \{0, 1\}$, which is called the strategy set of agent i.

We distinguish between two types of neighbors whose influence on individual i might vary: closest neighbors -who are located in the same neighborhood g- and distant neighbors who reside in adjacent neighborhoods. Let $G(g)$ be the set of neighborhoods that are adjacent to g, i.e. $G(g) = \{\tilde{g} : \tilde{g} \text{ adjacent to } g\}$. Define $\mathcal{N} = \cup_{g=1}^{N} g$, the union of all neighborhoods, then $G(g) \subseteq \mathcal{N}$ and it represents a set of neighboring areas of g, exclusively.

Suppose that $I_t^g < I$ agents live in g and $I_t^G < I$ agents live in G at time t. The choices of all agents other than i in g at t are denoted by $y_{-it}^g = \{y_{1gt}, y_{2gt}, ..., y_{i-1gt}, y_{i+1gt}, ..., y_{I^g gt}\}$[21] and the choices of all agents in $G(g)$ at t are denoted by $y_t^G = \{y_{1Gt}, ..., y_{I^G Gt}\}$.

Each agent i in g at t chooses y_{igt} in order to maximize individual utility $U()$, which is assumed to depend on a vector of individual observable characteristics, x_{igt}[22], an unobservable taste variation, $\epsilon_{igt}(y_{igt})$, the individual choice y_{igt}, and the number of voucher recipients in previous rounds $t - s$[23] in both g and G, which are denoted by $\overline{y}_{ig(t-s)}^g$ and

[21] Notation $-i$ indicates that agent i is not included or it is omitted from the collection.

[22] For simplicity we consider vector x_{igt} of observable characteristics to have one dimension. However, this formulation can be easily extended to the case of k-dimension vector.

[23] Note that s is an index representing the history of rounds before t.

$\overline{y}^{G}_{ig(t-s)}$, respectively.

For agent i in round t, previous voucher recipients in g are the sum of past choices of her closest neighbors weighted by the probability of being offered the benefit in rounds previous to t, P_{t-s}.[24] Therefore, $\overline{y}^{g}_{ig(t-s)} = P_{t-s}\sum_{j=1}^{I^g} y_{jg(t-s)})$ with $j \neq i \in g$. Similarly, for agent i in g, previous voucher recipients in adjacent neighborhoods $G(g)$ can be written as $\overline{y}^{G}_{ig(t-s)} = P_{t-s}\sum_{l=1}^{I^G} y_{l\tilde{g}(t-s)})$ with $l \in G(g)$. Then, we define the individual utility of agent i as follows:

$$U(y_{igt}, x_{igt}, \overline{y}^{g}_{ig(t-s)}, \overline{y}^{G}_{ig(t-s)}, \epsilon(y_{igt})) = B(y_{igt}, x_{igt}) - C(y_{igt}, \overline{y}^{g}_{ig(t-s)}, \overline{y}^{G}_{ig(t-s)}) + \epsilon_{igt}(y_{igt}) \tag{3.1}$$

Equation 3.1 indicates that, in every period, individual utility is assumed to be linear in three elements: a private utility term that represents the benefits from application, $B(y_{igt}, x_{igt})$, minus the costs from application to the program, $C(y_{igt}, \overline{y}^{g}_{ig(t-s)}, \overline{y}^{G}_{ig(t-s)})$, and the unobservable taste variation $\epsilon_{igt}(y_{igt})$. We define the social utility component in application costs to have the following form (Brock & Durlauf, 2001):

$$C(y_{igt}, \overline{y}^{g}_{ig(t-s)}, \overline{y}^{G}_{ig(t-s)}) = y_{igt}\left[\delta CF(\overline{y}^{g}_{ig(t-s)}, \overline{y}^{G}_{ig(t-s)}) + \gamma TC(\overline{y}^{g}_{ig(t-s)}, \overline{y}^{G}_{ig(t-s)})\right] \tag{3.2}$$

In equation 3.2 we assume that there are two types of application costs that interact with the choice of individual i, y_{igt}. First, we consider costs that emerge from social norms or cultural factors (CF), such as preferences for homeownership or for residential immobility[25]. Second, we include transaction costs (TC), such as paperwork, information, and housing search costs. We model these costs as weighted average of continuous and differentiable functions that depend on the number of neighbors in the immediate neighborhood $\overline{y}^{g}_{ig(t-s)}$ and more distant neighborhood $\overline{y}^{G}_{ig(t-s)}$. Then, $\eta CF(\overline{y}^{g}_{ig(t-s)}) + (1-\eta)CF(\overline{y}^{G}_{ig(t-s)})$

[24]Even though P_{t-s} depends on the number of applicants and pre-determined available vouchers, it is not manipulable by agent i. From her point of view, her own choice may not affect the overall probability of being offered the benefit. As a consequence, we may think of this probability as given for i. We explain this in further detail in the next section.

[25]See Chetty (2015) for a more detailed description of potential behavioral biases affecting residential mobility of voucher recipients.

captures the effect of neighbors' proximity on cultural factors and $\rho TC(\overline{y}^{g}_{ig(t-s)}) + (1 - \rho)TC(\overline{y}^{G}_{ig(t-s)})$ captures the effect of neighbors' proximity on transaction costs. η and $\rho \in [0, 1]$.

Equation 3.2 can then be re-written as:

$$C(y_{igt}, \overline{y}^{g}_{t-s}, \overline{y}^{G}_{t-s}) = y_{igt}\left[\delta(\eta CF(\overline{y}^{g}_{t-s}) + (1-\eta)CF(\overline{y}^{G}_{t-s})) + \gamma(\rho TC(\overline{y}^{g}_{t-s}) + (1-\rho)TC(\overline{y}^{G}_{t-s}))\right] \tag{3.3}$$

The choice of agent i given the choices of all other agents is derived by taking the difference between the choice-specific utility from $y_{igt} = 1$ and the choice-specific utility from choosing $y_{igt} = 0$, presented in equation 3.4. If $\Delta U > 0$ agent i will prefer to apply to the program.

$$\Delta U = U(1, x_{igt}, \overline{y}^{g}_{t-s}, \overline{y}^{G}_{t-s}, \epsilon_{igt}(1)) - U(0, x_{igt}, \overline{y}^{g}_{t-s}, \overline{y}^{G}_{t-s}, \epsilon_{igt}(0)) \tag{3.4}$$

The model assumes that agents act non-cooperatively. This means that individuals do not coordinate their decisions and agents make choice y_{igt} in order to maximise their utility given an expectation of both closest and distant number of voucher recipients, which is independent of the realizations of $\epsilon(y_{igt})$, $\forall i$ in neighborhood g at time t.

In this setting, neighborhood spillovers in application choice y_{igt} is measured by the change in the discrete change in individual utility of agent i (equation 3.4), caused by an increase in the number of past voucher recipients in g:

$$\frac{\partial \Delta U(y_{igt}, x_{igt}, \overline{y}^{g}_{ig(t-s)}, \overline{y}^{G}_{ig(t-s)}, \epsilon(y_{igt}))}{\partial \overline{y}^{g}_{ig(t-s)}} = -\left[\delta\eta\frac{\partial CF}{\partial \overline{y}^{g}_{ig(t-s)}} + \gamma\rho\frac{\partial TC}{\partial \overline{y}^{g}_{ig(t-s)}}\right] \tag{3.5}$$

Similarly, neighborhood spillovers from past voucher recipients in $G(g)$ can be written as:

$$\frac{\partial \Delta U(y_{igt}, x_{igt}, \overline{y}^{g}_{t-s}, \overline{y}^{G}_{ig(t-s)}, \epsilon(y_{igt}))}{\partial \overline{y}^{G}_{ig(t-s)}} = -\left[\delta(1-\eta)\frac{\partial CF}{\partial \overline{y}^{G}_{ig(t-s)}} + \gamma(1-\rho)\frac{\partial TC}{\partial \overline{y}^{G}_{ig(t-s)}}\right] \tag{3.6}$$

Equations 3.5 and 3.6 are an extension of the proportional spillover case in Brock and

Durlauf (2001). We obtain neighborhood spillovers from terms that depend on the interaction between constant spillovers $(\delta, \gamma, \eta, \rho)$ and allow spillovers to vary with barriers faced by those who have participated in the program. In particular, transaction costs and cultural factors, that are a function of previous voucher recipients in the neighborhood. Hence, neighborhood spillovers might be positive, negative, or nonexistent, depending on the number of past voucher recipients in g and G and functional forms of cultural factors and transaction costs.

As we noted before, the best response of agent i given the choices of all other agents is derived by taking the difference between the utility from choosing $y_{igt} = 1$ and the utility from choosing $y_{igt} = 0$. If we assume that the benefits from application or the private utility term are a linear function of exogenous characteristics, x_{igt}, the choice-specific private utility terms would be $B(1, x_{igt}) = \beta_1 x_{igt}$ and $B(0, x_{igt}) = \beta_0 x_{igt}$. Then, equation 3.4 could be re-written as:

$$
\begin{aligned}
y^*_{igt} &= B(1, x_{igt}) + C(1, \overline{y}^g_{ig(t-s)}, \overline{y}^G_{ig(t-s)}) + \epsilon_{igt}(1) - u(0, x_{igt}) - C(0, \overline{y}^g_{ig(t-s)}, \overline{y}^G_{ig(t-s)}) - \epsilon_{igt}(0) \\
&= \beta_1 x_{igt} + \delta(\eta CF(\overline{y}^g_{ig(t-s)}) + (1-\eta) CF(\overline{y}^G_{ig(t-s)})) + \gamma(\rho TC(\overline{y}^g_{ig(t-s)}) + (1-\rho) TC(\overline{y}^G_{ig(t-s)})) \\
&+ \epsilon_{igt}(1) - \beta_0 x_{igt} - \epsilon_{igt}(0) \\
&= \beta x_{igt} + \delta(\eta CF(\overline{y}^g_{ig(t-s)}) + (1-\eta) CF(\overline{y}^G_{ig(t-s)})) + \gamma(\rho TC(\overline{y}^g_{ig(t-s)}) + (1-\rho) TC(\overline{y}^G_{ig(t-s)})) + \epsilon_{igt}
\end{aligned}
\tag{3.7}
$$

Where $\beta = \beta_1 - \beta_0$ and $\epsilon_{igt} = \epsilon_{igt}(1) - \epsilon_{igt}(0)$. Thus, the best response function of agent i can be represented as:

$$
y_{igt} = \begin{cases} 1, & \text{if } y^*_{igt} > 0 \\ 0, & \text{if } y^*_{igt} \leq 0 \end{cases} \tag{3.8}
$$

In this research, the available data does not include information about individuals that do not apply to the Chilean rental voucher program. Therefore, we cannot estimate the discrete choice model of application decision (y_{igt}) in equation 3.8. Instead, we estimate neighborhood spillovers using aggregated population data at the census tract level. In the next Section we explain how we tackle multiple risks of biases to provide clean neighborhood spillovers estimates.

4 Empirical strategy

We are interested in estimating neighborhood spillovers or the effect of neighborhood exposure to an additional voucher recipient on the number of applicants in round t. To do so, we consider a neighborhood as the census tract established by the 2017 Chilean census. We distinguish between closer neighbors in the same census tract g and distant neighbors in adjacent census tracts G.[26]

The literature recognizes three important challenges in identifying neighborhood spillovers. First, a reflection problem arises due to simultaneous movements in outcomes among neighbours (Manski, 1993). Second, unobserved shocks and the institutional environment that affects the entire neighbourhood could lead to correlations in unobserved attributes. Therefore, observed co-movements in outcomes among individuals of the same neighbourhood may be due to the presence of correlated unobserved factors at the neighbourhood level rather than the presence of social interactions (Topa, 2011). Third, in the case of interactions among neighbours, individuals may sort into different neighbourhoods on the basis of their neighbours' characteristics or because they have similar preferences (Topa, 2001) This positive sorting may lead to a correlation in unobserved attributes (Weinberg, Reagan, & Yankow, 2004).

To avoid any source of bias, we would ideally have random variation in treatment assignment and treatment intensity. In particular, the ideal experiment would first randomly assign neighborhoods to treatment and control groups and then randomly assigned different number of treatments among neighborhoods in the treatment group (Crepon, Duflo, Gurgand, Rathelot, & Zamora, 2013; Miguel & Kremer, 2004).[27] If there were no spillovers, control groups of treated neighborhoods with different number of treated units would have the same outcomes.

In the absence of experimental data, our empirical strategy addresses identification threats rigorously as follows. First, we estimate neighborhood spillovers on application by using

[26]Census tracts are established by the Institute of National Statistics (INE). Each census tract is a set of census blocks. We do not use census blocks since the program is still relatively small. Furthermore, Link and Valenzuela (2018) suggest that a census tract coincides with the area that their residents perceive as their neighborhoods. See Section 5 for a description of census tract characteristics in Chile.

[27]Random assignment of rental vouchers alone is not enough since comparing treated and controls estimates the total effect, including direct and indirect effects (spillovers).

the following census tract fixed effect model:

$$\overline{y}_{g,t}^{Applicants} = \beta_0 + \beta_1 \overline{y}_{g,t-s}^{Vouchers} + \beta_2 \overline{y}_{g,t-s}^{Vouchers^2} + \beta_3 \overline{y}_{G,t-s}^{Vouchers} + \beta_4 \overline{y}_{G,t-s}^{Vouchers^2} + \beta_5 \overline{y}_{g,t-s}^{Applicants} + \beta_6 \overline{y}_{G,t-s}^{Applicants} + \theta_g + \lambda_t + \epsilon_{g,t} \tag{4.1}$$

Where the dependent variable, $\overline{y}_{g,t}^{Applicants}$, corresponds to the number of applicants in neighborhood g in round t. Then, the variables $\overline{y}_{g,t-s}^{Vouchers}$ and $\overline{y}_{G,t-s}^{Vouchers}$ represent the total number of applicants that have received a voucher from round s to t in neighborhood g and G, respectively.[28] Equivalently, these variables are the sum of previous applicants i whose application score $X_{i,g,t-s}$ was above the cutoff c in previous rounds ($t-s$) in g. Same variables can be constructed for the geographical area G.

Note that $\overline{y}_{g,t-s}^{Vouchers}$ and $\overline{y}_{G,t-s}^{Vouchers}$ are equivalent to $\overline{y}_s^g$ and $\overline{y}_s^G$ in the theoretical model. We change the notation here since the empirical model is estimated at the neighborhood, not individual level. We use individual administrative data on applicants and voucher recipients to calculate neighborhood level variables. Therefore:

$$\overline{y}_{g,t}^{Applicants} = \sum_{i=1}^{I_g} I(Apply_{i,g,t} = 1) \tag{4.2}$$

$$\overline{y}_{g,t-s}^{Vouchers} = \sum_{i=1}^{I_g} I(X_{i,g,t-s} > c_{t-s}) \tag{4.3}$$

$$\overline{y}_{G,t-s}^{Vouchers} = \sum_{g=1}^{G} \sum_{i=1}^{I_g} I(X_{i,g,t-s} > c_{t-s}) \tag{4.4}$$

Where $I(.)$ is and indicator function that equals one if the inside condition is satisfied, and s is an index representing the history of rounds before t.[29]

In equation 4.1 we also include quadratic terms to capture the observed non-linear relation in the data (see Figure 3). Vector θ_g includes census tract fixed effects, λ_t contains round fixed effects and $\epsilon_{g,t}$ is an unobserved heterogeneity that varies per neighborhood and

[28]Note that we define treatment variables to be always increasing in consecutive rounds (List et al., 2020). Table 4 shows that the average number of voucher offers in previous rounds per census tract increases from less than one in 2014 to eleven in 2019.

[29]For instance, if $t = 2019$ and $s = 3$, $t - s$ pools together three rounds previous to the round in 2019.

round.

The parameters of interest are from β_1 to β_4. Note that β_1 and β_3 measure the effect on application in neighborhood g in t of an additional voucher recipient in previous rounds in g and G, respectively. If β_1 is non-zero, then previous voucher recipients have a spillover effect on new applicants within the same census tract g.[30] Similarly, if β_3 is non-zero, there is a spillover effect from previous voucher recipients in adjacent census tracts G on prospective applicants in census tract g.

We refer to β_1 and β_3 as within and across census tract spillovers, respectively. In addition, β_2 and β_4 reflect the non-linear effect, i.e how neighborhood spillovers in application change as the number of voucher offers increases in g and G, respectively.

Second, including neighborhood fixed effects θ_g eliminates any bias from endogeneous group membership and (time-invariant) correlated unobservables in the parameters of interest. Note that we use neighborhoods at the time of application.[31] In addition, we include pre-determined (lagged) covariates, eliminating biases from simultaneous decisions made by neighbors or reflection problem.

Third, to reduce identification threats we rely on the recent work by List et al. (2020) who assume conditional exogeneity of the treatment. In our context, we assume that the number of voucher recipients in previous rounds in each census tract g is exogenous conditional on the number of applicants in previous rounds in g.[32]

In the Chilean rental voucher program, while the number of offers depend on the score cutoff and the national (or regional since 2019) distribution of the score, we argue that reforms to eligibility, randomization of vouchers at the cutoff, multiple cutoffs during the same round, and mistakes in voucher assignment by MINVU (see Section 2) can be leveraged to assume conditional exogeneity of the number of voucher offers in previous rounds

[30]We consider each round of the program as a different cohort of applicants since very few applicants reapply to the program in multiple rounds. Identifying the exact number is not straightforward since MINVU has arbitrarily included previous non-voucher recipients to the pool of applicants in certain rounds or unexpectedly selected new vouchers holders using any remaining budget at the end of the fiscal year. A conservative approximation of the reapplication rate is less than ten percent. Therefore, we consider each round of the program as a different cohort of applicants.

[31]Spillovers may affect lease-up rates and location decisions. Therefore, using neighborhoods in which families leased up may introduce bias, specially given the low lease-up rates in Chile.

[32]A similar strategy was used by (Chyn et al., 2019) to estimate impacts of neighbors previous lease-up behavior on lease-up in t of Section 8 voucher holders in the US.

at the census tract g level.[33]

In practice, conditional exogeneity is implemented by adding $\overline{y}_{g,t-s}^{Applicants}$ and $\overline{y}_{G,t-s}^{Applicants}$ in equation 4.1. By doing so, β_1 and β_3 provide an intuitive neighborhood spillover effects: the effect on application in g in t of moving one family from the non-recipients group to receive a voucher offer, within g or in adjacent census tracts G. This way of measuring neighborhood spillovers is intuitive in that it makes it easier to compare the benefits and the costs of treating an additional family in the neighborhood List et al. (2020).

Fourth, despite using census tract fixed effects, pre-determine covariates and assuming conditional treatment exogeneity, neighborhoods with different number of applicants could have different characteristics, raising concerns about time-variant correlated unobservables driving the results.[34] Hence, any remaining identification threat comes from time varying unobservables correlated with both the number of voucher recipients in g in previous rounds and with the number of applicants in t.

For causal interpretation, we would need to assume that changes in vulnerability over time in census tract g would have only an indirect effect on application in t through the number of voucher offers in previous rounds in g. Indeed, conditional on the number of previous applicants, any short term or recent changes in eligibility at the census tract level would hardly change the number of voucher offers in the neighborhood.[35] Therefore, we argue that it is reasonable to assume that any change to vulnerability over time would affect application through voucher offers.

Nonetheless, to avoid any remaining bias, we create a sample of comparable census tracts in terms of eligibility. Specifically, we use matching propensity score techniques to match census tracts in terms of their probability of having an applicant in previous rounds in 2016 i.e. census tract eligibility.[36] In this subset of census tracts we expect that any relevant time

[33] Following (Topa, 2001), we also assume that location of voucher offers is random within census tracts.

[34] Voucher assignment exogeneity alone is not sufficient for identifying neighborhood spillovers since comparing treated and controls provides estimates of the total effect, including any direct and indirect effects (Dahl, 2020).

[35] Eligibility for the rental voucher program is defined broadly in terms of vulnerability using administrative data from other government agencies that it is not annually updated. Also, income eligibility is based on 7-month average income data. Furthermore, there is a fixed pre-determined number of available vouchers each round. Importantly, this number has not changed during a round for any contingencies since the program started.

[36] MINVU implemented the last big reform to the program in terms of eligibility and voucher assignment in 2016. We also did a round by round matching varying the number of census tracts used to estimate the model

varying covariate affecting neighborhood voucher acceptance rate is balanced. Section A2 in the Appendix describes the propensity score matching method and its results.

Our matched sample comprises 2,698 census tracts with common support in terms of eligibility in 2016.[37]

To asses balance in this subset of census tracts, we regress the number of voucher offers (treatment) $\overline{y}_{g,t-s}^{Vouchers}$ per round on multiple covariates at the g and G level. Table A2 in the Appendix shows balance tests and provides evidence supporting the conditional exogeneity assumption in the matched sample of census tracts.[38] Controlling for the number of previous applicants, only a couple of covariates are significant determinants of the number of treated units per round in the matched sample. Furthermore, F-tests of join significance show that conditional on the number of applicants, the number of voucher offers is not determined by the large set of covariates in most rounds.[39] We conclude that it is reasonable to assume conditional treatment exogeneity.

Importantly, recall that neighborhood spillover identification do not rely on the conditional exogeneity assumption exclusively (List et al., 2020). Indeed, none of the four strategies by itself would provide clean spillover estimates. In this paper, we obtain such estimates by implementing all these strategies simultaneously and using longitudinal data to reduce threats to identification of the parameters in equation 4.1. Next section describes the data and section 6 presents the results.

5 Data

This study uses data from several administrative sources to create a consolidated data set including information about applicants to the rental voucher program, their eligibility and several characteristics of their neighborhoods at the time of application. We analyze applicants in the period between March 2014 September 2019. Over this period, there have

over time. The results did not vary, however, to simplify coefficient interpretation we keep the matching in 2016 and use a balance panel of census tracts.

[37]Figure 2 shows the distribution of applicants to the program in 2016 in this sample. Similarly to We find variation in the number of applicants across the territory, even in this comparable set of census tracts.

[38]Table A3 in the Appendix show balance tests in the unmatched sample. We observe many statistically significant differences between census tracts with and without applicants.

[39]Only in the two most recent rounds we observe slightly larger F-test, only one significant at the 99% of confidence.

been eight rounds: two rounds each year in 2014 and 2018 and annual rounds in 2015, 2016, 2017 and 2019.

The main data set is built using application data gathered by MINVU. Specifically, for every round of the program we access administrative and self-reported information used by MINVU to calculate the application score. This includes socioeconomic, demographic and housing characteristics. Furthermore, we observe the application score and who received a voucher offers.

Using geocoded data of families location at the time of application, we link administrative data to the National Census 2017 of the INE. By using the carthography, we are able to link each applicant to its corresponding census tract and identify adjacent census tracts surrounding each census tract. Furthermore, census data contains several individual and housing characteristics that we use to create census tract level characteristics.

In total, Chile has 4,865 census tracts in urban areas, 219 of which do not have any adjacent or neighboring census tract.[40]. The Average census tract covers an area of 0.8 squared kilometers - its length is about 7 blocks (0.7 km.)-, houses 3,100 individuals (total distribution is in the 10-11,700 range) and has 4.7 adjacent census tracts (total distribution is in the 1 to 18 range). Importantly, this administrative unit cannot exceed two thousand housing units.

With this data in hand we identify applicants that reside close to each other. Then, for each census tract, we calculate the number of applicants and voucher offers in the same census tract and in adjacent census tracts. Table 3 present summary statistics per round and Table 4 show the history (cumulative data) of applicants and voucher offers in previous rounds per census tract. Figure A2

Using the raw data set, Figure 3 shows a positive yet non-linear spatial correlation between the number of applicants in a t and the number of voucher recipients in previous rounds among immediate neighbors in census tract g and distant neighbors in adjacent census tracts G.

[40]Census tracts are defined exclusively for urban areas. Localities is the equivalent geographic unit in rural areas.

6 Results

This section presents neighborhood spillovers estimates using equation **??**. We begin by presenting overall neighborhood spillover effects and discuss the robustness of our estimates. Then, we provide evidence to discuss the main takeaways of our theoretical model in Section 4. In particular, we show how neighborhood spillovers vary with program size and proximity and analyze how spillovers vary across neighborhoods where past voucher recipients may have faced larger barriers to voucher use.

6.1 Neighborhood spillovers

We estimate neighborhood spillovers in application to the rental voucher program. Specifically, we estimate the effect of an additional voucher recipient in previous rounds in census tract g and neighboring census tracts G over application in g between 2016 and 2019. We use the history of previous voucher recipients in the program since its first round in 2014.[41] Table 5 shows the number of voucher offers in previous rounds per census tract in the sample of analysis.

Our main results are presented in Table 6. Columns 1 to 4 consider all census tracts and columns 5 and 8 use the matched sample: the sample of comparable census tracts in terms of eligibility in 2016. Our preferred specification in column 8 includes quadratic terms and controls for the number of previous applicants in g and G. All specifications include census tract fixed effects.

Results show that an additional previous voucher offer in the own census tract g reduces the number of applicants in g in t in 0.374 (β_1) and an additional past voucher recipient in neighboring census tracts G increases the number of applicants in g in t in 0.024 (β_3). We refer to these effects as within and across census tract spillovers, respectively. These results are similar in the full sample of census tracts (column 4).[42]

[41] We exclude the first three rounds of the program in which most applicants received a voucher to avoid multi-collinearity problems. In addition, results in Table 6 provide evidence that conditioning on the number of previous applicants does not introduce instability to our estimates. Figure A3 in the Appendix shows the difference between the number of applicants and voucher recipients in each round.

[42] We have access to census tract characteristics from the 2017 census, collected two years after the program was first implemented. While residential mobility in Chile is very low (median residential mobility in the last 5 years using census data is 15%), it may raise concerns about endogenous group membership in our estimates. Table **??** in the Appendix show estimates in census tract with residential mobility below the median. We do not find any evidence that estimates in column 8 in Table 6 are biased by endogenous residential mobility:

Adding the number of previous applicants to the model reduces the coefficients and, as mentioned above, has implication for the interpretation of our parameters of interest. Neighborhood spillovers in Table 6 imply that moving one family in neighborhood g (G) from the group of non-recipients to receive a voucher offer has a negative (positive) effect on application in g in t.

According to our analytical framework in Section 3.1, negative spillovers may occur in rental voucher programs if there are barriers to voucher use in the private rental market. In particular, by an increase in competition for affordable housing in very local rental markets or by the spread of negative information shared by previous voucher recipients that have faced difficulties to use their vouchers. Positive spillovers, on the other hand, may be driven by an increase in information about the program, housing search methods and housing availability, or by a reduction in costs of deviating from social norms in a largely homeownership biased society.

The evidence provided in Table 6 suggests that any positive spillover within census tracts is canceled out by negative spillovers. In contrast, our estimates suggest that any negative spillovers across census tracts may be offset by positive spillovers. In other words, mechanisms generating negative spillovers may be stronger within immediate neighbors than among distant neighbors. On the one hand, sharing negative experiences in the program may be more likely to occur among closer neighbors. On the other hand, as shown in Section 3.1, applicant to the Chilean rental voucher program may search more actively for a unit nearby their initial location.

Table 6 shows that these effects are non-linear. Spillovers within and across census tracts increase at a decreasing rate as the number of voucher recipients get larger in g and G.

To further analyze non-linearities in neighborhood spillovers, Figure 4 plots the predicted value of $\overline{y}_{g,t}^{Applicants}$ for different levels of $\overline{y}_{g,t-s}^{Vouchers}$ (Figure 4a) and $\overline{y}_{G,t-s}^{Vouchers}$ (Figure 4b). In addition, Table 7 presents the results of equation 6.1, including dummy variables $V_{(k)g,t-s}$

estimates for census tracts with low residential mobility do not change.

and $V_{(k)}G, t-s$ for level k of past voucher recipients in g and G, respectively.

$$\overline{y}_{g,t}^{Applicants} = \delta_0 + \delta_1 V_{(1)g,t-s} + \delta_2 V_{(2-4)g,t-s} + \delta_3 V_{(5-7)g,t-s} + \delta_4 V_{(8-13)g,t-s} + \delta_5 V_{(14^+)g,t-s} + \\ \gamma_1 V_{(2-10)G,t-s} + \gamma_2 V_{(11-19)G,t-s} + \gamma_3 V_{(20-33)G,t-s} + \gamma_4 V_{(34-58)G,t-s} + \gamma_5 V_{(59^+)G,t-s} + + \\ \rho_5 \overline{y}_{g,t-s}^{Applicants} + \rho_6 \overline{y}_{G,t-s}^{Applicants} + \theta_g + \lambda_t + \epsilon_{g,t} \tag{6.1}$$

Non-linear neighborhood effects are confirm: negative spillovers within census tracts are large but decreasing in the number of voucher recipients. The solid and dotted line in Figure 4a shows the median number of past voucher recipients observed in the data in g (4) and the level at which the model predicts that negative spillovers reach a minimum (46). Everything else the same, we may expect negative spillovers to continue to be negative as the program continues to increase.[43]

Table 7 shows that positive spillovers across census tracts are non significant for small number of voucher recipients in neighboring census tracts. Then, they increase at decreasing rates until are again not statistically significant. This non-linear pattern is illustrated in Figure 4b.

Summarizing the evidence so far, we conclude that previous voucher offers have important spillovers over prospective applicants in the Chilean rental voucher program. Interaction within census tracts has negative consequences in application and interaction across census tracts has positive consequences over application. However, positive spillovers may vanish as the program increases and negative spillovers would dominate.

Robustness check

The lack of experimental data may raise some concerns about the causal interpretation

of our neighborhood spillover estimates. Therefore, before moving forward into deeper analyses, we run a robustness check to provide additional evidence validating the interpretation of the estimated effects as spillovers.

[43]The actual number of voucher recipients is not large enough to fully characterize the non-linear effects in Figure 4 using dummy variables. For this reason, this paper uses continuous variables and quadratic terms to estimate neighborhood spillovers including census tract and round fixed effects. Using equation **??** in the heterogeneity analysis in Section 6.2 would require careful consideration of different program sizes over time, complicating interpretation of coefficients.

We follow intuition from experimental settings to conduct a simple spillover test. We compare similar census tracts g (with similar neighboring census tracts G) that are exposed to different treatment intensities: above and below the median number of voucher recipients in neighboring census tracts G (seven).

For comparable census tracts g, if there were no spillovers, the effect of neighbors in adjacent census tracts G (β_2) should not be different between census tracts g with more or less voucher offers in neighboring census tract G (Crepon et al., 2013).[44]

Table 8 in the Appendix presents estimates using the matched sample of census tracts g with few and many voucher recipients in neighboring census tracts G (columns 2 and 3). Across census tract spillovers are only significant and different from 0 if there are more than just a few voucher offers in neighboring census tract G i.e. in census tracts g with higher treatment intensity. We conclude that our estimates are identifying spillovers in application to the rental voucher program in Chile.

6.2 Heterogeneity analysis

The main contribution of the model in Section 3.2 is that we allow spillovers to vary with barriers faced by those who have participated in the program in the past. In the model, neighborhood spillovers are affected by barriers to voucher use, which are a function of previous voucher recipients in the neighborhood. Also, as social interaction (direct and indirect) between closest and distant neighbors may differ, neighborhood spillovers may vary with proximity between neighbors.

To further explore the implications of the model, this section analyzes how the estimated neighborhood spillovers change with program size, proximity between neighbors and barriers to voucher use.

Exposure to previous voucher recipients

Results in Table 6 show non-linear neighborhood spillovers with respect to the number of past voucher recipients in the neighborhood. Those coefficients are weighted averages of

[44] This literature has been focused on contemporaneous spillovers across neighborhoods. For this reason, we implement this additional spillover test focusing on across census tract spillovers.

neighborhood spillovers for all rounds of the program together.

In this research, the number of previous voucher recipients within a certain neighborhood (our treatment) is always increasing over time (See Table 5). Therefore, to analyze how neighborhood spillovers vary with different levels of exposure to past voucher recipients, we divide the sample in two consecutive periods and estimate the model in each period, separately.

The first period includes the 2016, 2017 and 2018-1st rounds. The second period refers to the two most recent rounds: 2018-2nd and 2019. In the first five years of the program, results in Table 9 show that negative spillover within census tract have increased and positive spillovers have decreased and are no longer positive neither significant.

These results confirm our previous findings: negative within census tracts spillovers increase as the program increases and across census tracts spillovers are positive but decrease with program scale. As the program gets larger every year, negative spillovers may dominate.

Proximity between the closest and distant neighbors

We now turn to proximity between neighbors. As we explained in Section 5, census tracts are an administrative unit that cannot exceed the two thousand unit standard. Hence, more dense census tracts are also smaller census tracts where people live closer together and closer to their neighbors in adjacent census tracts G. [45].

Columns 1 and 2 in Table 10 present estimates for low and high density census tracts g, which we define according to the median of the population density distribution. We find that negative spillovers are larger in census tracts where immediate neighbors live closer together i.e. where direct and indirect interaction among neighbors in g and G is more likely to occur. An additional past voucher recipient in g reduces the number of applicants in t in -0.413 in denser census tracts and in -0.34 in lower density census tracts. In contrast, positive spillovers across census tracts are larger and significant when neighbors in g live farther apart.

[45]Unfortunately, with the available data is not possible to construct a segregation measure of eligible population at the census tract level, which would be a more accurate proximity indicator for this analysis

To analyze the effect of past voucher recipients living in closer and farther away neighboring census tracts, columns 3 to 6 in Table 10 fix the density in g and vary the density of their neighboring census tracts. We show the results in low and high density neighboring census tracts G surrounding low (columns 3 and 4) and high (columns 5 and 6) density census tracts g.

Regardless of the density in census tract g, an additional voucher offer in neighboring census tracts G has a positive and significant effect only if interaction among neighbors in G is more likely to occur i.e. in denser G (columns 4 and 6). Furthermore, while the negative effect of one additional voucher recipient in g is larger in census tracts where immediate neighbors live closer together, they are slightly reduced if neighbors in neighboring census tract are closer and live closer together in G. To further understand this result we would need more information about the relevant local rental market for applicants to the program.

We conclude that negative spillovers within census tract are stronger if neighbors live closer to each other and positive spillovers across census tracts are stronger if neighbors in different census tracts live closer to each other. These results are consistent with previous literature suggesting that intensity of social interaction depends on distance.[46]

Next, we analyze how neighborhood spillovers vary with application costs faced by previous voucher recipients. We study neighborhood spillovers in the presence of high (low) aggregated barriers to voucher use by analyzing census tracts with low (high) lease-up rates. Then, we use baseline census tract characteristics to take a closer look at two different barrier to voucher use: transaction costs and costs from deviating from social norms towards renting (cultural factors).

Aggregate barriers to voucher use

Six out of ten vouchers are left unused in Chile. Figure A4 in the Appendix shows the fraction of voucher recipients that use their vouchers (lease-up rate) in previous rounds per census tract.

Using the observed spatial variation in lease-up behavior, Table 11 analyzes spillovers in

[46]Patacchini, Picard, and Zenou (2015) shows that students tend to interact more with agents who are geographically closer. Similar results are shown in earlier studies by (Wellman, 1996, 2001)

comparable census tracts where previous voucher recipients faced different levels of aggregated barriers: below and above median lease up rate (33%).[47] Then, Figure 5 characterizes neighborhood spillovers over the full range of the distribution of past voucher recipients in g and G. We restrict this analysis to matched census tracts that have previous voucher recipients (column 1).

Negative spillovers within census tracts are larger in census tracts with higher barriers to voucher use. One additional voucher recipient in the past in census tracts g with low lease-up rates reduces application to the program in t by -0.459 (column 2) and by -0.336 in census tracts g with high lease-up rate (column 3). Similarly, an additional past voucher recipient in neighboring census tracts G has a positive and significant average effect on application in g in t only in census tracts if past voucher recipients in g faced large difficulties to voucher use.

Figure 5 illustrates these results over the full range of past voucher recipients. Negative spillovers are smoother (Figure 5a)[48] and across census tracts are positive and increasing in a larger range of the distribution of past voucher recipients in G in census tracts with low barriers to voucher use (Figure 5b). In contrast, in census tracts with higher barriers to voucher use, across census tracts spillovers switch to negative at moderate numbers of past voucher recipients in G (Figure 5d).

These findings suggests that reducing barriers to voucher use would generate positive neighborhood spillovers in application as the program increases.

Transaction costs

In the Chilean rental voucher program both local housing authorities (SERVIUs) and Municipalities are sources of formal information about the program. However, families must visit a SERVIU to start using their vouchers (See Section 2). Therefore, transaction costs of voucher use are only reduced by proximity to one of the 51 SERVIUs in the country and

[47]The median lease-up rate is 33% at every round of the program. Since in some rounds the same census tract g can be above or below the median, the number of census tracts across all columns may exceed the total number of census tracts. Estimates using average lease up rates in previous rounds to build these groups produce the same results.

[48]Among census tract with voucher recipients, negative spillovers reach a minimum at 32 past voucher recipients, not 46.

not by proximity to any of the 346 Municipalities in Chile.[49]

Table 12 shows spillover effects in census tract with different transaction costs of voucher use according to their distance to a SERVIU (columns 1 to 3) and different transaction costs of application -or different levels of formal information about the program- according to their distance to a Municipality (columns 4 to 6).[50] Using these estimates, Figure 6 illustrates spillovers for census tracts that have lower or higher transaction costs for the full range of past voucher recipients in the data.

An additional past voucher recipient in g has a stronger negative effect in census tracts that are farther away from a SERVIU, where previous recipients had faced higher transaction costs of voucher use. Farther away from a SERVIU, the effect of an additional past voucher recipient in neighboring census tracts G over application in g gets smaller and not significant. Furthermore, Figure 6c shows that negative spillovers within census tracts increase at a constant rate (linear) and Figure 6d shows that positive spillover across census tracts are smaller and rapidly switch to negative.

In areas with low transaction costs we observe very different results: negative spillovers within census tract switch to positive at moderate numbers of past voucher recipients (Figure 6b) and spillovers across census tracts are positive and increasing in a larger range of the distribution of past voucher recipients in G (Figure 6b).

These findings are similar to those for aggregated barriers to voucher use and might have important policy consequences: reducing transaction costs to voucher use e.g. reducing the individual costs of paperwork submission could generate positive neighborhood spillovers in application as the program increases.

Finally, columns 4 to 6 in Table 12 show how neighborhood spillovers change with distance to municipalities. We find that in census tracts farther away from a municipality, negative spillovers within census tract decrease and across census tract spillovers increase. These results suggest that formal information through the municipality and informal information through social interactions may be substitutes.

[49] Figure A5 in the Appendix shows the how far are census tracts to the closest SERVIU and Municipality.

[50] We do not have location of every unit in a census tract, therefore, we measure distance to the census tract's centroid as a proxy for access.

Cultural factors

Section 2 shows that the population of applicants to the Chilean rental voucher program has strong preferences for participating in homeownership programs and that these preferences prevent voucher recipients from using their vouchers (Table 1).[51]

In this section we study spillovers in census tracts with and without public housing to analyze how they may be affected by high and low costs of deviating from social norms regarding rental housing (cultural factors). If residents in census tracts with a larger fraction of subsidized homeowners have even higher preferences for homeownership we may expect larger but decreasing negative spillovers within census tracts, and small and increasing positive spillovers across census tract spillovers.

Table 13 show that negative spillovers are larger but decrease at a much faster rate if g has public housing. Figure 7c shows that negative spillovers within census tracts switch to positive at moderate numbers of past voucher recipients in g. In addition, average spillovers across census tract are small and not significant in these neighborhoods. However, 7d shows that while they are small, they are positive and increasing in the full range of the distribution of past voucher recipients in neighboring census tracts. These results are consistent with decreasing costs of deviating from social norms as more individuals participate in the program.

The small difference in spillovers within census tracts in columns 1 and 2 in Table 13 could be explained by differences in public housing across the country. Preferences for homeownership might be higher in neighborhoods with higher quality or older public housing. Columns 3 to 6 in Table 13 desegregate the number of public housing units according to the year in which they were built. We consider four periods that include important reforms to public housing policies in the country; during the first two periods fewer public housing units were provided but of much higher quality and in better locations.[52]

[51] Survey data shows that 13% of those who have not used their benefit declare to be waiting for the results of an application to a homeownership program, or have already been selected in one of the two largest homeownership programs (See Section 2). Although they applied to the rental voucher program and could use the voucher while applying to a ownership program, they fear that using their vouchers will reduce their chances of getting a subsidized home (Selman, 2019).

[52] Public housing has increased over these periods but the quality of the units and their location has dramatically decreased over the years. Between 1936 and 1973 there were very few public housing built but their quality was higher. The second period (1974-1990) represents the dictatorship, in which public housing did not increase yet quality started to decrease as demand voucher policy were implemented and the private sec-

We observe that census tracts with older public housing have much larger negative spillovers from neighbors in g. Moreover, across census tracts spillovers are only significant in neighborhoods with the oldest public housing. While small sample sizes might be taken with caution, this evidence suggests that costs of deviating from social norms may have important consequences in neighborhood spillovers in application to the rental voucher program.

7 Discussion

This paper studies neighborhood spillovers in application to the recently implemented rental voucher program in Chile and find that the interaction with previous voucher offers may have large negative spillovers in application. Specifically, we find that interaction within census tracts has large negative spillovers in application and interaction across census tracts has positive but small spillovers in application.

Negative spillovers may be driven in the rental voucher programs by an increase in competition for affordable housing in very local rental markets or by the spread of negative information shared by previous voucher recipients that have faced important barriers to use their vouchers. Positive spillovers, on the other hand, may be driven by an increase in information (about the program or housing search in the private market) or by a reduction in costs of deviating from social norms in a largely homeownership biased society.

Spillovers are stronger if neighbors live closer to each other, within the same or in different census tracts. Moreover, negative spillovers within census tracts are slightly reduced if neighbors in neighboring census tract are closer and their residents live closer together in G. With the available evidence we cannot determine whether this result is caused by people sharing information but searching for a unit in different local rental markets or by people participating in a larger rental market including multiple (denser) census tracts that are closer together. Future research could explore these alternative explanations.

We estimate not linear spillovers: as the number of voucher recipients in previous rounds in the neighborhood increases, positive and negative spillovers increase at decreasing

tor started to build this houses. After the dictatorship (1991-2005) that model was boosted and thousand of new public housing were built at the periphery across the country. Finally, during the period between 2006 and 2017 homeownership programs have introduced some reforms to provide better location.

rates. Considering the current small scale and low lease-up rate of the rental voucher program in Chile, these results imply that negative spillovers may prevail as the program continues to increase. However, the evidence provided here also suggests that suggest that past voucher recipients could generate positive neighborhood spillovers if barriers to voucher use were effectively tackled by MINVU. Furthermore, this research suggests that small changes to the administration of the program reducing individual costs of paperwork submission to local housing authorities could increase application.

These findings are consistent with recent evidence showing that variation in the effectiveness of housing mobility programs using rental vouchers in the US depends on whether tenant counseling, tenant search assistance, and landlord outreach by local housing authorities are successful in relaxing rental housing supply barriers (Aliprantis, Martin, & Tauber, 2020). Our research suggest that such strategies may have an important social multiplier as more people apply, successfully use their vouchers, and the spread of negative information about the program is reduced.

Our results have important policy implications that could inform future reforms to the design of the Chilean rental voucher program, that has already inspired rental voucher programs in Mexico, Argentina, Peru, Brazil, Colombia and other Latin American countries. In particular, increase access to local housing authorities and improve their performance (e.g. through counseling to voucher recipients) could contribute to the experience of voucher holders in the program, generating positive spillovers in application. Importantly, in programs that assign limited number of subsidies according to relative vulnerability of their applicants, positive spillovers in application could improve targeting of public resources.

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Tables

Table 1: Summary statistics of applicants, voucher recipients and leased-up families

	Applicants			Voucher Recipients			Leased-up		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Baseline Administrative Data									
Age	64,112	33.57	10.70	44,086	32.72	10.19	15,034	31.91	9.57
Female	64,087	0.82	0.38	44,075	0.82	0.38	15,032	0.81	0.39
Spouse/partner	64,112	0.25	0.43	44,086	0.25	0.43	15,034	0.25	0.44
Santiago MSA	64,112	0.24	0.43	44,086	0.25	0.43	15,034	0.16	0.36
Chilean	64,087	0.93	0.25	44,075	0.94	0.24	15,032	0.95	0.22
Children younger than 18 in the household	64,112	0.84	0.36	44,086	0.90	0.30	15,034	0.92	0.28
Elderly member in the household	64,112	0.02	0.13	44,086	0.02	0.13	15,034	0.02	0.13
Overcrowding indicator (MINVU)	64,112	0.33	0.47	44,086	0.44	0.50	15,034	0.46	0.50
Tenant in baseline	64,112	0.51	0.50	44,086	0.44	0.50	15,034	0.44	0.50
Saving balance on application day (US)	64,112	579.24	6,591.25	44,086	583.94	7,935.74	15,034	659.15	13,563.83
Family income (US)	64,111	566.96	209.71	44,086	557.35	210.18	15,034	550.13	209.89
Poor (poverty line adjusted by family size)	64,111	0.16	0.37	44,086	0.17	0.38	15,034	0.17	0.38
Online application	64,087	0.29	0.46	44,075	0.28	0.45	15,032	0.22	0.41
Months from round opening	64,112	3.47	1.57	44,086	3.83	1.69	15,034	4.11	1.62
Application score	64,112	293.36	107.14	44,086	312.74	114.76	15,034	311.49	114.56
Vulnerability index 2017-2019: 40th percentile	41,738	0.71	0.45	23,554	0.84	0.36	6,976	0.88	0.32
Vulnerability Index 2014-2016: score	22,374	8,201.45	3,951.06	20,532	7,929.98	3,940.10	8,058	7,699.23	3,900.13
Rent (US)	13,565	241.83	100.92	7,994	245.21	101.87	1,991	239.75	99.99
Baseline application to ownership programs	64,112	0.14	0.35	44,086	0.14	0.35	15,034	0.15	0.36
Rent burden	13,560	0.46	0.25	7,993	0.48	0.26	1,991	0.48	0.27
B. Baseline Survey Data									
Answered Baseline Survey	41,738	0.69	0.46	23,554	0.68	0.47	6,976	0.68	0.47
Complete or incomplete secondary studies	18,144	0.47	0.50	11,293	0.45	0.50	3,633	0.46	0.50
Employed	22,184	0.84	0.37	11,849	0.82	0.38	3,705	0.82	0.39
Shelter deprivation (slum, shared room or other)	20,717	0.04	0.20	10,749	0.05	0.21	3,369	0.03	0.16
Formal Lease	8,845	0.65	0.48	4,136	0.64	0.48	1,158	0.70	0.46
Preferences to stay in the same neighborhood	24,771	0.54	0.50	13,651	0.54	0.50	4,156	0.55	0.50
Preferences to stay in the same county with the voucher	24,771	0.87	0.34	13,651	0.87	0.34	4,156	0.88	0.32
Believe renting is a waste of money	21,924	0.56	0.50	11,741	0.59	0.49	3,799	0.58	0.49
Expected time to lease < 1 month	11,074	0.43	0.50	6,510	0.44	0.50	1,600	0.55	0.50
Know other applicants (baseline)	24,250	0.38	0.49	13,366	0.39	0.49	4,078	0.44	0.50
Applied to save for ownership	24,209	0.27	0.44	13,339	0.25	0.44	4,073	0.27	0.45
C. Follow-up Survey Data									
Answered Follow-up Survey	64,112	0.46	0.50	44,086	0.45	0.50	15,034	0.51	0.50
Invalid Email	64,112	0.16	0.36	44,086	0.16	0.37	15,034	0.16	0.36
Mobility November 2020	15,061	0.44	0.50	10,207	0.49	0.50	3,979	0.54	0.50
Mobility November 2020 < 1 km	15,061	0.66	0.47	10,207	0.61	0.49	3,979	0.57	0.49
Applied to save for ownership	24,209	0.27	0.44	13,339	0.25	0.44	4,073	0.27	0.45
D. Follow-up Administrative Data									
Application to Ownership Programs	64,112	0.36	0.48	44,086	0.39	0.49	15,034	0.43	0.49
Time to lease-up				16,726	8.80	10.05	15,034	8.90	10.25
Voucher mobility				14,545	0.75	0.44	13,070	0.75	0.43
Voucher mobility < 1km				14,545	0.43	0.49	13,070	0.42	0.49
No lease up reason: supply side barriers				8,538	0.53	0.50			
No lease up reason: homeonwership				8,538	0.13	0.33			

Note: This table presents descriptive statistics of the population of applicants, voucher recipients and those families who have successfully leased-up with their vouchers. Sample size, mean and standard deviation of multiple characteristics are presented for each group. Covariates are classified in four panels, according to their data source. Blank spaces mean that covariate in follow up data is only available for some of these groups.

Table 2: Program Descriptive Statistics

	Applicants	Voucher Recipients	Ever Lease-up May-20	Lease-up Rate May-20	Active Leases May-20
	(1)	(2)	(3)	(4)	(5)
1-2014 Regular	5023	5004	1994	40%	85
2-2014 Regular	2045	2045	906	44%	180
2015 Regular	3525	3001	1391	46%	624
2016 Regular	11892	10576	4676	44%	2858
2017 Regular	13634	8785	3809	43%	2809
1-2018 Regular	8350	3002	1345	45%	1122
2-2018 Regular	9175	4238	1816	43%	1619
2019 Regular	10584	7536	2775	37%	2694
Total Regular Rounds	64228	44187	18712	42%	11991

Note: 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. Columns 3-5 use data on all leases that voucher recipients activated between April 2014 and May 2020. Column 3 presents the total number of voucher recipients that ever used their vouchers, even if they were not using it in May 2020. Column 4 presents the lease up rate i.e. column 3 divided by column 2. Column 5 shows the number of those who leased up in the program that had an active lease by May 2020.

Table 3: Number of applicants and voucher recipients per census tracts in the sample

			Geocoded Sample			
Round	Applicants	Voucher Recipients	Applicants per CT	Vouchers per CT	Acceptance Prob. per CT	CT w/ applicants
2014-1	4,055	4,055	0.83	0.83	100%	2204
2014-2	1,708	1,708	0.35	0.35	100%	1276
2015	2,746	2,355	0.57	0.48	86%	1755
2016	7,992	7,229	1.65	1.49	90%	3045
2017	10,646	6,742	2.19	1.39	63%	3407
2018-1	6,588	2,336	1.36	0.48	35%	2883
2018-2	7,011	3,187	1.44	0.66	46%	2928
2019	7,928	5,623	1.63	1.16	72%	3048

Note: This table presents descriptive statistics at the census tract level. It uses geocoded administrative data from 2014 to 2019 linked to census tracts in urban areas in Chile. Columns 1 and 2 show the total number of applicants and number of vouchers offers in the geocoded sample and columns 3 and 4 present this statistics per census tract in each round. Columns 5 shows the acceptance rate i.e. voucher offers over total applications and column 6 shows the number of census tracts with at least one applicant per round.

Table 4: History of applications and voucher offers per census tracts in the sample

	Geocoded Sample				
Round	Applicants per CT	Vouchers per CT	Acceptance Prob. per CT	CT w/ applicants	CT w/ recipients
Prior to 2014-2	0.83	0.83	0.85	2204	2204
Prior to 2015	1.19	1.19	0.85	2604	2604
Prior to 2016	1.75	1.67	0.80	3062	3011
Prior to 2017	3.40	3.16	0.85	3663	3606
Prior to 2018-1	6.72	4.93	0.71	4140	3961
Prior to 2018-2	9.07	5.77	0.62	4279	4073
Prior to 2019	11.26	6.58	0.57	4349	4135

Note: This table presents descriptive statistics about the history of applicants and voucher offers per census tract. It uses geocoded administrative data from 2014 to 2019 linked to census tracts in urban areas in Chile. Columns 1 and 2 show the total number of applicants and number of vouchers offers in previous rounds per census tract. Columns 3 shows the total acceptance rate i.e. total voucher offers over total applications in previous rounds and columns 4 and 5 show the number of census tracts with at least one applicant and voucher offer in some previous round, respectively.

Table 5: History of applications and voucher offers per census tracts in the sample of analysis

	Geocoded Sample			
Round	Applicants per CT	Vouchers per CT	Acceptance Prob. per CT	Number CT
Previous to 2016	1.921	2.009	0.773	2698
Previous to 2017	3.710	3.995	0.884	2698
Previous to 2018-1	5.244	7.673	0.810	2698
Previous to 2018-2	5.785	10.268	0.729	2698
Previous to 2019	6.512	12.729	0.686	2698

Note: This table presents descriptive statistics about the history of applicants and voucher offers per census tract in the matched sample of census tracts in the period of analysis. It uses geocoded administrative data from 2014 to 2019 linked to census tracts in urban areas in Chile. Columns 1 and 2 show the total number of applicants and number of vouchers offers in previous rounds per census tract. Columns 3 shows the total acceptance rate i.e. total voucher offers over total applications in previous rounds and column 4 shows the number of census tracts in the matched sample.

Table 6: Neighborhood Spillovers: Main Results

Number of applicants in g in t	(1) All	(2) All	(3) All	(4) All	(5) Matched Sample	(6) Matched Sample	(7) Matched Sample	(8) Matched Sample
Number of Voucher Recipients in t-s in g	-0.315***	-0.292***	-0.401***	-0.364***	-0.316***	-0.285***	-0.425***	-0.373***
	(0.012)	(0.022)	(0.020)	(0.027)	(0.016)	(0.028)	(0.027)	(0.036)
Number of Voucher Recipients in t-s in g ^{2}			0.004***	0.004***			0.005***	0.005***
			(0.001)	(0.001)			(0.001)	(0.001)
Number of Voucher Recipients in t-s in G	0.023***	0.016**	0.040***	0.030***	0.021***	0.011	0.035***	0.024***
	(0.002)	(0.007)	(0.005)	(0.008)	(0.003)	(0.009)	(0.007)	(0.009)
Number of Voucher Recipients in t-s in G ^{2}			-0.000***	-0.000***			-0.000**	-0.000**
			(0.000)	(0.000)			(0.000)	(0.000)
Constant	2.044***	2.050***	2.033***	2.041***	2.387***	2.400***	2.440***	2.445***
	(0.035)	(0.041)	(0.048)	(0.050)	(0.050)	(0.058)	(0.073)	(0.074)
Observations	23,180	23,180	23,180	23,180	13,490	13,490	13,490	13,490
R-squared	0.671	0.671	0.673	0.673	0.632	0.632	0.635	0.635
Round FE	YES	YES	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES	YES	YES
Previous Applicants in g	NO	YES	NO	YES	NO	YES	NO	YES
Previous Applicants in G	NO	YES	NO	YES	NO	YES	NO	YES
Dependent Var Mean	1.706	1.706	1.706	1.706	1.855	1.855	1.855	1.855
Dependent Var SD	2.032	2.032	2.032	2.032	1.958	1.958	1.958	1.958
Unique CTs	4636	4636	4636	4636	2698	2698	2698	2698

Note: This table shows estimates of equation **??**. Columns 1 to 4 use the full sample of census tracts and columns 4 to 8 use the matched sample of census tracts. All columns include census tracts and rounds fixed effects. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Table 7: Non-Linear Neighborhood Spillovers

Number of applicants in g in t	(1) All	(2) Matched Sample
1 Voucher Recipients in t-s in g	-0.384***	-0.478***
	(0.051)	(0.072)
2-4 Voucher Recipients in t-s in g	-0.653***	-0.743***
	(0.069)	(0.092)
5-7 Voucher Recipients in t-s in g	-1.101***	-1.192***
	(0.098)	(0.127)
8-13 Voucher Recipients in t-s in g	-1.699***	-1.840***
	(0.149)	(0.182)
14 or more Voucher Recipients in t-s in g	-2.190***	-2.203***
	(0.241)	(0.292)
2-10 Voucher Recipients in t-s in G	0.076	0.162
	(0.066)	(0.119)
11-19 Voucher Recipients in t-s in G	0.329***	0.426***
	(0.088)	(0.144)
20-33 Voucher Recipients in t-s in G	0.392***	0.413**
	(0.107)	(0.166)
34-58 Voucher Recipients in t-s in G	0.391***	0.420**
	(0.141)	(0.199)
59-78 Voucher Recipients in t-s in G	0.167	0.304
	(0.212)	(0.278)
79 or more Voucher Recipients in t-s in G	-0.103	0.097
	(0.308)	(0.373)
Constant	2.071***	2.421***
	(0.080)	(0.139)
Observations	23,158	13,479
R-squared	0.669	0.632
Round FE	YES	YES
Census Tract FE	YES	YES
Previous Applicants in g	YES	YES
Previous Applicants in G	YES	YES
Dependent Var Mean	1.706	1.855
Dependent Var SD	2.032	1.958
Unique CTs	4636	2698

Note: This table shows estimates of equation **??**. Columns 1 to 4 use the full sample of census tracts and columns 4 to 6 the matched sample. All columns include census tracts and rounds fixed effects. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Table 8: Spillovers from neighboring census tract with different treatment intensity

	(1)	(2)	(3)	(4)	(5)	(6)
	All	(G)	(G)	Matched	(G)	(G)
		Recipients	Recipients	Sample	Recipients	Recipients
Number of applicants in g in t		< 7	> 7		< 7	> 7
Number of Voucher Recipients in t-s in g	-0.364***	-0.358***	-0.401***	-0.373***	-0.595***	-0.393***
	(0.027)	(0.084)	(0.034)	(0.036)	(0.134)	(0.044)
Number of Voucher Recipients in t-s in g ^{2}	0.004***	0.002	0.006***	0.005***	0.015**	0.007***
	(0.001)	(0.005)	(0.001)	(0.001)	(0.007)	(0.002)
Number of Voucher Recipients in t-s in G	0.030***	0.006	0.025**	0.024***	0.002	0.027**
	(0.008)	(0.050)	(0.010)	(0.009)	(0.108)	(0.011)
Number of Voucher Recipients in t-s in G ^{2}	-0.000***	0.011**	-0.000*	-0.000**	0.011	-0.000
	(0.000)	(0.006)	(0.000)	(0.000)	(0.011)	(0.000)
Constant	2.041***	0.797***	2.669***	2.445***	1.542***	2.790***
	(0.050)	(0.063)	(0.094)	(0.074)	(0.159)	(0.116)
Observations	23,180	6,289	16,891	13,490	2,601	10,889
R-squared	0.673	0.812	0.668	0.635	0.808	0.656
Round FE	YES	YES	YES	YES	YES	YES
Previous applicants	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
Dependent Var Mean	1.706	0.788	2.048	1.855	1.258	1.997
Dependent Var SD	2.032	1.389	2.126	1.958	1.557	2.016
Unique CTs	4636	2336	3835	2698	1221	2453

Table 9: Program size

Number of applicants in g in t	(1) 2016 2017 2018-1	(2) 2018-2 2019
Number of Voucher Recipients in t-s in g	-0.327***	-0.458***
	(0.060)	(0.126)
Number of Voucher Recipients in t-s in g ^{2}	0.008***	0.019***
	(0.002)	(0.006)
Number of Voucher Recipients in t-s in G	0.071***	-0.015
	(0.018)	(0.041)
Number of Voucher Recipients in t-s in G ^{2}	-0.000	0.000*
	(0.000)	(0.000)
Constant	2.534***	5.673***
	(0.099)	(0.815)
Observations	8,094	5,396
R-squared	0.728	0.807
Round FE	YES	YES
Previous applicants	YES	YES
Census Tract FE	YES	YES
Dependent Var Mean	1.972	1.678
Dependent Var SD	2.014	1.856
Unique CTs	2698	2698

Note: This table shows estimates of equation **??** in the sample of matched census tracts in the first 3 and two more recent rounds separately. Significance levels: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 10: Proximity

Number of applicants in g in t	(1) (g) Low < p50	(2) (g) High > p50	(3) (g) Low (G) Low	(4) (g) Low (G) High	(5) (g) High (G) Low	(6) (g) High (G) High
Number of Voucher Recipients in t-s in g	-0.340***	-0.413***	-0.357***	-0.349***	-0.436***	-0.394***
	(0.050)	(0.047)	(0.069)	(0.066)	(0.074)	(0.058)
Number of Voucher Recipients in t-s in g ^{2}	0.003**	0.008***	0.000	0.008***	0.009***	0.006***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
Number of Voucher Recipients in t-s in G	0.030**	0.022	0.034	0.028*	0.012	0.036*
	(0.013)	(0.015)	(0.022)	(0.017)	(0.021)	(0.018)
Number of Voucher Recipients in t-s in G ^{2}	-0.000	-0.000**	-0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.117***	2.753***	1.928***	2.327***	2.967***	2.511***
	(0.093)	(0.122)	(0.116)	(0.142)	(0.169)	(0.166)
Observations	6,745	6,745	3,375	3,370	3,380	3,365
R-squared	0.657	0.614	0.649	0.668	0.636	0.583
Round FE	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
Previous Applicants	YES	YES	YES	YES	YES	YES
Dependent Var Mean	1.772	1.937	1.692	1.853	2.046	1.828
Dependent Var SD	2.071	1.835	2.006	2.130	1.974	1.676
Unique CTs	1349	1349	675	674	676	673

Note: This table shows estimates of equation **??** in the sample of matched census tracts. Columns 1 and 2 split census tracts g as high and low density, defined as above or below the median of the density distribution of g. Columns 3 and 4 (5 and 6) split low (high) density census tract g according to the density in their neighboring census tracts G, also using the median of the density distribution of G. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Table 11: Spillover heterogeneity by neighborhood lease-up rate

Number of applicants in g in t	(1) All Voucher Recipients	(2) (g) Low Lease-up < 33%	(3) (g) High Lease-up > 33%	(4) (G) Low Lease-up < 33%	(5) (G) High Lease-up > 33%
Number of Voucher Recipients in t-s in g	-0.388***	-0.459***	-0.336***	-0.340***	-0.366***
	(0.040)	(0.052)	(0.058)	(0.046)	(0.053)
Number of Voucher Recipients in t-s in g ^{2}	0.006***	0.010***	0.005***	0.008***	0.004**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Number of Voucher Recipients in t-s in G	0.020*	0.035**	0.017	0.022	0.030**
	(0.011)	(0.015)	(0.015)	(0.014)	(0.014)
Number of Voucher Recipients in t-s in G ^{2}	-0.000	-0.000***	-0.000	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.769***	2.396***	2.935***	2.332***	2.689***
	(0.099)	(0.115)	(0.159)	(0.114)	(0.118)
Observations	11,907	6,068	6,479	6,054	7,066
R-squared	0.635	0.628	0.682	0.632	0.677
Round FE	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES
Previous Applicants	YES	YES	YES	YES	YES
Dependent Var Mean	1.992	1.709	2.242	1.609	2.126
Dependent Var SD	2	1.611	2.219	1.582	2.218
Unique CTs	2543	1817	1723	1587	1803

Note: This table shows estimates of equation **??** in the sample of matched census tracts. Column 1 uses the subset of census tracts with at lease one voucher offer in the past. Columns 2 to 5 split census tracts according to median lease up rate of voucher recipients in previous rounds. Low and high lease up rate are defined as above or below the median rate (33% in both g and G). Since in some rounds g can be above or below the median, the number of census tract may exceed the total number of census tracts. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Table 12: Transaction Costs: Proximity to SERVIUs and Municipalities

	(1)	(2)	(3)	(4)	(5)	(6)
	PHA	PHA	PHA	Municipality	Municipality	Municipality
	Access	Access	Access	Access	Access	Access
Number of applicants in g in t	< 6 km	6-11 km	> 11 km	< 1 km	1-4 km	> 4 km
Number of Voucher Recipients in t-s in g	-0.355***	-0.332***	-0.420***	-0.475***	-0.360***	-0.278***
	(0.055)	(0.058)	(0.064)	(0.076)	(0.045)	(0.097)
Number of Voucher Recipients in t-s in g ^{2}	0.006***	0.008***	0.001	0.008***	0.005***	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of Voucher Recipients in t-s in G	0.037***	0.019	0.014	0.021	0.020*	0.080***
	(0.014)	(0.016)	(0.018)	(0.024)	(0.011)	(0.027)
Number of Voucher Recipients in t-s in G ^{2}	-0.000**	-0.000***	-0.000	-0.000	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.403***	2.344***	2.470***	2.663***	2.522***	1.709***
	(0.116)	(0.147)	(0.114)	(0.160)	(0.094)	(0.188)
Observations	6,065	3,515	3,910	2,815	8,965	1,710
R-squared	0.640	0.605	0.651	0.601	0.635	0.687
Round FE	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
Previous Applicants	YES	YES	YES	YES	YES	YES
Dependent Var Mean	1.991	1.608	1.865	1.742	1.879	1.915
Dependent Var SD	2.081	1.641	2.001	1.821	1.931	2.283
Unique CTs	1213	703	782	563	1793	342

Note: This table shows estimates of equation **??** in the sample of matched census tracts. Columns 1 to 3 split census tracts according to the distance to the closest PHA (SERVIU) and columns 4 to 6 according to their distance to the closest municipality. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

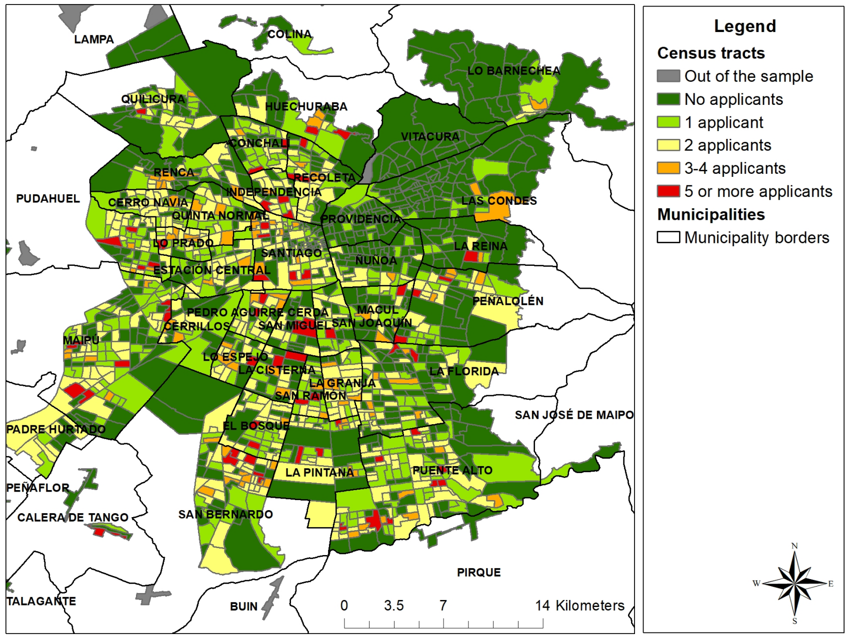
Table 13: Cultural Factors: Preferences for Homeownership (Presence of Public Housing)

	(1)	(2)	(3)	(4)	(5)	(6)
Number of applicants in g in t	(g) No Public Housing	(g) Public Housing	(g) Public Housing 36-73	(g) Public Housing 74-90	(g) Public Housing 91-05	(g) Public Housing 06-17
Number of Voucher Recipients in t-s in g	-0.374***	-0.386***	-0.416***	-0.405***	-0.284***	-0.333**
	(0.041)	(0.058)	(0.119)	(0.113)	(0.077)	(0.163)
Number of Voucher Recipients in t-s in g ^{2}	0.004***	0.007***	0.011	0.003	0.007***	0.002
	(0.002)	(0.002)	(0.008)	(0.004)	(0.002)	(0.005)
Number of Voucher Recipients in t-s in G	0.030***	0.006	0.050*	0.008	-0.015	0.014
	(0.011)	(0.018)	(0.029)	(0.030)	(0.031)	(0.034)
Number of Voucher Recipients in t-s in G ^{2}	-0.000***	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.165***	3.310***	2.749***	3.338***	4.100***	2.792***
	(0.082)	(0.157)	(0.202)	(0.245)	(0.323)	(0.373)
Observations	10,040	3,450	880	1,065	1,365	655
R-squared	0.629	0.643	0.652	0.591	0.674	0.668
Round FE	YES	YES	YES	YES	YES	YES
Census Tract FE	YES	YES	YES	YES	YES	YES
Previous Applicants	YES	YES	YES	YES	YES	YES
Dependent Var Mean	1.733	2.208	1.842	2.065	2.566	2.379
Dependent Var SD	1.917	2.033	1.756	1.793	2.299	2.327
Unique CTs	2008	690	176	213	273	131

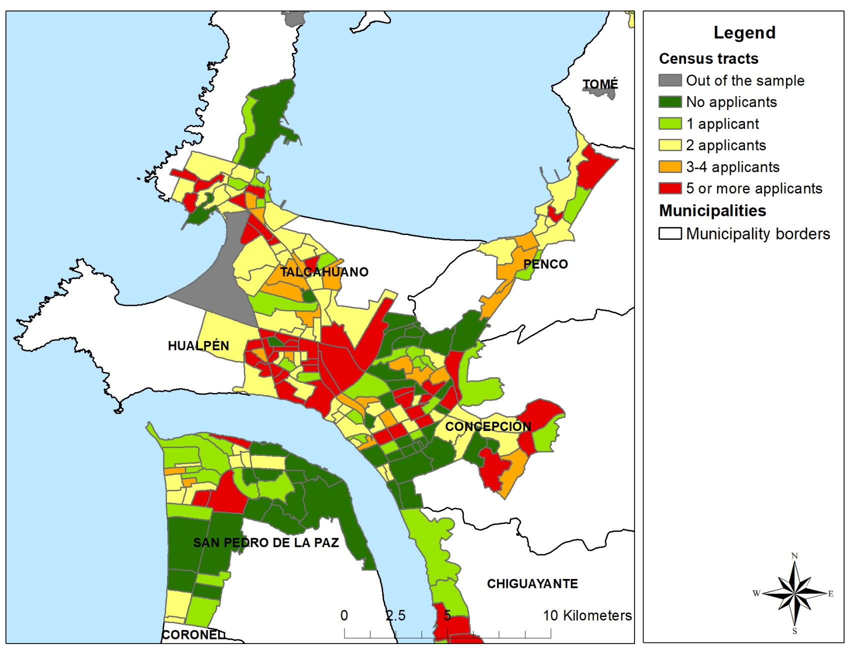
Note: This table shows estimates of equation **??** in the sample of matched census tracts. Columns 1 and 2 show census tracts g with and without public housing. Columns 3 to 6 differentiate public housing according to the year built. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Figures

Figure 1: Spatial distribution of applicants to the Chilean rental voucher program in 2016

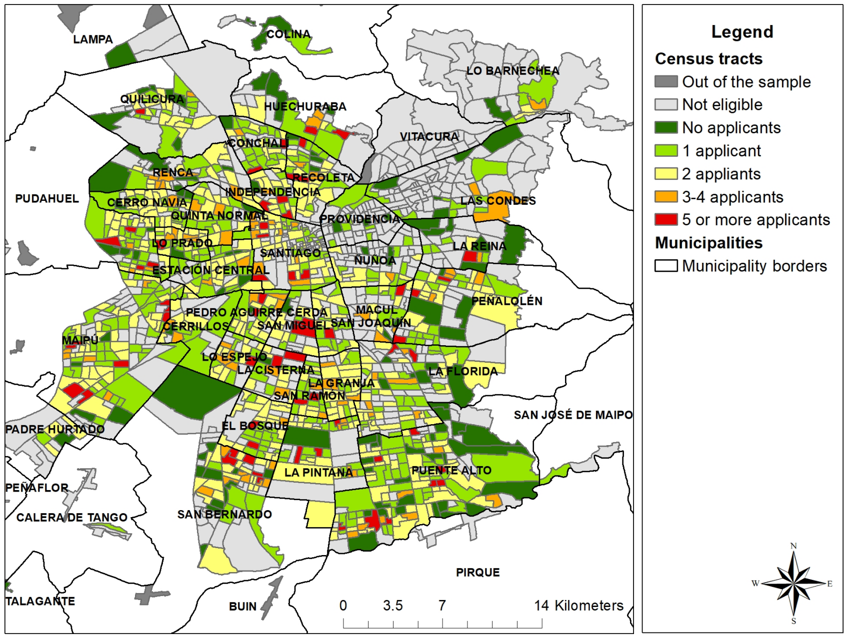


(a) Application in 2016-Santiago

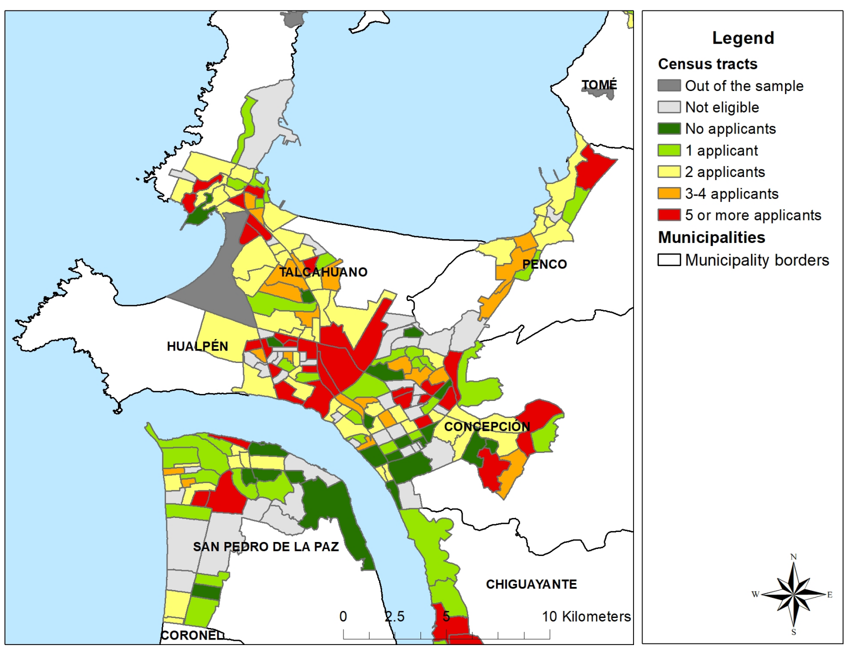


(b) Application in 2016-Concepcion

Figure 2: Spatial distribution of applicants to the Chilean rental voucher program in 2016- Matched sample of census tracts

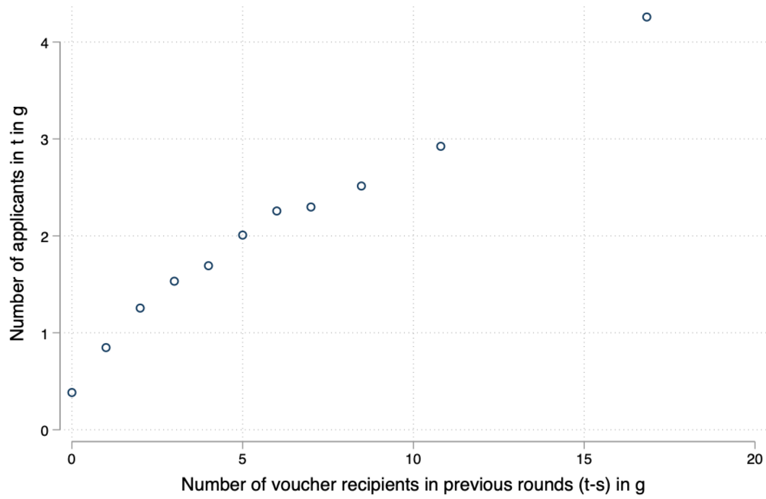


(a) Application in 2016-Santiago

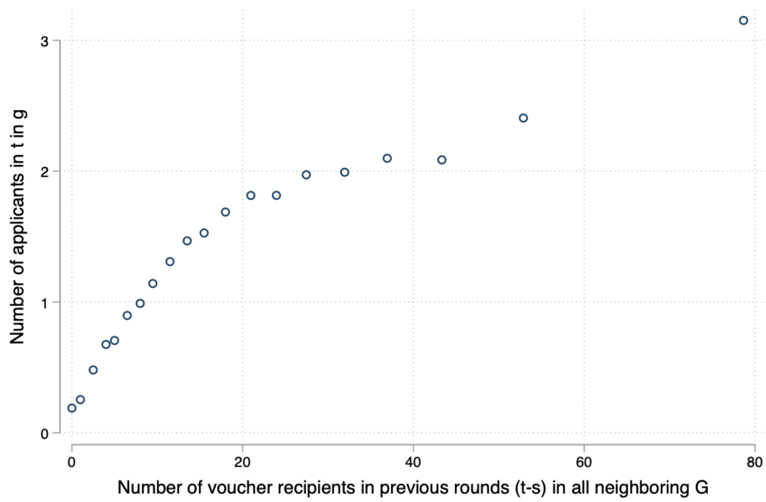


(b) Application in 2016-Concepcion

Figure 3: Spatial correlation between the number of applicants and previous voucher recipients

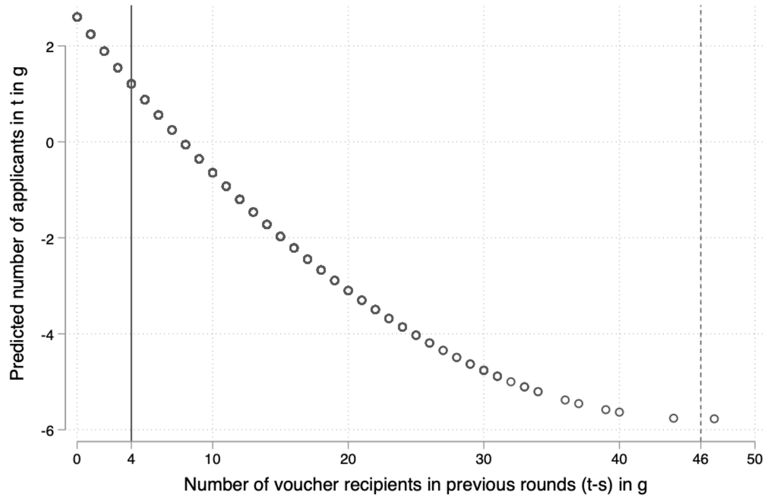


(a) Number of applicants in g and previous voucher recipients in g

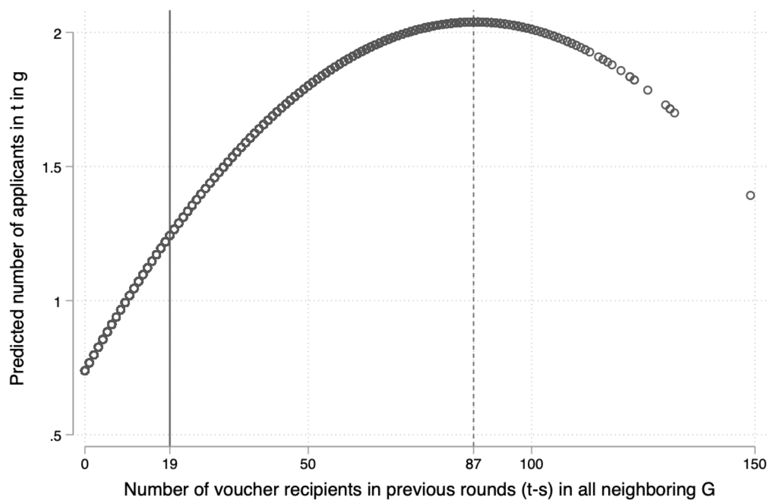


(b) Number of applicants in g and previous voucher recipients in neighboring census tracts

Figure 4: Non-Linear Neighborhood Spillovers

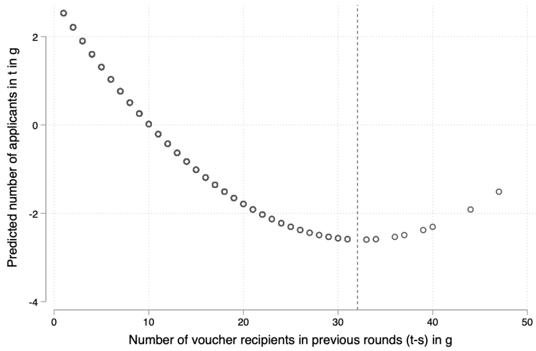


(a) Within census tract spillovers

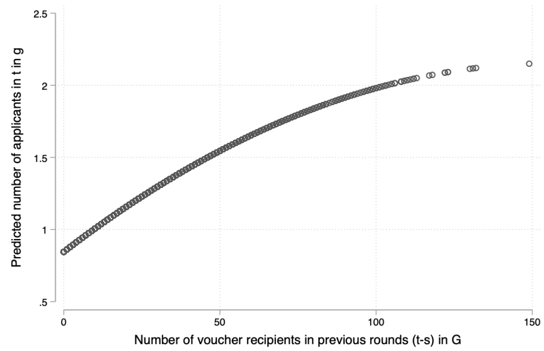


(b) Across census tracts spillovers

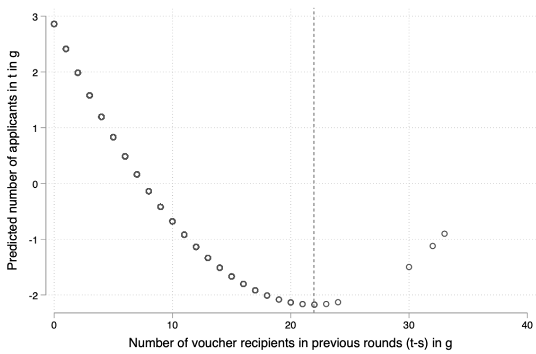
Figure 5: Non-Linear Neighborhood Spillovers: low vs high aggregated barriers to voucher use



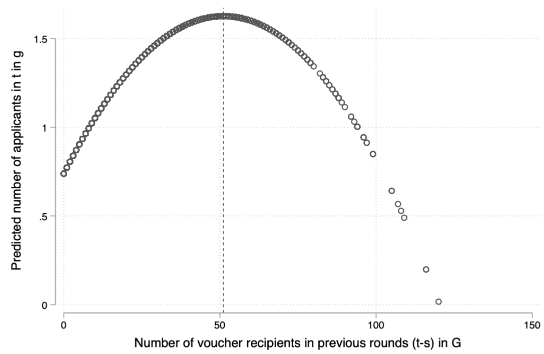
(a) Within census tract spillovers
$>$ 33% Lease-Up Rate



(b) Across census tracts spillovers
$>$ 33% Lease-Up Rate

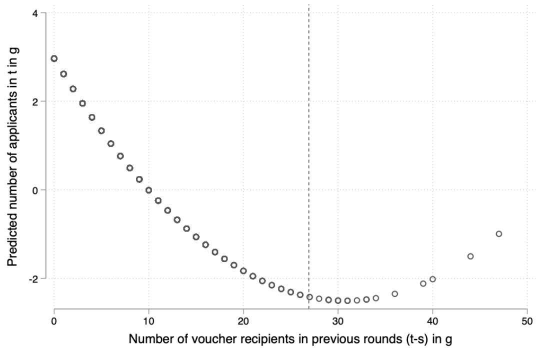


(c) Within census tracts spillovers
$\leq$ 33% Lease-Up Rate

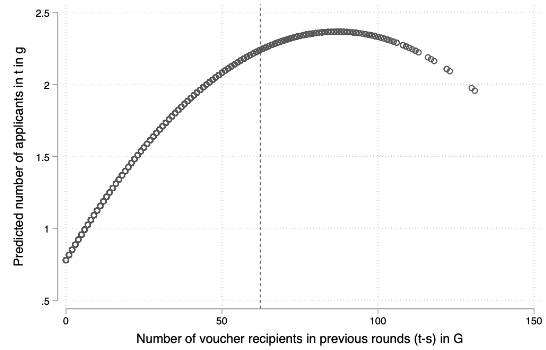


(d) Across census tracts spillovers
$\leq$ 33% Lease-Up Rate

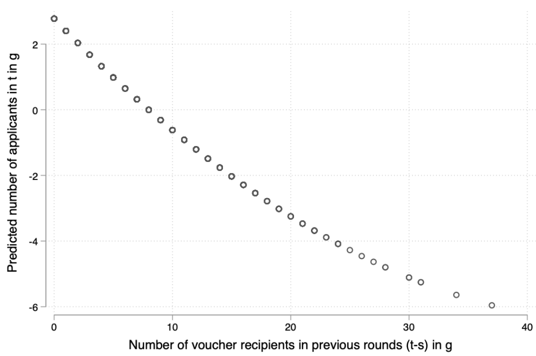
Figure 6: Non-Linear Neighborhood Spillovers: low vs high transaction costs



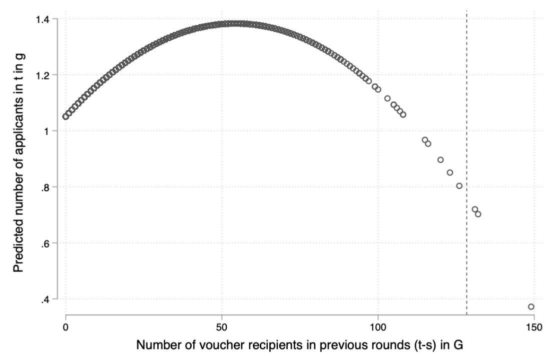
(a) Within census tract spillovers
$\leq$ 6 km from SERVIU



(b) Across census tracts spillovers
$\leq$ 6 km from SERVIU

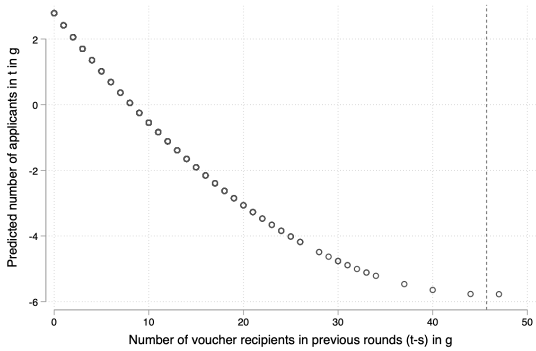


(c) Within census tracts spillovers
$>$ 6 km from SERVIU

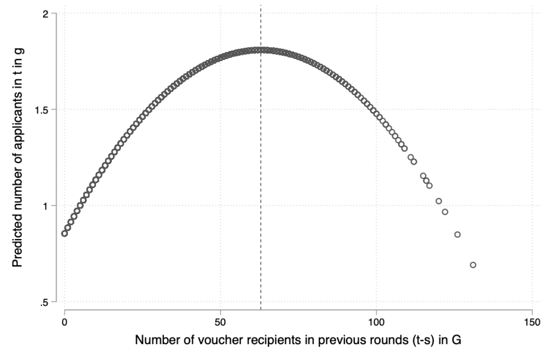


(d) Across census tracts spillovers
$>$ 6 km from SERVIU

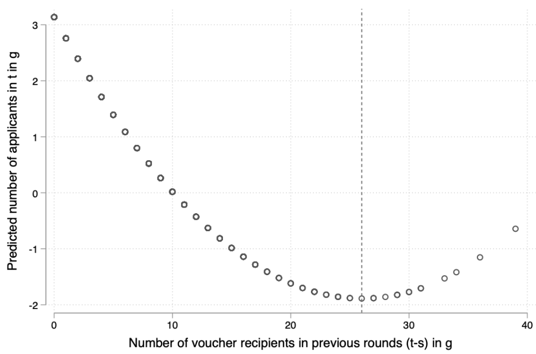
Figure 7: Non-Linear Neighborhood Spillovers: low vs high costs of deviating for social norms (cultural factors)



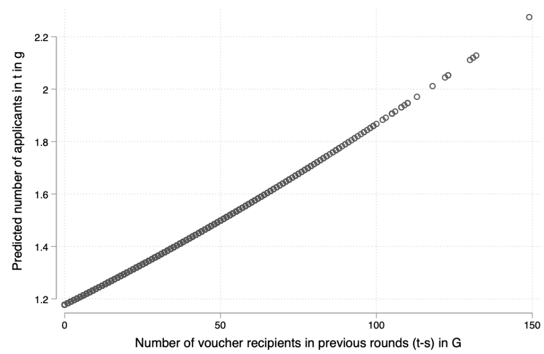
(a) Within census tract spillovers
No Public Housing



(b) Across census tracts spillovers
No Public Housing



(c) Within census tracts spillovers
Public Housing



(d) Across census tracts spillovers
Public Housing

A1 Appendix: Tables and Figures

Table A1: Application Score

	Dimension	Score
1	Household member*	40 each
2	Children under 5**	30 each
3	Children between 6 and 18**	20 each
4	Elderly*	30 each
5	Single Parent of 18 or younger children	0 or 35
6	Physical discapacity	30 each
7	Tortured in dictatorship (applicant, partner)	0, 100, 200
8	Military Service	20 each
9	Gendarmerie Service (applicant, partner)	0, 40, 80
10	Previous Applications (max 3)	0, 20, 40, 60
11	Social Vulnerability	
	2014-2016	(13484-FPS Score)/100
	RSH Reform	0, 45, 90, 135, 180
12	Housing Vulnerability	0, 20, 40, 60, 80, 100, 120, 140, 160

Note: (*) Applicants are excluded. (**) Age by the end of the application year. Housing Vulnerability score is the sum of scores for crowding, housing quality, access to reliable water and basic sanitation.

Table A2: Balance Tests in Matched Sample

Number of voucher offers in g in t-s	(1) 2016	(2) 2017	(3) 2018-1	(4) 2018-2	(5) 2019
(g) % Households with married hh	0.124	-0.036	0.021	-0.675	-0.729
	(0.178)	(0.328)	(0.612)	(0.812)	(0.967)
(g) % Households with hh age 18-30	0.171	17.628	0.079	-28.335	-31.833
	(6.766)	(12.686)	(22.410)	(29.142)	(34.694)
(g) % Households with hh age 30-35	-0.020	16.550	-0.065	-28.370	-32.465
	(6.721)	(12.610)	(22.331)	(29.073)	(34.599)
(g) % Households with hh age 36-60	0.371	17.906	0.892	-26.652	-29.285
	(6.739)	(12.663)	(22.345)	(29.053)	(34.606)
(g) % Households with hh age 61 or older	0.235	17.771	0.378	-27.013	-30.509
	(6.737)	(12.646)	(22.322)	(29.054)	(34.599)
(g) % Households with hh female	0.395**	0.644**	-0.565	-0.420	0.245
	(0.189)	(0.302)	(0.580)	(0.787)	(0.923)
(g) % Households double-up	-0.265	-0.066	0.307	1.957**	2.566**
	(0.213)	(0.388)	(0.739)	(0.981)	(1.138)
(g) % Households with single parent hh (tenants)	-0.194	-0.452	-0.756	-2.365	-2.840
	(0.378)	(0.662)	(1.230)	(1.615)	(1.905)
(g) Fraction of apartments/units	0.002	-0.075	0.052	0.108	0.349
	(0.053)	(0.092)	(0.176)	(0.252)	(0.300)
(g) % Population migrant	0.044	-0.357	0.164	0.118	0.550
	(0.142)	(0.352)	(0.716)	(0.956)	(1.100)
(g) % Population not moved since 2012	-0.003	-0.321	0.169	-0.116	0.442
	(0.119)	(0.247)	(0.433)	(0.569)	(0.650)
(g) % Population age 0-5	0.360	1.002	0.933	2.704	5.728*
	(0.519)	(0.988)	(1.864)	(2.481)	(3.014)
(g) % Population age 6-17	0.179	1.358*	-0.400	1.068	-0.204
	(0.436)	(0.769)	(1.394)	(1.843)	(2.165)
(g) % Population employed	0.216	0.933**	-0.227	0.284	-0.643
	(0.265)	(0.451)	(0.823)	(1.091)	(1.307)
Average years of education of adult population > 12	-0.021	-0.027	-0.097	-0.109	-0.122
	(0.022)	(0.038)	(0.071)	(0.091)	(0.104)
(g) Average household size	0.004	0.006	0.088	0.004	-0.050
	(0.023)	(0.038)	(0.071)	(0.095)	(0.110)
(g) Low housing quality characteristics	0.010	-0.040	-0.055	-0.047	0.030
	(0.017)	(0.028)	(0.055)	(0.071)	(0.083)
Number of Public Housing	-0.000	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(G) High density	0.013	0.002	-0.030	-0.074	-0.009
	(0.017)	(0.031)	(0.059)	(0.075)	(0.088)
(G) Short distance to municipality	0.008	-0.005	0.021	0.050	-0.037
	(0.014)	(0.026)	(0.049)	(0.063)	(0.074)
(G) Large distance to municipality	0.007	0.015	-0.038	-0.074	-0.138
	(0.023)	(0.040)	(0.079)	(0.108)	(0.128)
(G) Number of neighboring census tracts	0.003	0.000	0.004	0.007	0.002
	(0.004)	(0.007)	(0.012)	(0.016)	(0.020)
(G) % Households with married hh	-0.035	-0.034	-0.143*	-0.167	-0.121
	(0.026)	(0.051)	(0.085)	(0.110)	(0.132)
(G) % Households double-up	0.047	0.007	-0.214	-0.365*	-0.261
	(0.047)	(0.084)	(0.147)	(0.200)	(0.241)
(G) Fraction of apartments/units	0.015*	0.012	0.005	0.024	0.062
	(0.009)	(0.017)	(0.032)	(0.045)	(0.053)
(G) % Population migrant	-0.045	-0.039	0.089	0.142	0.010
	(0.034)	(0.072)	(0.148)	(0.191)	(0.225)
(G) % Population employed	0.024	0.008	-0.221	-0.097	-0.002
	(0.047)	(0.086)	(0.159)	(0.202)	(0.232)
(G) Average household size	0.028	-0.032	0.080	0.152	0.294
	(0.044)	(0.108)	(0.171)	(0.212)	(0.248)
(G) Average crowding	0.072	0.319*	0.527	0.584	0.565
	(0.100)	(0.184)	(0.349)	(0.454)	(0.562)
(G) Low housing quality characteristics	0.003	0.022	-0.003	0.002	0.007
	(0.017)	(0.031)	(0.059)	(0.076)	(0.088)
(G) % Population not moved since 2012	-0.015	0.003	0.089	0.152	0.090
	(0.023)	(0.041)	(0.076)	(0.101)	(0.113)
Constant	-0.735	-18.561	-0.224	26.712	28.881
	(6.738)	(12.640)	(22.279)	(29.039)	(34.578)
Observations	2,698	2,698	2,698	2,698	2,698
R-squared	0.982	0.977	0.954	0.932	0.924
Round FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
Previous Applicants	YES	YES	YES	YES	YES
F-test	0.816	1.427	1.354	1.574	2.446
p-value	0.753	0.060	0.092	0.023	0.000
Unique CTs	2698	2698	2698	2698	2698

Table A3: Balance Tests in Unmatched Sample

Number of voucher offers in g in t-s	(1) 2016	(2) 2017	(3) 2018-1	(4) 2018-2	(5) 2019
(g) % Households with married hh	0.192	0.321	-0.851	-0.705	-0.839
	(0.741)	(1.227)	(1.605)	(1.795)	(2.005)
(g) % Households with hh age 18-30	-41.897	-64.711	-74.769	-60.504	-73.996
	(27.965)	(44.281)	(59.111)	(64.160)	(71.439)
(g) % Households with hh age 30-35	-46.317*	-70.890	-82.545	-69.813	-84.746
	(27.872)	(44.132)	(58.905)	(63.959)	(71.246)
(g) % Households with hh age 36-60	-42.837	-65.571	-76.111	-62.657	-77.211
	(27.875)	(44.166)	(58.970)	(64.026)	(71.312)
(g) % Households with hh age 61 or older	-44.816	-68.943	-81.198	-67.969	-82.847
	(27.868)	(44.149)	(58.936)	(63.991)	(71.270)
(g) % Households with hh female	3.179***	5.839***	7.143***	8.071***	9.014***
	(0.756)	(1.234)	(1.631)	(1.795)	(2.005)
(g) % Households double-up	6.004***	9.217***	13.150***	14.310***	15.443***
	(0.873)	(1.411)	(1.849)	(2.023)	(2.229)
(g) % Households with single parent hh (tenants)	1.255	4.643**	8.282***	9.365***	10.534***
	(1.374)	(2.239)	(3.012)	(3.269)	(3.653)
(g) Fraction of apartments/units	-0.054	-0.908**	-1.361***	-1.506***	-1.765***
	(0.229)	(0.368)	(0.495)	(0.541)	(0.585)
(g) % Population migrant	0.012	0.589	1.574	2.446	3.344
	(0.674)	(1.128)	(1.590)	(1.772)	(2.069)
(g) % Population not moved since 2012	0.764	0.869	1.451	1.760	2.414*
	(0.488)	(0.815)	(1.103)	(1.199)	(1.335)
(g) % Population age 0-5	0.492	2.090	3.567	5.340	7.156
	(2.431)	(4.054)	(5.517)	(6.025)	(6.750)
(g) % Population age 6-17	1.340	0.096	1.671	2.467	3.786
	(1.714)	(2.856)	(3.797)	(4.169)	(4.651)
(g) % Population employed	4.501***	7.094***	8.664***	9.239***	10.982***
	(0.865)	(1.556)	(2.052)	(2.245)	(2.567)
Average years of education of adult population > 12	-0.574***	-0.919***	-1.191***	-1.302***	-1.346***
	(0.088)	(0.141)	(0.184)	(0.200)	(0.219)
(g) Average household size	-0.059	-0.057	-0.089	-0.135	-0.201
	(0.105)	(0.171)	(0.221)	(0.252)	(0.284)
(g) Low housing quality characteristics	0.024	0.067	0.004	-0.009	0.045
	(0.070)	(0.108)	(0.143)	(0.155)	(0.170)
Number of Public Housing	0.001***	0.002***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(G) High density	-0.480***	-0.934***	-1.348***	-1.417***	-1.580***
	(0.077)	(0.120)	(0.157)	(0.170)	(0.187)
(G) Short distance to municipality	-0.162***	-0.353***	-0.438***	-0.475***	-0.521***
	(0.062)	(0.095)	(0.124)	(0.136)	(0.149)
(G) Large distance to municipality	-0.402***	-0.650***	-0.800***	-0.831***	-0.908***
	(0.106)	(0.168)	(0.226)	(0.241)	(0.261)
(G) Number of neighboring census tracts	0.126***	0.239***	0.327***	0.363***	0.395***
	(0.016)	(0.025)	(0.032)	(0.035)	(0.039)
(G) % Households with married hh	-0.034	-0.053	-0.148	-0.223	-0.185
	(0.117)	(0.186)	(0.257)	(0.285)	(0.317)
(G) % Households double-up	0.024	-0.069	-0.286	-0.281	-0.123
	(0.187)	(0.291)	(0.390)	(0.424)	(0.467)
(G) Fraction of apartments/units	0.056	0.123*	0.089	0.054	0.061
	(0.045)	(0.067)	(0.087)	(0.094)	(0.103)
(G) % Population migrant	-0.331**	-0.279	-0.294	-0.219	-0.155
	(0.143)	(0.232)	(0.316)	(0.343)	(0.383)
(G) % Population employed	0.151	0.270	0.295	0.308	0.146
	(0.166)	(0.275)	(0.367)	(0.399)	(0.438)
(G) Average household size	0.582**	1.237***	1.611**	1.783**	1.888**
	(0.280)	(0.427)	(0.630)	(0.708)	(0.796)
(G) Average crowding	0.963**	1.369**	2.009**	2.276**	2.343**
	(0.419)	(0.659)	(0.876)	(0.955)	(1.062)
(G) Low housing quality characteristics	-0.217***	-0.261**	-0.270*	-0.323*	-0.378*
	(0.078)	(0.121)	(0.161)	(0.175)	(0.193)
(G) % Population not moved since 2012	-0.119	-0.137	-0.127	-0.157	-0.120
	(0.088)	(0.147)	(0.203)	(0.220)	(0.239)
Constant	37.147	55.798	64.376	49.498	62.052
	(27.838)	(44.114)	(58.917)	(63.943)	(71.207)
Observations	4,636	4,636	4,636	4,636	4,636
R-squared	0.386	0.455	0.483	0.487	0.495
Round FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
Previous Applicants	NO	NO	NO	NO	NO
F-test	30.66	34.43	38.02	39.36	40.69
p-value	0.000	0.000	0.000	0.000	0.000
Unique CTs	4636	4636	4636	4636	4636

Table A4: Spillover effect in census tracts with low residential mobility

VARIABLES	(1) All	(2) Low Mobility	(3) High Mobility
Number of Voucher Recipients in t-s in g	-0.373***	-0.385***	-0.377***
	(0.036)	(0.048)	(0.046)
Number of Voucher Recipients in t-s in g ^{2}	0.005***	0.005***	0.006***
	(0.001)	(0.002)	(0.001)
Number of Voucher Recipients in t-s in G	0.024***	0.025*	0.023*
	(0.009)	(0.013)	(0.013)
Number of Voucher Recipients in t-s in G ^{2}	-0.000**	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)
Constant	2.445***	2.701***	2.202***
	(0.074)	(0.120)	(0.086)
Observations	13,490	6,990	6,500
R-squared	0.635	0.639	0.629
Round FE	YES	YES	YES
Census Tract FE	YES	YES	YES
Previous Applicants	YES	YES	YES
Dependent Var Mean	1.855	1.986	1.713
Dependent Var SD	1.958	2.035	1.862
Unique CTs	2698	1398	1300

Figure A1: Score Distribution and Cutoffs

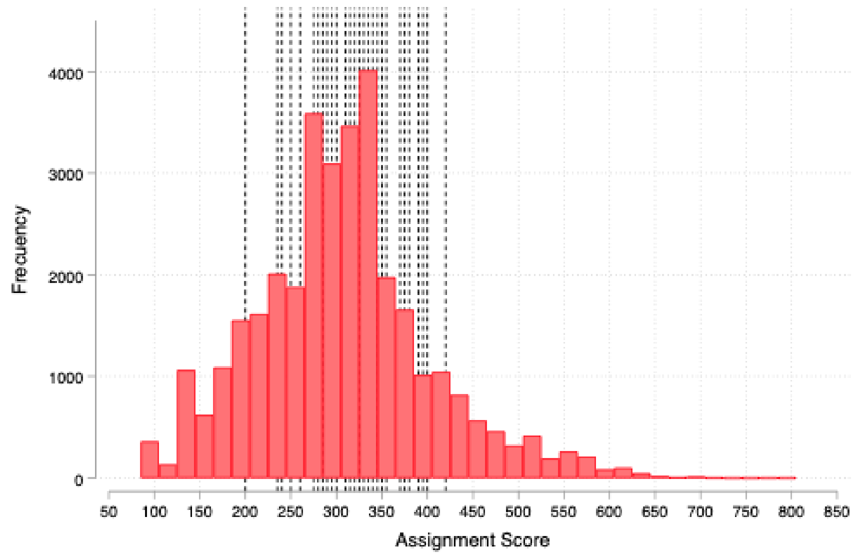


Figure A2: Distribution of previous voucher recipients by census tract per round

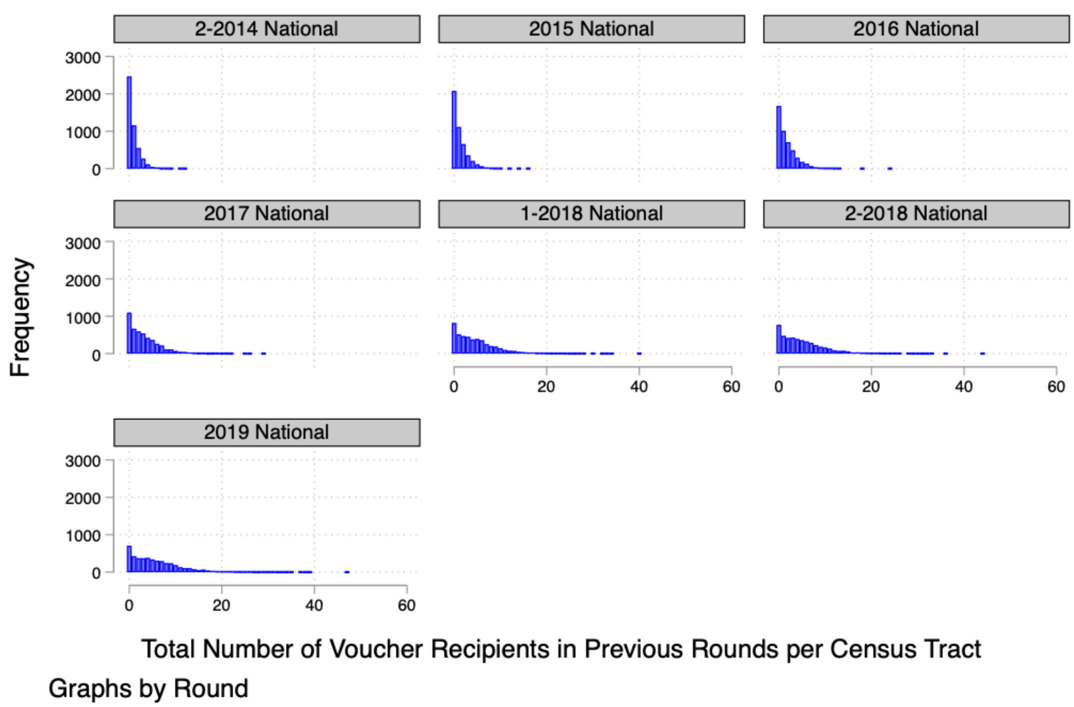


Figure A3: Number of applicants and number of voucher recipients per census tract per round

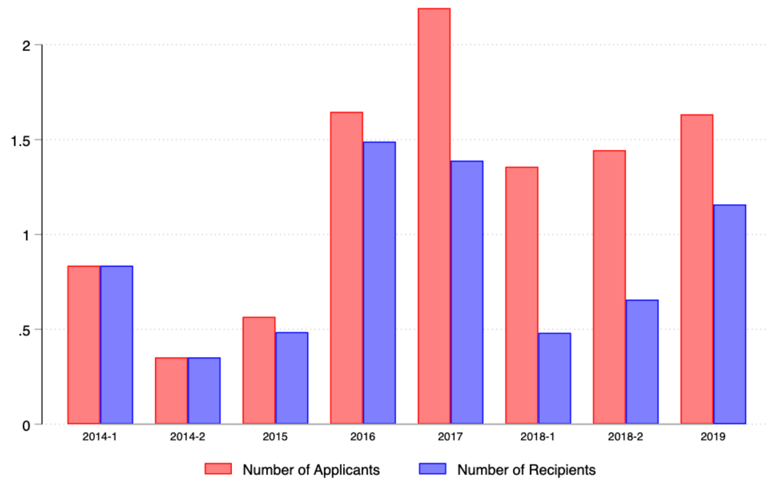


Figure A4: Successful voucher use (lease-up rate) per census tracts

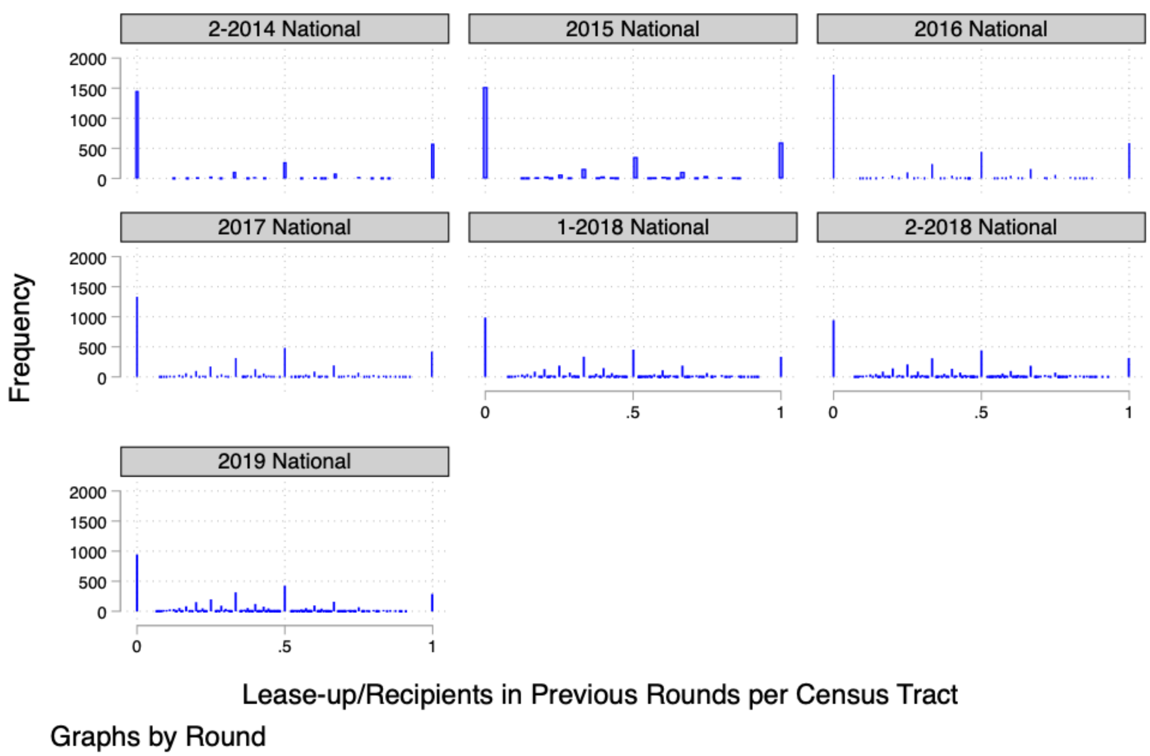
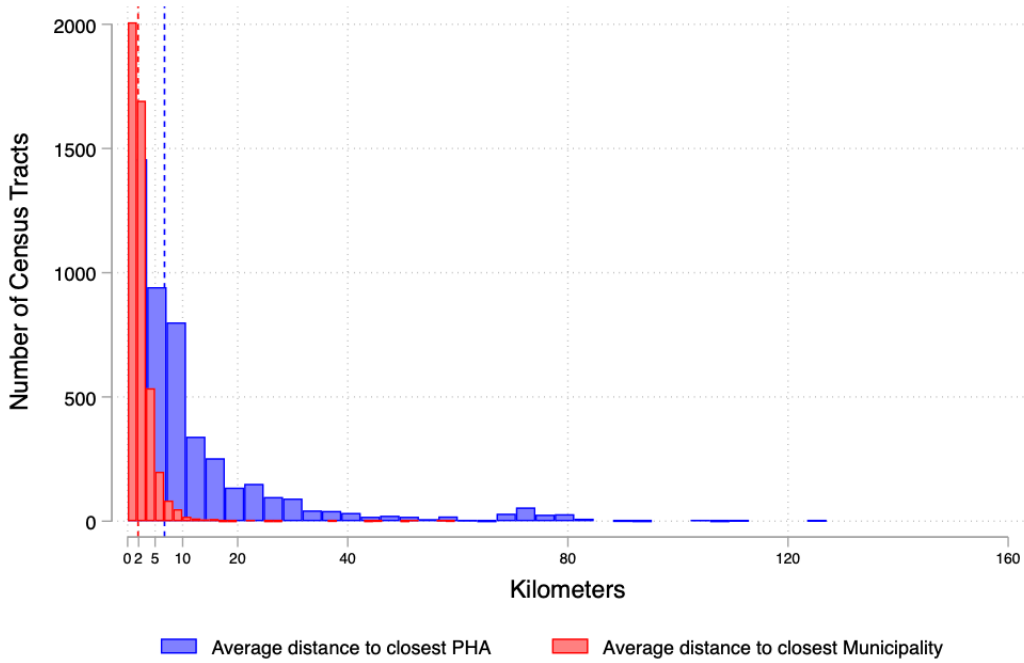


Figure A5: Distance to SERVIUs and Municipalities



A2 Propensity Score Matching

We implement a Propensity score matching to consider the non-random distribution of eligible population over the territory and analyze spatial variation in voucher recipients across comparable census tracts.

The propensity score represents the probability (Abadie & Imbens, 2016; Rosenbaum & Rubin, 1983):

$$p(X_g) = Pr(D_g = 1|X_g) \tag{A2.1}$$

Where treatment D in census tract g in round t is an indicator variable for having at least one applicant in the 2016 round, after the last reform to eligibility was implemented. In other words, for each census tract g with applicants in previous rounds ($D_g = 1$) we identify a group of comparable census tracts (based on their observed characteristics, X_g) with no previous applicants ($D_g = 0$).

Vector X_g includes dummy variables for county, population size, density, residential mobility, fraction of units that are a house, fraction of apartments, fraction of married population, average household head education, average household size, number of children (5, 6-18), fraction of women ages 18-30, number of single headed household with kids who live in rental housing, number of families doubling-up, average overcrowding, fraction of female headed household and ages 18-30, 30-35 and 36-60, average years of education of adult population, fraction of migrant population, distance to the closes municipality and local housing authority, and housing vulnerability (living in slums, or with no access to reliable water, or basic sanitation), presence of public housing, number of units, number of neighboring census tracts and number of applicants the elderly rental voucher program. We include some of these covariates at the neighboring census tract level. In particular, we consider those more closely related to the dimensions used by Minvu to calculate the application score upon which vouchers recipients are selected.[53].

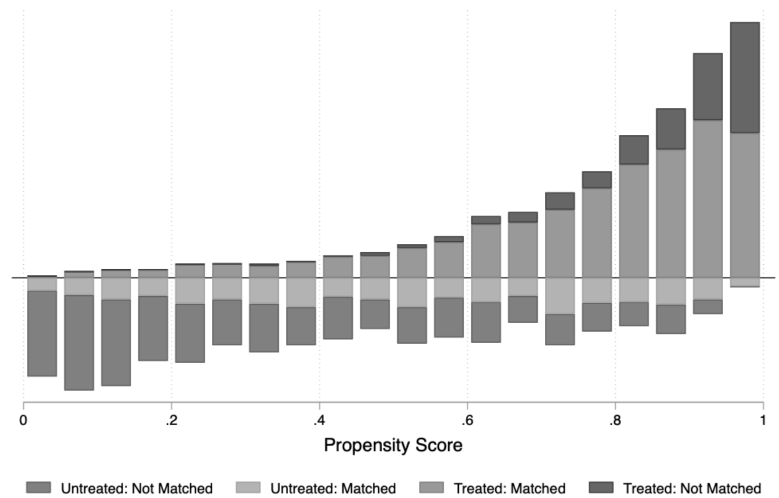
We use a one to one nearest matching using the stata command psmatch2. We select the two nearest neighbors and use a caliper of 0.05[54]

[53]Head of household characteristics and housing arrangements and vulnerability. See Table A2 for the full list of covariates included in the marching

[54]We use mahalanobis distance for household size (as it is the main application score component) and

Overall, 707 census tracts with applicants have no common support. Among the 3,701 census tracts on the common support, 2,698 are matched. Our model predicts treatment status correctly in 80% of the 2698 census tracts. Also, the difference in previous applicants between 2014 and 2015 is decreased by almost half in the matched sample, from 1.616 to 0.912. Figure A6 shows how all census tracts with different propensity score are included in the matched sample.

Figure A6: Propensity score matching of matched and unmatched census tracts



categorical covariates for density, province and number of previous applicants in neighboring census tracts.