Targeting and Price Pass-Through in Housing Voucher Design*

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November 17, 2025

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Housing vouchers are a common policy for expanding access to homeownership, yet their effectiveness is called into question due to concerns over subsidies increasing housing prices and being poorly targeted. I study the equilibrium and distributional effects homeownership vouchers through the case of Santiago's DS1 program, which subsidizes 7% of the city's transactions and is the largest such program in the OECD. I build an equilibrium model of a housing market with targeted and rationed homeownership vouchers. The model features endogenous voucher take-up and supply responses through existing unit sales and new construction. I estimate the model using novel data on voucher applications and usage, linked to the universe of real estate transactions and new development surveys. I evaluate the equilibrium impacts of the program relative to a scenario without the program, finding that it increases homeownership rates while raising prices. New development plays a significant role in dampening price inflation by increasing the supply of affordable units. Overall, I estimate that each dollar spent yields 61 cents in surplus. Although half of policy spending is transferred to beneficiaries, pecuniary externalities harm non-beneficiaries, reducing net consumer transfers to 25 cents per dollar spent. Counterfactual policies reveal a trade-off between targeting and price pass-through: policies that reduce price pass-through worsen targeting, as assistance goes to households more likely to become homeowners without the program.

*I am indebted to Giulia Brancaccio, Christopher Conlon, Christopher Neilson, and Daniel Waldinger for invaluable advice and support. I also thank Constanza Abuin, Claudia Allende, Mauricio Bauzá, Michael Dickstein, Jeff Gortmaker, Martin Rotemberg, Sebastián Otero, Paul Scott, Sharon Traiberman and participants of the NYU Applied Microeconomics, Econometrics, and IO workshops. I am grateful to Inciti and MINVU research department for sharing key datasets and providing institutional knowledge that made this project possible. I gratefully acknowledge financial support from Microsoft Research PhD Fellowship. All errors are my own.

1. Introduction

Governments worldwide subsidize homeownership to expand ownership rates; every OECD country does so, with the US spending $243 billion annually in tax deductions alone.[1] Yet the effectiveness of these policies remains unclear for at least two reasons. First, subsidies may pass through to prices, reducing assistance value while harming non-beneficiaries (Hilber and Schöni, 2022). Second, poorly targeted programs may transfer resources to households who would purchase without assistance (Glaeser and Shapiro, 2003). Policymakers face a trade-off between targeting disadvantaged households and reducing price pass-through: because preferences for housing and neighborhood attributes correlate with socioeconomic status, improving targeting concentrates subsidized demand in specific segments, amplifying price pressures (Bayer et al., 2007; Piazzesi and Schneider, 2016).

This paper empirically examines the equilibrium and distributional effects of large-scale homeownership vouchers, and quantifies the trade-off between targeting and price pass-through in subsidy design. Two features of housing markets have long hindered understanding these effects. First, supply responses to vouchers operate through both sales from existing housing stock and new development. Quantifying supply incidence across housing segments requires data and a framework to disentangle responses from each channel. Second, housing vouchers are often rationed, with their targeting resulting from both households' application decisions and governments' assignment rules. Evaluating alternative voucher policies requires understanding not only how subsidies distort beneficiaries' choices, but also who takes up assistance and the pecuniary externalities they induce in the housing market (Akerlof, 1978).

To address these challenges, I build an equilibrium model of a city's housing market with targeted and rationed vouchers, featuring endogenous voucher take-up and supply responses through existing unit sales and new construction. I estimate the model using novel administrative data from Chile's DS1 homeownership voucher program—the OECD's largest and oldest such program—linking voucher applications and usage to the universe of real estate transactions and new development surveys in Santiago. The estimated model yields preferences and supply elasticities for housing segments defined by neighborhood and physical characteristics. Relative to a counterfactual without the program, DS1 vouchers increase homeownership and new development but also raise housing prices, with an estimated Marginal Value of Public Funds (MVPF) of 0.61. While half of policy spending transfers to beneficiaries, pecuniary externalities harm non-beneficiaries, reducing net consumer transfers to 25 cents per dollar spent. Sellers capture 35% of policy spending, with gains concentrated almost entirely among resale unit owners rather than developers. In counterfactual simulations, I find that alternative

[1] Despite diverse justifications—externalities, credit market failures, redistribution—their common goal is expanding homeownership. See Sodini et al. (2023) and the references therein for a review of empirical evidence on homeownership effects.

OECD countries typically employ multiple subsidy types simultaneously: of 38 members, 23 use vouchers or grants, 33 offer subsidized mortgages, and 31 provide tax benefits (OECD, 2023). The US figure excludes federal mortgage guarantees ($1.5 trillion annually via FHA, VA, and GSEs) and state/local homeownership programs (Congressional Budget Office, 2022).

policies that reduce price pass-through come at the cost of worsening targeting as assistance is taken up by higher-SES and inframarginal households.

Santiago's DS1 program offers several advantages for studying the equilibrium effects of homeownership vouchers. Established in 2011, DS1 consolidated all subsidies for private-market housing purchases into a single, centrally-managed system. The program subsidizes 7% of Santiago's transactions through a menu of means-tested vouchers providing discounts on eligible units—those priced below voucher-specific caps. Eligible households decide whether and which voucher to apply for, with available vouchers rationed by priority scores. More generous vouchers impose tighter price caps and are reserved for lower-SES households; these have higher cutoff scores and often require multiple applications to win. Transparent allocation rules and data on voucher applications enable tractable modeling of voucher application and allocation. Two major reforms—a new voucher type in 2013 and increases in generosity and price caps in 2016—shifted both application incentives and voucher use patterns. These reforms, combined with temporal variation in total vouchers awarded and their distribution across types, generate variation in the composition and size of subsidized demand as well as the exposure of housing segments to the policy. I exploit this variation for descriptive analysis that informs modeling choices and as identifying variation for demand and supply parameters.

I begin by documenting three facts about DS1 and Santiago's housing market. First, voucher use concentrates in lower-SES neighborhoods on the city's periphery and in resale houses, despite broader unit eligibility. This concentration reflects two factors: beneficiaries tend to purchase in their origin neighborhoods—half buy within their home county—and demographic sorting patterns. Large families prioritized by the program purchase small resale houses on the periphery, while younger, childless recipients buy newly developed apartments in more central locations.[2] Second, exploiting spatial and temporal variation in voucher concentration across segments, I show that greater exposure to subsidized demand correlates with higher housing prices and increased new development. Finally, voucher design changes—increased generosity and relaxed price caps—affect both recipient choices and applicant composition. More generous vouchers lead recipients to choose larger houses in higher-SES neighborhoods while simultaneously attracting higher-SES applicants, changing the composition of subsidized demand. This evidence, though not causal, suggests that voucher take-up and its distortionary effects respond to design features, thereby affecting the policy's impact across housing segments.

Motivated by these facts, I build a model of housing supply and demand with rationed homeownership vouchers. The housing market is competitive and segmented, with discrete housing types—defined by location and physical characteristics (size, apartment/house, new/resale)—traded each period at equilibrium prices and quantities. Demand comes from both subsidized and unsubsidized households deciding whether and which housing type to purchase. Household preferences vary by demographics (income, age, family composition, location) and unobserved components

[2] In Chile, "comunas" (translated here as counties) are administrative divisions similar to municipalities or boroughs in the US. Santiago comprises 43 counties, each with its own local governments.

capturing price sensitivity and homeownership value. Eligible households first decide whether and which voucher to apply for, weighing purchase delays and choice restrictions against price discounts. The rationing mechanism and application distribution jointly determine equilibrium cutoff scores that allocate vouchers. Vouchers distort choices through both price discounts and caps for beneficiaries, while pecuniary externalities affect non-beneficiaries' choices.

The supply of each housing type comes from the stock of unit owners deciding whether to sell. For new housing types, forward-looking, price-taking developers set the stock by optimally choosing construction quantities each period given heterogeneous construction costs and the value of a new unit. Once built, new units solve an inventory management problem: deciding whether to sell at market price or hold for future sale while paying maintenance costs. This creates two supply margins responsive to subsidized demand. First, inventory owners adjust selling decisions based on current or anticipated subsidized demand—for instance, responding to changes in total vouchers awarded over time. Second, developers adjust construction based on types' exposure to subsidized demand—responding to permanent shifts such as policy elimination. The stock of resale housing types consists of owner-occupied units whose owners make myopic decisions between selling and continuing occupancy, with heterogeneous occupancy values across types. Consequently, resale supply is static but exhibits heterogeneous price elasticities—family houses may be less elastic than studio apartments.

In equilibrium, housing market outcomes and voucher allocations are jointly determined. Housing prices clear the housing market, determining transaction and development quantities for each type. Voucher cutoff scores clear voucher assignment, determining recipients and wait times for each voucher. The effects of voucher policies are determined in equilibrium by the interaction of household preferences and supply elasticities across housing types.

To recover the distribution of preferences for housing types, I jointly estimate the housing and voucher choice models via Maximum Likelihood. Although vouchers provide variation in housing prices and choice sets, the fact that subsidized households are selected on preferences precludes the use of off-the-shelf estimation methods. I build methods combining microdata on observed choices with macrodata on market shares to estimate discrete choice demand models via MLE (Goolsbee and Petrin, 2004; Grieco et al., 2025), to account for the endogeneity of voucher status exploiting the voucher application model.[3] Several sources of policy variation provide identifying variation. Discontinuities in eligibility and scoring rules generate within-market variation in vouchers available for households that are orthogonal to their housing preferences, updates to these rules and voucher supply over time generates variation across markets. As I account for selection into vouchers, voucher status provides variation in prices and choice sets that identifies price sensitivity parameters (McFadden, 1972). On top of that, government updates to voucher features are applied to all recipients that have not yet used their vouchers, providing quasi-experimental variation in the prices and choice sets of voucher

[3] In practice, I face an extra identification challenge as my microdata consist of voucher applicants and recipients making it a selected sample. I account for this in estimation, accounting for both dimensions of selection.

recipients across time.

Estimation of new housing supply proceeds in two-steps. First, I exploit the finite dependence of the inventory problem to obtain a linear estimating equation relating the differences in the share of units selling across periods to differences in equilibrium prices and maintenance costs (Hotz and Miller, 1993; Arcidiacono and Miller, 2011; Scott, 2014). Both the sell shares and prices are observed from the new development survey and transaction data, however, maintenance costs have an unobserved component. With the estimated parameters, I can recover the value of a new unit for each type and market. Second, I estimate development cost parameters using developers' first-order conditions and recovered unit values, the unobserved component of development costs captures, for instance, differences in the difficulty to obtain land and construction permits for different types of new housing. For resale housing types, the logit structure of owners' problems permits direct IV logit estimation. All specifications face endogeneity from correlation between unobserved costs and equilibrium prices. The DS1 program generates quasi-experimental variation in housing type exposure: voucher quantities vary over time, while beneficiary locations and price caps concentrate demand in specific neighborhoods. However, approaches exploiting this variation through treatment categories, such as shift-share instruments, are invalid due to within-city demand substitution violating SUTVA (Alves et al., 2023). I construct instruments using the estimated demand model to capture policy-induced demand changes for each housing type while incorporating substitution effects.

I use the estimated model to evaluate alternative voucher designs' effects on housing prices and supply, as well as their distributional consequences across households. In the first set of counterfactuals, I evaluate the equilibrium effects of the DS1 program by comparing to a baseline without the program. Overall, the policy increases housing prices by 1.5%, new development by 0.9%, and homeownership rates by 1.2%, with an MVPF of 0.61. The policy increases ownership rates in beneficiaries by 30% and transfers around half of the policy cost to beneficiaries. The price inflation is localized in affordable resale segments, where voucher use concentrates. New development plays a crucial role at dampening price inflation, reacting to both increases in demand due to voucher use but also capturing demand from non-beneficiaries substituting away from resale units. However, the policy significantly harms non-beneficiaries who lose 25 cents in consumer surplus for each dollar of subsidy spent. This is not a progressive transfer, as the losses are mostly borne by low income households that are unsubsidized. This might seem puzzling, as only 10% of the population receives vouchers, with the number of poor households unsubsidized still larger than the subsidized. The reason of the net positive effects on homeownership rates and consumer surplus is due to the policy allocating vouchers to extramarginal households that would not have purchased without the program. Harmed low-SES households are more likely to become homeowners without the program than the ones targeted.

In the second set of counterfactuals, I evaluate alternative budget-balanced policy designs. First, I simulate an All-High and All-Low policy where the entire DS1 budget is allocated to the most generous and most restrictive voucher, or to the least generous, least restrictive, and least targeted voucher. Allocating everything to the High voucher mechanically improves targeting due to the means-testing, but concentrates the demand into housing segments below the price cap and that are preferred by the poorest households. The opposite is true for the All-Low policy, where targeting is worse but the policy is less concentrated, both by the higher price cap and by being attractive to a broader range of households. I find that these policies are dominated by the DS1 policy, highlighting the gains from offering a menu of alternatives to screen households. While the most targeted, the All-High policy has lower impacts on homeownership rates, due to its high price pass-through so both beneficiaries and non-beneficiaries are less likely to become homeowners relative to the DS1 policy. The All-Low policy has a lower price pass-through than the DS1 policy, but lower overall impacts on homeownership rates as it ends up targeting inframarginal households. Notably, low-income households reduce their application rates relative to the DS1 policy, since the benefit is insufficient, so richer households end up getting vouchers.

Finally, motivated by the findings on new housing types being more elastic due to the response of developers, I evaluate a policy that replicates the DS1 voucher menu but only allows new housing units to be purchased. I find that this policy has lower price pass-through, higher impacts on new development, and almost negligible effects on the homeownership rates of non-beneficiaries. However, this comes at the cost of dramatically changing the composition of beneficiaries, with younger, smaller, and slightly richer households receiving assistance. Interestingly, the losers of the policy are the poorer, older, and larger households who lost their vouchers relative to the DS1 policy. However, the non-beneficiaries under the DS1 policy benefit from this policy change.

Contribution. This paper's main contribution is to the literature studying the design and equilibrium effects of housing assistance programs; including how program rules affect targeting and beneficiary outcomes (Van Dijk, 2019; Waldinger, 2021; Cook et al., 2023; Lee et al., 2023), as well as its impact on the housing market and welfare (Hanson, 2012; Hilber and Turner, 2014; Sommer and Sullivan, 2018; Diamond et al., 2019; Diamond and McQuade, 2019; Gruber et al., 2021; Bishop et al., 2023). I focus on the design of large-scale homeownership vouchers, where both voucher take-up and supply-side responses are endogenous. Most studies on the impact of voucher design changes treat either recipient composition or supply as fixed (Galiani et al., 2015; Chetty et al., 2016; Collinson and Ganong, 2018; Bergman et al., 2024), limiting their ability to evaluate the consequences of scaling or redesigning programs (Kline and Walters, 2016; Walters, 2018). Meanwhile, studies on the equilibrium impacts of assistance on housing markets typically treat both program features and targeting as exogenous (Susin, 2002; Eriksen and Ross, 2015; Davis et al., 2021; Soltas, 2023). I bridge these literatures by endogenizing both voucher take-up and supply-side responses, and quantitatively showing the relevance of both for the design of large-scale homeownership vouchers.

More broadly, this paper contributes to the literature on the equilibrium effects and design of voucher policies in high-stakes settings such as education (Neilson, 2013; Armona and Cao, 2023; Sanchez, 2023; Bodéré, 2023) and health (Einav et al., 2019; Finkelstein et al., 2019; Decarolis et al., 2020; Tebaldi, 2025). In particular, to the strand of the literature quantitatively measuring the relevance of *tagging* for the effectiveness of such programs (Dobbin et al., 2021; Polyakova and Ryan, 2023), which has focused in the costs and benefits of assigning subsidies to certain demographic groups when firms' strategic responses are considered. I study tagging effects in a new setting, where the composition of beneficiaries is endogenous and the cost of targeting certain groups comes from how they concentrate the subsidy shock across market segments. I show that *tagging* effects are quantitatively relevant even with a competitive supply.

Second, this paper contributes to the literature on the determinants of housing supply in segmented housing markets (Saiz, 2010; Piazzesi and Schneider, 2016; Calder-Wang, 2021; Abramson, 2021; Baum-Snow and Han, 2024; Almagro and Domínguez-Iino, 2024; Mabille et al., 2024). The main contribution is to provide a unified analysis of both housing flows (transactions) and stock (new construction), as the literature typically focuses on one or the other. My empirical results highlight the relevance of both unit characteristics and location when defining housing segments; I find that the former are more important than the latter for the heterogeneity in supply elasticities within a city. More broadly, my results highlight the relevance of understanding supply determinants and heterogeneity when evaluating demand-side housing policies.

Third, I build on the literature estimating housing demand using discrete choice models (Bayer et al., 2007; Calder-Wang, 2021; Almagro and Domínguez-Iino, 2024), and more broadly, on studies using microdata and exploiting individual-level variation in prices or choice sets to identify demand parameters (Berry and Pakes, 2007; Bundorf et al., 2012; Neilson, 2013; Bodéré, 2023; Berry and Haile, 2024; Tebaldi, 2025). I provide a simple model-based approach to exploit the identifying variation induced by subsidies by jointly estimating selection and demand models in a challenging setting. First, individuals select into subsidies based on preferences, making the variation unexploitable with standard methods (Nevo, 2001; Petrin, 2002; Berry et al., 2004; Conlon and Gortmaker, 2025; Grieco et al., 2025). Second, microdata is only available for subsidized households, precluding non-parametric selection correction methods (Heckman and Robb, 1985; Imbens and Newey, 2009; Agarwal, 2015). As governments are making data on assistance programs increasingly available, and data on non-treated households is often limited, this approach may be useful for applied work.

Finally, my results provide empirical support for the relevance of the trade-offs studied in the theoretical literature on the design of assistance programs under imperfect information (Nichols and Zeckhauser, 1982; Akerlof, 1978; Dworczak et al., 2021; Yang et al., 2023; Akbarpour et al., 2024; Banerjee et al., 2024). While motivated by this literature, I do not aim to characterize the optimal voucher design and instead evaluate simple, policy-relevant reforms. One of the main reasons for this choice is the lack of tractable theoretical results for the design of assistance. In particular, direct revelation mechanisms are not feasible to allocating housing vouchers due to the high dimensionality of housing preferences, which highlights the need for theoretical results on the implementation of the optimal mechanisms.

The rest of the paper is organized as follows. Section 2 describes the DS1 program and the datasets used in the analysis. Section 3 presents descriptive facts that motivate the model of voucher application, housing demand and supply presented in Section 4. Section 5 describes the estimation procedure used to recover the parameters governing supply and demand, and discusses the results. Section 6 evaluates the equilibrium effects of the DS1 program and Section 7 evaluates alternative policy designs. Section 8 concludes.

2. Background and Data

This section describes data sources, construction, and key institutional features of the DS1 program. Detailed descriptions of the institutional setting and data construction are provided in Appendix H and Appendix B.

Chilean Housing Assistance System. Chile has one of the world's oldest and largest homeownership assistance systems, becoming the first country to implement homeownership vouchers in 1977. The policy influenced global homeownership assistance as international development institutions promoted vouchers as cost-effective alternatives to public housing during the 1990s and 2000s.[4] As of 2023, Chile ranks second in OECD homeownership assistance spending and leads in voucher spending as GDP share (OECD, 2023).

> *"[Chile's homeownership voucher program features] a clearly defined and sustainable progressive subsidy policy [for] well-defined target groups; an easily understood and impartial system for beneficiary selection; [and] increased participation of private sector construction entities."* —Persaud (1991), World Bank

DS1 Voucher Program. I focus on the Integrated Housing Subsidy System (DS1), a nationwide program offering targeted and rationed vouchers subsidizing downpayments for first-time homebuyers. Vouchers vary in generosity and restrict beneficiaries to purchasing private-market housing below price caps, with subsidy amounts contingent on unit price. Means-tested households apply for one preferred voucher during application calls, with limited vouchers rationed via priority scores. The Ministry of Housing and Urbanism (MHU) tailors DS1 design and budget regionally, making voucher allocation independent across regions.

Empirical Setting. I study Santiago's homeownership market from 2012 to 2018. Santiago houses 40% of Chile's population and 80% of the Metropolitan Region's (MR) residents. DS1 is the only large-scale program subsidizing private-market housing purchases in Santiago during this period, with MHU allocating most of DS1's national budget to the MR.[5] Santiago is the only large city in the MR, concentrating 94% of regional voucher usage within its boundaries.

[4] See (World Bank, 1993, 2000; Rojas and Greene, 1995; Ferguson et al., 1996; Rojas, 1999; Gilbert, 2001, 2004) for detailed history of the Chilean Housing Assistance System and its global influence.

[5] Nationally, DS1 allows three uses: purchasing market units, purchasing publicly sponsored units, or self-building, through individual or collective applications. In the MR, DS1 is restricted to individual applications for market purchases due to high land costs making other versions unfeasible. The DS49, Santiago's other homeownership subsidy, serves almost exclusively slum communities through collective applications for below-market publicly sponsored developments, unlike other regions where it substitutes for DS1. Other programs were small-scale and introduced late in the study period. See Appendix H for details.

2.1 Data Sources and Sample Definition

Voucher Application and Use. The MHU provided household-level panel data on DS1 applications and use from 2011 to 2022. For each application, I observe household identifiers, voucher choice, score components, and demographics including income, household composition, age, and county of residence. For awarded vouchers, I observe purchase decisions and unit characteristics: price, size, structure type (house or apartment), vintage (new or resale), and county. I track program changes through legal updates and official MHU announcements.

Real Estate Transactions and Stock. A real estate research firm provided the universe of transactions and stock data for Santiago from 2012 to 2019. Transactions include price, date, address, vintage, and buyer and seller names. Stock data include each unit's address, size, structure type, and construction year. I match DS1 voucher use to transactions to recover units' precise location.[6]

New Development Survey. The firm also provided their new development survey, covering nearly all developments in the study period. For each development, I observe address, construction dates (beginning and completion), and sales dates (beginning and sold out). Units within developments are classified by type based on size, rooms, bathrooms, and features. Biannual surveys report stock of each unit type until sold out. I match transactions to developments and unit types using address and unit characteristics.

Household Population and Neighborhoods. I use 2017 Chilean Census tracts as the most granular neighborhood definition. I use 2011, 2013, 2015, and 2017 National Household Survey (CASEN) editions to obtain household demographics across MR counties and time.[7] Throughout, I restrict analysis to demographics available in both CASEN and DS1 data.

Predicted DS1 Eligibility and Scores. I predict DS1 eligibility and priority scores for each CASEN household, representing the unsubsidized population. Main DS1 eligibility requirements and priority score components are observed in CASEN (e.g., income thresholds). For remaining components, I use Random Forest trained on DS1 applicants accounting for rule changes over time. Potential selection bias is mitigated because unobserved components are largely functions of demographics (e.g., ocupation) that are highly correlated with observables (e.g., income, age, composition, location). The process hinges on institutional details deferred to Appendix B. I treat predictions for each CASEN household as data.

Sample Definition. I restrict analysis to Santiago housing transactions from 2012 to 2018 and DS1 regular calls for individual households, comprising 99.3% of MR vouchers. The applicant sample includes all study period DS1 applicants. The voucher use sample additionally includes pre-period

[6] Transaction data comes from the Conservador de Bienes Raíces (CBR), Chile's real estate registry. While CBR records are public, they lack structured format; the firm digitizes records from each Santiago CBR office. Stock data comes from the Servicio de Impuestos Internos (SII), Chile's tax authority. I match 99.9% of DS1 voucher uses to unique transactions using fuzzy matching on price, unit characteristics, transaction dates, and beneficiary names from MHU winner announcements.

[7] The main limitation is unobserved census tract location for households, a limitation shared with voucher data.

winners who purchased during 2012-2018.[8] I define household population as CASEN households residing in the MR, as 99.1% of DS1 applicants live there despite nationwide eligibility.

2.2 The DS1 homeownership voucher menu

This section describes the DS1 program; I focus on main institutional features and policy variation leveraged for reduced-form and structural estimation. I aggregate DS1 menu design and application calls into half-years.[9] All prices are in Unidad de Fomento (UF), Chile's inflation-indexed currency standard for real estate and mortgage markets, used by MHU for voucher rules. UF$1,000 equals approximately USD$41,000 in 2025.

Voucher Generosity and Choice Restrictions. Vouchers provide decreasing discounts on housing purchases below a price cap. Recipients have 21 months to purchase eligible units.[10] The menu comprises three voucher types labeled by generosity: High, Medium, and Low.[11] Figure 1 shows that as of 2017, High vouchers subsidize 50%–100% of unit price, Medium 20%–70%, and Low 5%–70%. Over the study period, these vouchers subsidize 78.0%, 50.5%, and 16.9% of unit price on average (Table A.1). The decreasing schedules reflect MHU's premise that households purchasing lower-priced units have greater need; observed purchase dispersion across price ranges confirms beneficiaries make meaningful trade-offs between subsidy generosity and housing quality.

Higher generosity vouchers impose tighter price caps: As of 2017, High at UF$1,000, Medium at UF$1,400, and Low at UF$2,200. These caps' restrictiveness depends on market prices—across the study period, only 11.7% of Santiago transactions qualify for High vouchers, 27.4% for Medium, and 53.5% for Low. Spikes in purchase distributions at these price caps (Figure 1) suggest they are binding for some beneficiaries. The design thus serves dual roles: screening households who value subsidies over choice flexibility while simultaneously distorting beneficiary decisions through altered relative prices (decreasing schedules) and constrained choice sets.

Design Updates. MHU implemented two major updates during the study period. In 2014, High vouchers were introduced to improve targeting, matching Medium generosity while imposing stricter price caps (UF$500) and requiring mortgage-free purchases—MHU viewed households accepting these restrictions as having greater need. The 2016 update increased all price caps and generosity to offset housing inflation, notably converting High vouchers to flat UF$500 subsidies with UF$1,000 caps.

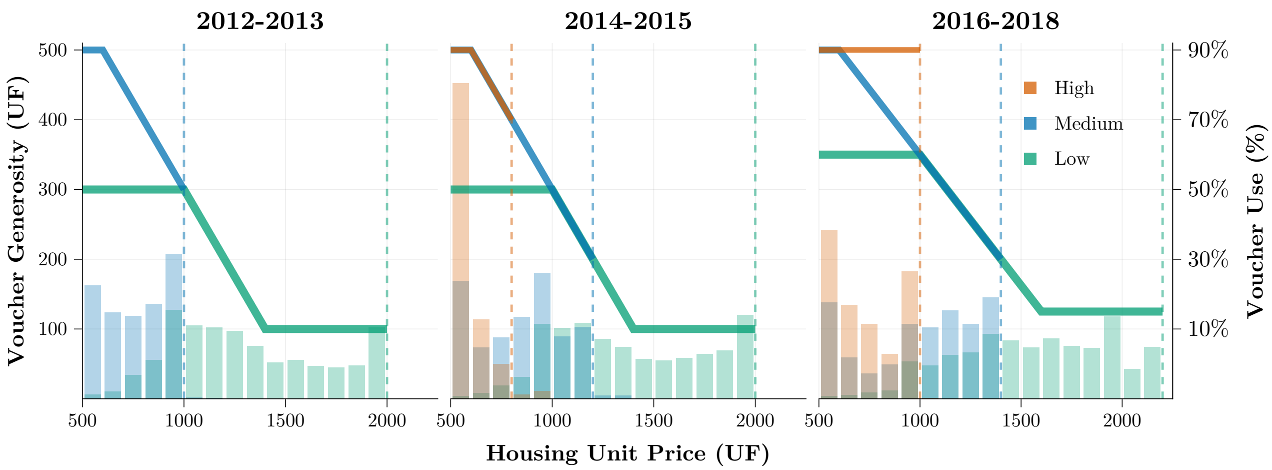
[8] DS1 was implemented in 2011 but excluded as transaction and development survey data begin in 2012. While data extend to 2022, I restrict to 2018 because the housing market and voucher program were disrupted by October 2019 social protests and COVID-19. Including these years would require ad-hoc adjustments without substantial value added.

[9] The aggregation is minimal as DS1 follows a biannual pattern for most of the study period, with calls each half-year and awards in the following period. When multiple calls occur within a half-year or winners are announced in the same period, I pool calls and assume awards occur in the following half-year. Table A.10 provides details.

[10] Units must be approved by the Servicio de Vivienda y Urbanismo (SERVIU), be in good condition, and not owned by relatives. In Santiago, nearly all legal units except slum housing meet these requirements. Beneficiaries cannot sell purchased units for 5 years.

[11] MHU labels vary over time; these correspond to Title I Segment I, Title I Segment II, and Title II for most of the study period.

Figure 1: DS1 Voucher Generosity, Price Caps, and Voucher Use Price Distribution



Notes: Plotted functions correspond to the the discount schedules (solid lines, left y-axis) and price caps (dashed lines) by voucher accross the three main DS1 designs. The histogram bars show the distribution of voucher use (right y-axis) by voucher and DS1 design. Sample used in the Figure corresponds to all voucher purchases in the study period. Table A.9 provides details

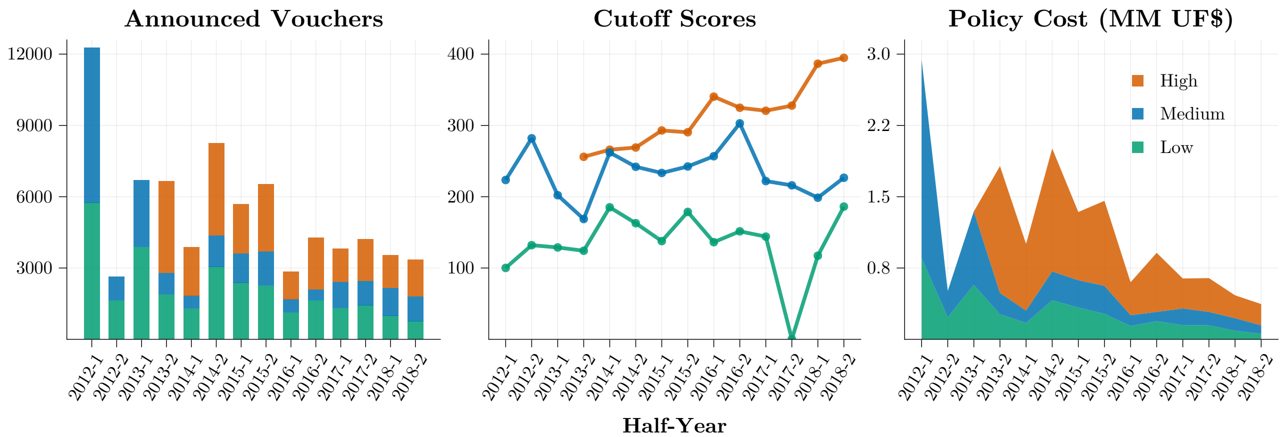
These updates apply retroactively to both future beneficiaries and current unused voucher holders, providing quasi-experimental variation exploited in reduced-form analysis and model estimation.

Voucher Supply and Rationing. Each half-year, MHU announces voucher quantities by type and opens applications. Eligible households apply for a single voucher; available vouchers are rationed by priority scores—generating endogenous cutoff scores determined by the distribution of applications and voucher supply. Figure 2 shows substantial variation in voucher supply. Total annual vouchers fell from 15,000 in 2012 to 6,000 in 2018, while composition shifted: Low vouchers decreased from half to under one-third of awards as MHU reallocated resources toward High vouchers. Despite these supply shifts, cutoff scores consistently rank High > Medium > Low, suggesting systematic sorting of applicants across voucher types. Two forces drive this variation: Congress nearly halved the annual budget, while MHU prioritized more generous vouchers that cost more per recipient. This generates variation along two margins—the voucher demand shock varies through both total quantities and mix across types, and supply-side shifts of equilibrium cutoff scores.

3. Descriptive Evidence

This section presents descriptive evidence of the DS01 voucher menu and its interaction with the housing market. I document three main facts that will guide the empirical model. First, I show that voucher use is concentrated in the product and geographic space, informing how I micro-found households's preferences for housing. Second, both voucher use and applications react to DS1 design updates, motivating how I model households' self-selection into vouchers. Finally, I document the large scale of the DS1 program and significant heterogeneity in exposure across housing segments, which I

Figure 2: Voucher Supply, Cutoff Scores, and Policy Cost



Notes: Calls are aggregated to half-years, see Table A.10 for details. Total announced vouchers correspond to the sum of vouchers announced in each half-year. Cutoff scores correspond to the minimum cutoff score by voucher type and half-year. The policy cost corresponds to the total transfers to voucher winners of each call. UF$ 1MM = USD$ 41.2MM in 2025.

exploit to show that voucher introduction correlates both with higher prices and new development. This motivates a segmented housing supply-side model where voucher system has heterogeneous incidence, and where developers' reactions need to be taken into account.

3.1 Voucher Use is Concentrated Across Housing Segments

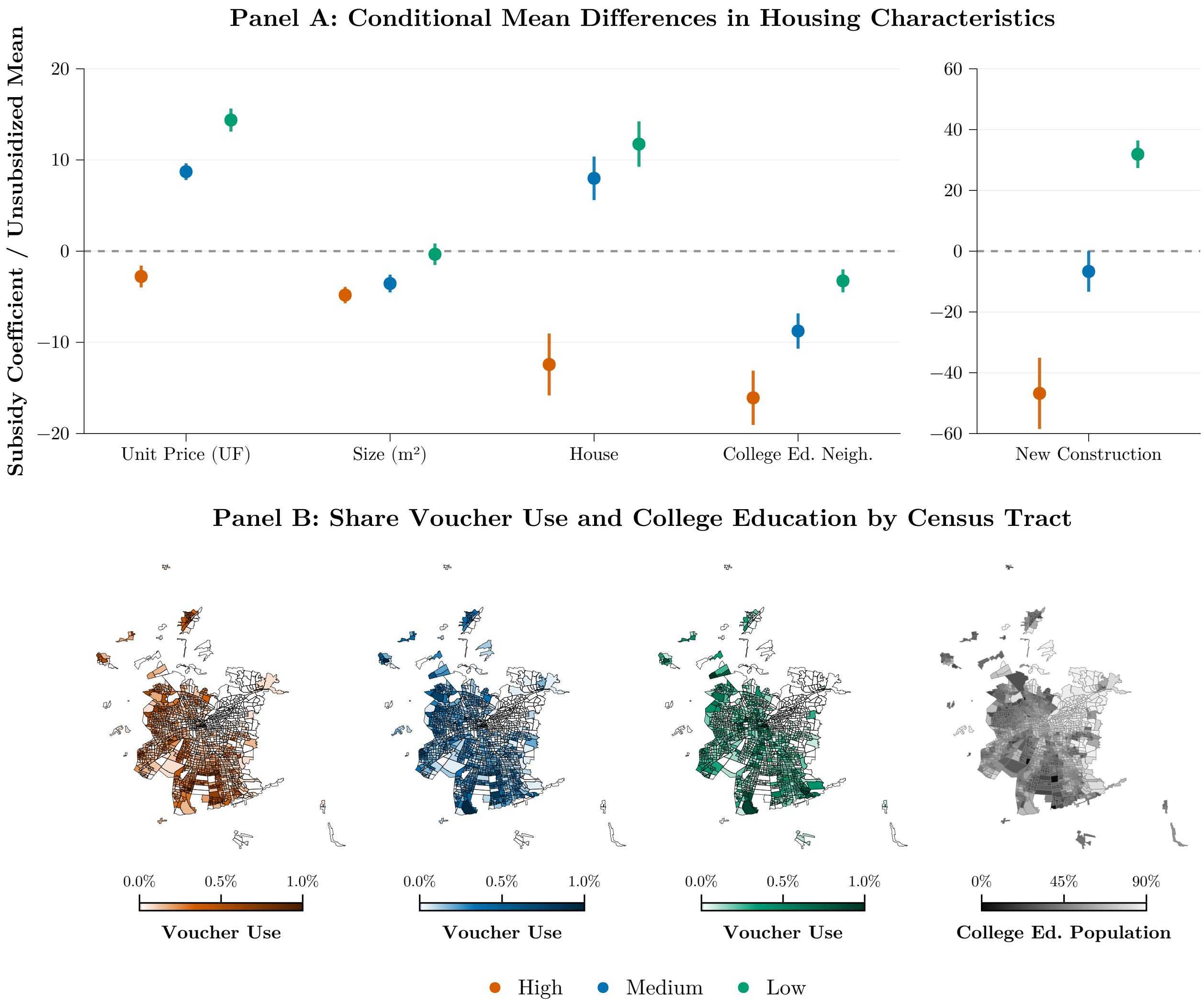
Scale of DS1 Program. DS1 operates at substantial scale in Santiago's housing market. Table A.1 shows the program subsidizes 21% of eligible High voucher transactions, 10% of Medium, and 7% of Low, representing 6.5% of all transactions in the City.

Low Use and Residential Mobility Rates. Despite substantial subsidies, 40% of beneficiaries let vouchers expire—similar rates across types rule out choice restrictions as primary explanation. Among users, approximately half purchase in their residence county, suggesting strong location preferences. These patterns have two key modeling implications: households make sequential rather than simultaneous application and purchase decisions, and strong heterogeneous preferences for housing characteristics and homeownership value lead some to prefer rental over unsuitable ownership despite large subsidies.

Panel B of Table A.1 compares average characteristics across subsidized and unsubsidized eligible transactions by voucher type. Since housing attributes are jointly distributed, raw comparisons can be misleading. I therefore regress each housing attribute on a subsidy indicator while controlling for all other attributes and county-by-time fixed effects, estimating separately by voucher type using only eligible transactions. The subsidy indicator coefficient captures conditional mean differences between subsidized and unsubsidized distributions. For instance, a positive coefficient when house is the outcome indicates subsidized transactions are more likely to be houses than apartments, conditional on price, location, and other physical attributes. Table A.2 reports full results; Panel A of Figure 3 plots estimates relative to the mean of unsubsidized eligible transactions.

Price Concentration Differs Across Vouchers. Transaction prices reflect two opposing forces from the DS1 design: subsidies reduce beneficiaries' price sensitivity, incentivizing more expensive purchases, while decreasing generosity schedules make cheaper units relatively more attractive. Conditional on physical and location attributes, on average,Low and Medium voucher transactions are priced 14% and 8% above eligible unsubsidized units, respectively, while High voucher transactions are 2.7% below. These patterns align with Figure 1: High vouchers concentrate at lower prices while others bunch at price caps, consistent with generosity schedules shaping the distribution of use across price segments. These patterns are consistent with voucher generosity schedules influencing the distribution of use across price segments.

Figure 3: Subsidized Transactions Concentration over Housing Attributes and Location



Notes: Panel A: Estimated coefficients show conditional mean differences on housing attributes between subsidized and eligible transactions, each outcome is regressed on subsidy indicator controlling for all other attributes and county-by-time fixed effects. The sample for each regression considers all eligible transactions for each voucher type over the study period. Panel B: Each polygon represents a census tract of Santiago, the color of the polygon corresponds to the share of voucher use by voucher type and DS1 design. College shares are shown in grayscale.

Subsidized Transactions Concentrate in Lower-SES Neighborhoods. I use the neighborhood share of college-educated residents as an SES proxy.[12] Panel B of Figure 3 shows voucher use concentrates heavily in lower-SES neighborhoods, though some concentration is mechanical due to price caps. Panel A reveals concentration beyond this mechanical effect. Conditional on price, county, and physical attributes, High voucher transactions locate in neighborhoods with 17% lower college shares (4 p.p.) than unsubsidized eligible transactions, while Medium and Low vouchers show 5% (2

[12]Santiago's high segregation creates strong correlations across SES measures. Appendix B shows college shares correlate strongly with income, crime rates, school quality, transport access, and public goods availability.

p.p.) and 3% (1 p.p.) differences, respectively. This pattern emerges from DS1 targeting low-income households who predominantly originate from lower-SES areas, with around half of voucher users purchasing units in their origin county.

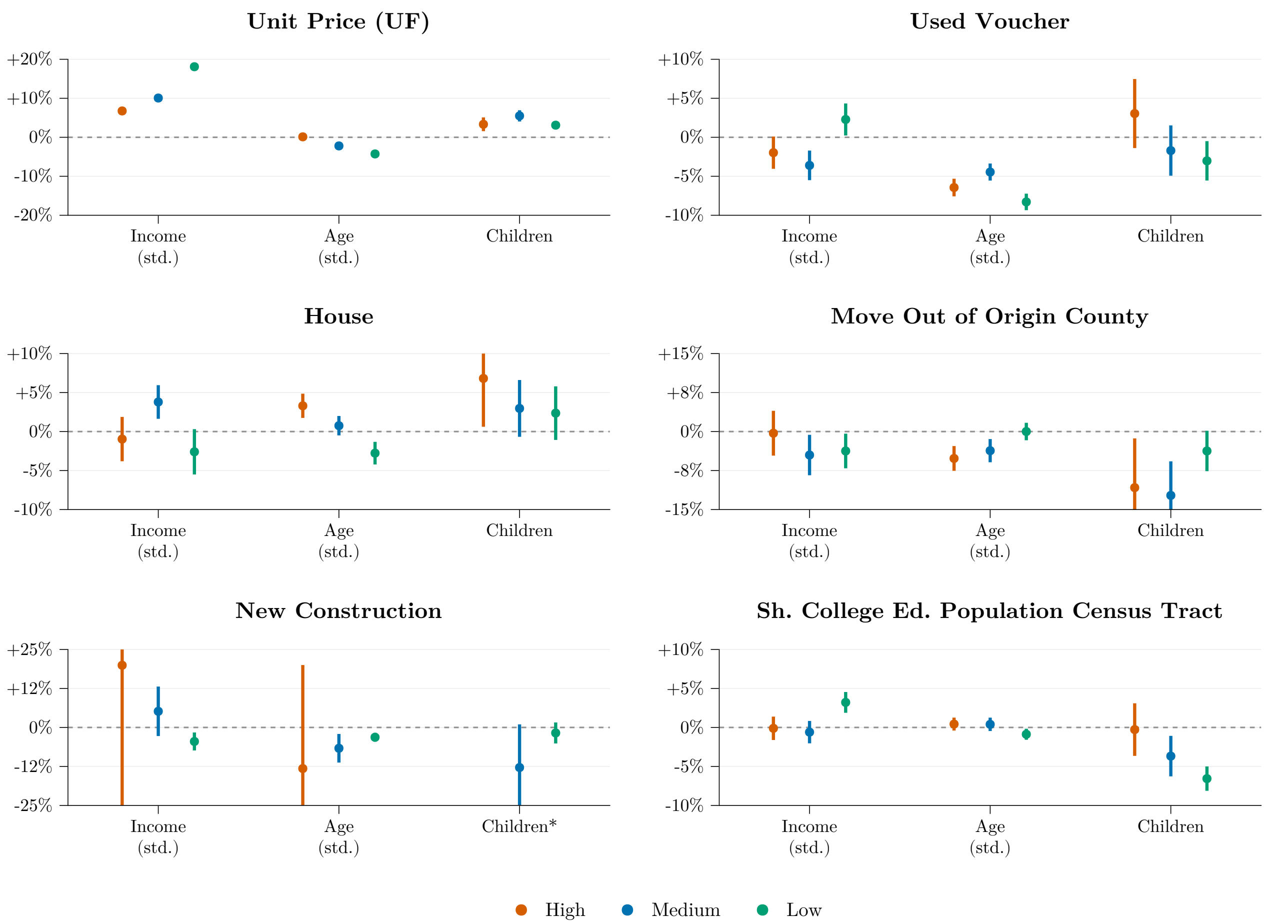
Physical Attribute Concentration Varies Across Vouchers. Voucher types show distinct patterns in structure type and vintage preferences. Conditional on price, neighborhood, and other attributes, Low voucher transactions are 5 p.p. more likely to be houses (11% increase) and 11 p.p. more likely new construction (33% increase) relative to unsubsidized units. High vouchers show opposite patterns: 7 p.p. less likely houses (12% decrease) and 9 p.p. less likely new construction (50% decrease).

These concentration patterns reveal heterogeneous exposure to DS1-induced demand shocks across housing segments and voucher types. This motivates granular segment definitions in the empirical model, as variation in voucher design and resource allocation across types might change the distribution of the voucher demand shock across segments.

Beneficiaries' Demographics and Voucher Concentration. To explore how beneficiary characteristics relate to concentration patterns, I analyze purchasing choices conditional on demographics. For each voucher type, I regress housing attributes on beneficiary demographics (income percentile, age, family size, presence of children), controlling for county of origin and award-purchase timing fixed effects. Table A.3 reports full results; Figure 4 plots coefficients for key outcomes.

These patterns cannot be interpreted as preference parameters for two reasons. First, vouchers are not universally or randomly allocated, wether and which voucher is hold by a households is determined by their housing preferences and the allocation mechanism. Second, conditional on voucher allocation, these patterns arise from the interaction between subsidized and unsusbsidized households' preferences and the supply of different housing segments.

Figure 4: Beneficiaries' Demographics and Voucher Concentration



4. An empirical model of the homeownership market

I build a model of a city's homeownership market with targeted and rationed government vouchers. The model consists of: (i) heterogeneous households considering voucher applications and housing purchases, (ii) housing unit owners deciding whether to sell, and (iii) developers who can build new units. The model provides a rational, full-information framework for interpreting these decisions and evaluate alternative voucher policies' effects on housing prices, development, and distributional consequences across demographics.

I model a segmented housing market with units grouped into discrete, homogeneous types, allowing supply and demand to respond to counterfactual policies through equilibrium price and quantity adjustments. The model incorporates two key features. On the demand side, the subsidized household set is endogenous—different policy designs shape *who* receives vouchers and *how* they're used. On the supply side, I differentiate new and resale housing segments—distinguishing stock growth (new development) from transaction flows (resales) and capture endogenous development responses to voucher-induced demand shocks.

4.1 Setting and Timing

Housing Market. Each market $t \in \mathcal{T}$ corresponds to a half-year period in which housing units of type $j \in \mathcal{J}$ are traded. Each housing type j is defined as a tuple of neighborhood, size tercile, structure type, and vintage—for example, small new apartments in Brooklyn. Housing units of type j are homogeneous goods, traded at equilibrium prices p_{jt} and quantities Q_{jt}.

Housing units are demanded by subsidized and unsubsidized households with heterogeneous housing preferences. The set of subsidized households is endogenously determined by applying for and receiving a voucher before making a housing choice. Units are supplied by price-taking owners deciding whether to sell. In each market, a fixed stock $\bar{Q}_{jt}$ of each type considers selling. Housing types partition into new and resale units: $\mathcal{J} = \mathcal{J}^{\text{new}} \cup \mathcal{J}^{\text{res}}$. Units of type $j \in \mathcal{J}^{\text{new}}$ are owned by forward-looking firms deciding when to sell; developers' building decisions affect new housing stock. Resale units are household-owned, with stock determined by the exogenous share of owners considering sale.

Housing Vouchers. The government offers a voucher menu $\boldsymbol{\mathcal{B}} = \{\mathcal{B}_t\}_{t \in \mathcal{T}}$. Each voucher type $b \in \mathcal{B}_t$ provides housing price discounts but only applies to units below a price cap. Limited vouchers are rationed via eligibility and scoring rules. Vouchers are awarded to applicants scoring above equilibrium cutoff $\bar{r}_{bt}$.

Timing. Each market t, given voucher menu $\boldsymbol{\mathcal{B}}$, equilibrium prices $\boldsymbol{p}$, and voucher cutoff scores $\bar{\boldsymbol{r}}$, agents act sequentially:

1. **Voucher Allocation.** Government announces available vouchers and allocation rules. Eligible households decide whether to apply; vouchers awarded among applicants.

2. **New Housing Development.** Small developers choose construction quantities, determining new housing stock.

3. **Housing Market.** Subsidized and unsubsidized households decide whether to purchase. Owners choose whether to sell.

4.2 Housing and Voucher Demand

Households. A continuum of households $i \in \mathcal{I}$ is characterized by observable characteristics $\boldsymbol{z}_{it}$, unobservable characteristics $\boldsymbol{\nu}_i$, and arrival market t_i^a. Each household has homeownership status $j_{it} \in \mathcal{J} \cup \{0\}$, voucher status $b_{it} \in \mathcal{B}_t \cup \{0\}$, and is scheduled to make a housing choice in market $t_i^h \geq t_i^a$. All households arrive as renters ($j_{it} = 0$), unsubsidized ($b_{it} = 0$), and initially scheduled to make a housing choice ($t_i^h = t_i^a$). Voucher application decisions can change voucher status and delay housing choice. Housing choice is a one-time terminal action potentially changing homeownership status. All households share discount factor ρ.

4.2.1 Housing Demand

Housing Attributes. Housing type $j \in \mathcal{J}$ in market t is characterized by market price p_{jt}, physical characteristics $\boldsymbol{X}_j^k$, location X_j^{Loc}, and amenities ξ_{jt}. Physical characteristics $k \in \mathcal{K}$ comprise size, structure, and vintage; X_j^{Loc} denotes county. Amenities ξ_{jt} capture unobserved quality observable to households but not the econometrician. The outside option $j = 0$ denotes not purchasing in the city.

Voucher Generosity and Choice Restrictions. Vouchers distort beneficiary prices and choice sets. Households with voucher $b_{it} \in \mathcal{B}_t \cup \{0\}$ face prices p_{ijt} and eligible housing types $j \in \mathcal{J}_{it}$:

$$p_{ijt} = p_{jt} - d(p_{jt}, b_{it}) \text{ and } \mathcal{J}_{it} = \{j \in \mathcal{J} : p_{jt} \leq \bar{p}(b_{it})\} \cup \{0\}, \tag{1}$$

where $d_{bt} : p \times b \to \mathbb{R}^+$ and $\bar{p} : b \to \mathbb{R}^+$ denote the discount schedule and price cap of voucher type $b \in \mathcal{B}_t$ as described in Section 2.2. Unsubsidized households ($b_{it} = 0$) face market prices $p_{ijt} = p_{jt}$ and all housing types $\mathcal{J}_{it} = \mathcal{J} \cup \{0\}$.[13]

Housing Preferences. Household i's utility from owning housing type j comprises mean utility δ_{jt}, household-specific component $\mu_{ijt}(\boldsymbol{z}_{it}, \boldsymbol{\nu}_i)$ capturing heterogeneous preferences, and idiosyncratic component ϵ_{ijt}^H. Demographics $d \in \mathcal{D}$ shifting housing attribute preferences include income, age of household head, family size, and presence of children. Location preferences use indicator variables X_{ij}^{Loc} for housing in i's county of origin.[14] Unobservable characteristics $\boldsymbol{\nu}_i = (\nu_i^p, \nu_i^h)$ shift price sensitivity and homeownership value. The random indirect utility of household i from purchasing housing type

[13] The assumption that subsidized households only consider eligible housing types might be strong in general, but it is unlikely to matter in the empirical application. Price caps are salient during application, so households preferring ineligible types would not apply (as modeled in the next section). Anecdotally, MHU officials mentioned that virtually all non-users remain as renters.

[14] Note that a county can contain multiple neighborhoods (e.g., census tracts). Preferences are modeled at the county level since county is the most granular location level I observe for households in both the DS1 and CASEN data.

$j \in \mathcal{J}_{it}$ in market t is:

$$U_{ijt} = \underbrace{\overbrace{-\alpha_i(\boldsymbol{z}_{it}, \nu_i^p)p_{ijt}}^{\substack{\text{Housing}\\ \text{Cost}}} + \overbrace{h_i(\boldsymbol{z}_{it}, \nu_i^h)}^{\substack{\text{Value of}\\ \text{Homeownership}}} + \overbrace{\sum_{k \in \mathcal{K}} \beta_i^k(\boldsymbol{z}_{it}) X_j^k}^{\substack{\text{Value of}\\ \text{Physical Attributes}}} + \overbrace{\beta_i^{Loc}(\boldsymbol{z}_{it}) X_{ij}^{Loc}}^{\substack{\text{Value of}\\ \text{Location}}}}_{\mu_{ijt}(\boldsymbol{z}_{it}, \boldsymbol{\nu}_i)} + \overbrace{\delta_{jt}}^{\substack{\text{Mean}\\ \text{Utility}}} + \epsilon_{ijt}^H, \tag{2}$$

where,

$$\alpha_i = \alpha_0 + \sum_{d \in \mathcal{D}} \alpha_d z_{it}^d + \sigma^p \nu_i^p, \qquad h_i = \sum_{d \in \mathcal{D}} \gamma_d z_{it}^d + \sigma^h \nu_i^h,$$

$$\beta_i^k = \sum_{d \in \mathcal{D}} \beta_d^k z_{it}^d, \qquad \beta_i^{Loc} = \beta_0^{Loc} + \sum_{d \in \mathcal{D}} \beta_d^{Loc} z_{it}^d,$$

$$\delta_{jt} = \gamma_0 + \gamma_t + \sum_{k \in \mathcal{K}} \beta_0^k X_j^k + \xi_{jt}, \qquad (\nu_i^p, \nu_i^h) \sim \mathcal{N}(0, \Sigma_\nu).$$

For the outside option, $U_{i0t} = \epsilon_{i0t}^H$-implying housing values are net of renting or purchasing outside the city. The idiosyncratic component ϵ_{ijt}^H is iid Type I Extreme Value.

Price sensitivity α_i and homeownership values h_i vary across demographics and unobserved characteristics via random coefficients. Price sensitivity captures heterogeneity in money's opportunity cost from unmodeled frictions (differential mortgage access, interest rates) and preferences (households with children prioritizing education expenses). Homeownership preference captures individuals' net homeownership value beyond prices and attributes, encompassing both benefits like housing stability and opportunity costs such as losing access to other means-tested programs. Unobserved heterogeneity (ν_i^p, ν_i^h) plays dual roles. Random coefficients deliver flexible substitution across housing types and along the homeownership margin—crucial since vouchers reshape choice sets and homeownership rates are the key outcome.[15] Economically, these unobserved preferences capture DS1's fundamental constraint: the government observes demographics but not preferences, making direct needs-based allocation impossible and necessitating screening through menu design.

Preference heterogeneity for physical characteristics and location (β_i^k, β_i^{Loc}) varies across demographics.[16] Demographic interactions reflect sorting patterns from Section 2.2, though those were conditional on voucher receipt. The structural parameters recover population-level preferences unconditional on voucher status.[17] Mean utility δ_{jt} captures homeownership's mean value γ_0, market

[15] Without random coefficients, the model would impose IIA, which is problematic when comparing the value of adding or subtracting products from choice sets. Random coefficients on the constant are best practice for minimizing the impact of market size assumptions; this is particularly relevant here as selection into the housing market is not microfounded (i.e., the rental market is not modeled).

[16] I treat housing amenities as exogenous, ruling out homophily preferences (i.e., preferences to live near similar households). The empirical relevance of homophily preferences is a matter of debate in the housing literature (Caetano and Maheshri, 2021; Bayer et al., 2022), and goes beyond the scope of this paper.

[17] It's worth noting that these parameters might also capture unmodeled frictions. For instance, if search costs are higher for housing types outside households' county of origin, these costs would be loaded into the location preference parameters.

fixed effects γ_t capturing its variation due to market conditions, physical attributes β_0^k, and unobserved amenities ξ_{jt} representing time-varying demand shocks—neighborhood infrastructure improvements or zoning regulations differentially affecting relative attractiveness. These amenities, known to households, affect equilibrium prices and must be accounted when estimating demand.

Housing Choice. Households make a one-time housing choice in market t_i^h, potentially changing homeownership status and becoming inactive. Upon realizing idiosyncratic preferences $\boldsymbol{\epsilon}_{it}^H$, i chooses housing type j to maximize utility:

$$j_{it}^*(b_{it}) = \underset{j \in \mathcal{J}_{it}(b_{it})}{\arg\max}\, U_{ijt}(b_{it}). \tag{3}$$

The probability that household i chooses housing type j in market t is:

$$q_{ijt}^H(b_{it}) = \frac{\exp\left(\bar{U}_{ijt}(b_{it})\right)}{\sum_{k \in \mathcal{J}_{it}(b_{it})} \exp\left(\bar{U}_{ikt}(b_{it})\right)}, \tag{4}$$

where $\bar{U}_{ijt} = U_{ijt} - \epsilon_{ijt}^H$.

Voucher Distortions. The model yields closed-form voucher-induced distortion characterizations. Let $\triangle^{\%} q_{it}(j,b)$ denote the percentage change in the probability i purchases j with voucher b versus no voucher. For eligible housing types $j, j' \in \mathcal{J}_{it}(b)$ with $p_{jt} < p_{j't}$:

$$\triangle^{\%} q_{it}(j,b) = \overbrace{\alpha_i d(p_{jt}, b)}^{\text{Discount Effect}>0} \; \overbrace{- \log\left(\frac{\sum_{j \in \mathcal{J}_{it}(0)} \exp(\bar{U}_{ijt}(0))}{\sum_{j \in \mathcal{J}_{it}(b)} \exp(\bar{U}_{ijt}(0))}\right)}^{\text{Choice Restrictions Effect }>0} > 0 \tag{5}$$

$$\triangle\% q_{it}(j,b) - \triangle\% q_{it}(j',b) = \alpha_i \underbrace{\left(d(p_{jt}, b) - d(p_{j't}, b)\right)}_{\text{Decreasing Discount Effect}\geq 0} > 0. \tag{6}$$

with $\frac{\partial \triangle^{\%} q_{it}(j,b)}{\partial \alpha_i} > 0$, $\frac{\partial \triangle\% q_{it}(j,b) - \triangle\% q_{it}(j',b)}{\partial \alpha_i} \geq 0$, and $\frac{\partial \triangle^{\%} q_{it}(j,b)}{\partial h_i} = \frac{\partial \triangle\% q_{it}(j,b) - \triangle\% q_{it}(j',b)}{\partial h_i} = 0$.[18]

Equations (5)–(6) formalize how discount schedules and choice restrictions distort beneficiaries' choices. Discount schedules (Discount Effect) and price caps (Choice Restrictions Effect) increase demand for all eligible housing types independent of preferences, while decreasing discounts concentrate demand towards cheaper units (Decreasing Discount Effect). The distortion magnitude increases with beneficiary price sensitivity, as they become more likely to become homeowners (extensive margin) and prefer cheaper units (intensive margin). This highlights one of the key design trade-offs: targeting price-sensitive households—extramarginal beneficiaries—concentrates voucher-induced demand towards lower-priced housing segments.

[18] See Appendix F for details.

4.2.2 Voucher Applications and Allocation

Voucher Types. Each voucher type $b \in \mathcal{B}_t$ has equilibrium cutoff score $\bar{r}_{bt}$, eligibility rules e_{bt}, scoring function r_{ibt}, discount schedule $d(p, b)$, and price cap $\bar{p}(b)$. Under the large market assumption (i.e., continuum of households), cutoff scores function as market-clearing prices that households take as given (Azevedo and Leshno, 2016).

Voucher Allocation Mechanism. The government announces voucher menu $\mathcal{B}_t$ and quantities A_{bt} to be awarded. Households may apply for one voucher among those for which they are eligible:

$$\mathcal{B}_{it} = \{b \in \mathcal{B}_t : e_{ibt} = 1\}, \tag{7}$$

where $e_{bt} : \boldsymbol{z}_i \times b_{it} \to \{0, 1\}$ denotes eligibility rules described in Section 2.2, depending on observable characteristics and not having a voucher. Applicants are prioritized by scoring function $r_{ibt} : \boldsymbol{z}_i \times a_{it} \to \mathbb{R}_+$ based on observable characteristics and previous applications. The A_{bt} highest-scoring applicants receive vouchers.

Assumption 1 (Exogenous Time to Use). *Household i awarded a voucher in market t has t_i^h updated uniformly from [t+1, t+4].*

These limits match the empirical setting: vouchers awarded within six months of application, with approximately two years to use. In practice, beneficiaries might shop across multiple markets; I abstract from this due to lack of data on unsubsidized households' time on market. In estimation, I assign users to their purchase market and uniformly assign non-users.[19]

Voucher Application Decision. When deciding whether to apply, households consider the value of entering housing market τ with voucher b:

$$\mathrm{IV}_{i\tau}(b) = \log \sum_{j \in \mathcal{J}_{i\tau}(b)} \exp\left(\bar{U}_{ij\tau}(b)\right), \tag{8}$$

which captures both the benefit of discounted prices and the cost of restricted choice sets. However, winning a voucher may require multiple applications, during which households remain renters while housing prices potentially increase. In general, households could also anticipate future changes in menu design or their own preferences and strategize accordingly. I abstract from these considerations:[20]

Assumption 2 (Non-strategic Applications). *Household i applying in market t behaves as if voucher menu $\mathcal{B}_t$ and housing preferences $\boldsymbol{\Omega_{it}} = [\boldsymbol{z}_{it}, \boldsymbol{\delta}_t]$ are fixed.*

[19] One could assign non-users according to the empirical distribution of voucher use conditional on demographics, application cohort, and voucher status. While this might fit the *actual* distribution better, extra assumptions are required to extrapolate random assignment in counterfactuals. I evaluate the sensitivity of the estimation results to this assumption in Appendix C. As voucher assignment is staggered across markets, the impact of this assumption is limited.

[20] Modeling beliefs over the space of possible menu designs and housing preferences is computationally infeasible. Changes to the menu design involve new voucher types, changes in discount schedules, and price caps. Housing preferences evolve due to changes in observable characteristics, which would require integrating over the joint distribution of demographics as well as the evolution of unobserved common preferences.

This collapses the problem to a repeated static decision—households behave as if continuing to apply for the same voucher until awarded. The value of applying for voucher $b \in \mathcal{B}_t \cup \{0\}$ in market t becomes:

$$V_{ibt}^B = \mathbb{E}_{\boldsymbol{p},\bar{\boldsymbol{r}}_b}\left[\sum_{\tau=t}^{\infty} \rho^{\tau-t}\, W_{ib}(\tau;\bar{\boldsymbol{r}}_b)\, \mathrm{IV}_{i\tau}(b;\boldsymbol{p}_\tau) \,\middle|\, \boldsymbol{\Omega_{it}}, \mathcal{B}_t\right] + \epsilon_{ibt}^B, \tag{9}$$

where $W_{ib}(\tau;\bar{\boldsymbol{r}}_b)$ is the probability of winning voucher b for use in market τ.[21] Not applying yields $V_{i0t}^B = \mathrm{IV}_{it}(0)$—immediate housing choice. Households that apply remain renters with zero flow utility while waiting.[22] Idiosyncratic preferences ϵ_{ibt}^B are iid Type I Extreme Value.

The value of applying for voucher b weighs three factors: voucher benefits (price discounts), voucher costs (choice restrictions and waiting), versus immediate unsubsidized choice. i making an application choice in market t chooses the voucher maximizing expected discounted value:

$$b_{it}^* = \underset{b\in\mathcal{B}_{it}\cup\{0\}}{\arg\max}\, V_{ibt}^B. \tag{10}$$

The probability household i applies for voucher b in market t is:

$$q_{ibt}^B = \frac{\exp(\bar{V}_{ibt}^B)}{\sum_{k\in\mathcal{B}_{it}\cup\{0\}} \exp(\bar{V}_{ikt}^B)}, \tag{11}$$

where $\bar{V}_{ibt}^B = V_{ibt}^B - \epsilon_{ibt}^B$. Applying delays housing choice to $t_i^h = t+1$ with no further action. Not applying triggers immediate housing market entry with no future applications.

Prices and Cutoff Beliefs. For tractability, I impose structure on households' beliefs:

Assumption 3 (Rational Expectations). *Households have rational expectations over future housing prices $\boldsymbol{p} = \{\boldsymbol{p}_\tau\}_{\tau\geq t}$ and cutoff scores $\bar{\boldsymbol{r}}_b = \{\bar{r}_{b\tau}\}_{\tau\geq t}$.*

In the baseline estimation, I implement rational expectations by letting households have perfect foresight over housing prices and use current cutoffs $\bar{\boldsymbol{r}}_t$ as best forecasts for future cutoffs.[23] This baseline specification reduces computational burden; the model framework accommodates richer belief structures for future sensitivity analysis.

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[21] Formally, the probability of being assigned to market $\tau > t$ is

$$W_{ib}(\tau) = \frac{1}{4}\sum_{k=t}^{\tau}\left(\prod_{j=t}^{k-1} \mathbb{P}(r_{ibj} < \bar{r}_{bj})\right)\mathbb{P}(r_{ibk} \geq \bar{r}_{bk}).$$

[22] This is consistent with households expecting to receive $U_{i0t} = \epsilon_{i0t}$ while renting, which has expected value zero before realizing the shock.

[23] The variation in cutoff scores across markets is mostly explained by changes in the number of vouchers announced by the government and design updates (introduction of new voucher types, changes in discount schedules, price caps, etc.). As a result, it is hard to predict future cutoff scores without modeling beliefs over changes in the voucher menu design; current cutoff scores outperform most simple forecasting models I tested.

4.3 Housing Supply and Development

Housing Stock. In each market t, units from a fixed stock $\bar{Q}_{jt}$ of type j may be sold at equilibrium prices p_{jt}. Each unit is owned by a price-taking owner $f \in \mathcal{F}$. New ($\mathcal{J}^{\text{new}}$) and resale ($\mathcal{J}^{\text{res}}$) segments differ in owner incentives and stock determination.

4.3.1 New Housing Supply

Inventory Management. Each unit in stock $\bar{Q}^{\text{new}}_{jt}$ is owned by a distinct forward-looking firm $f \in \mathcal{F}^{\text{new}}$ deciding when to sell their unit. Firms can sell now at market price and exit, or hold the unit anticipating higher future prices while paying maintenance costs. The indirect flow profits from action $a \in \{\text{sell}, \text{hold}\}$ are:

$$\pi^a_{fjt} = \begin{cases} \alpha^{\text{new}} p_{jt} + \omega^{\text{sell}}_{fjt} & \text{if } a = \text{sell} \\ -C^M_{jt} + \beta \mathbb{E}\Pi_{fjt+1} + \omega^{\text{hold}}_{fjt} & \text{if } a = \text{hold}, \end{cases} \tag{12}$$

Selling yields revenue $\alpha^{\text{new}} p_{jt}$ at market prices plus idiosyncratic shock $\omega^{\text{sell}}_{fjt}$, after which the firm exits. Holding incurs maintenance costs $C^M_{jt} = C_j + C_t + \xi^M_{jt}$ while earning expected continuation value $\beta \mathbb{E}\Pi_{fjt+1}$. Firm-specific shocks ω^a_{fjt} are iid Type I Extreme Value.

Keeping units on market is costly—developers pay for advertising, sales agents, and most importantly, interest on development loans. Type fixed effects C_j and time effects C_t capture systematic variation across housing types and market conditions. Unobserved costs ξ^M_{jt} capture type-time variation, particularly differential interest rates as banks evaluate project-specific risk based on expected sale speeds.[24]

Assuming perfect foresight and applying (Hotz and Miller, 1993) inversion, the share of new stock sold is:

$$s^{\text{sell}}_{jt} = \frac{\exp(\bar{\pi}^{\text{sell}}_{jt})}{\exp(\bar{\pi}^{\text{sell}}_{jt}) + \exp(\bar{\pi}^{\text{hold}}_{jt})}, \tag{13}$$

where $\bar{\pi}^a_{jt} = \pi^a_{fjt} - \omega^a_{fjt}$.

While stylized, this framework allows new housing stock to dynamically respond to evolving voucher-induced demand shocks—relevant for counterfactual analyses given the substantial variation in voucher quantities and mix across periods documented in Section 2.2. The key abstractions are no pricing decisions (units are price-takers) and no sale uncertainty (firms can always sell when they choose).

New Housing Development and Supply. Before each market clears, a representative developer for each housing type $j \in \mathcal{J}^{\text{new}}$ chooses how many units to build.[25] They earn revenue by selling

[24] Interest rates vary across projects as banks assess repayment probability mostly based on expected time-to-sale. I assume these rates are constant within type-time cells due to data limitations on developer financing.

[25] The representative developer abstracts from many small price-taking developers competing to sell units.

completed units to firms at expected value $\mathbb{E}_\omega \Pi_{jt}$—the price that ensures zero profits for risk-neutral firms—while facing increasing marginal costs that reflect factors like securing buildable land and obtaining permits. Following (Abramson, 2021), I parametrize total development cost as $C^D_{jt}(Q^D_{jt}) = \frac{1}{\psi^0_j}\frac{(Q^D_{jt})^{(\psi^1_j)^{-1}+1}}{(\psi^1_j)^{-1}+1}$, where $\psi^0_j \geq 0$ is the scale parameter and $\psi^1_j > -1$ is the supply elasticity. The first-order condition yields optimal development:

$$Q^{D*}_{jt} = \left(\psi^0_j \mathbb{E}_\omega \Pi_{jt}\right)^{\psi^1_j}. \tag{14}$$

As a result, stock comprises new development plus unsold inventory from previous periods:

$$\bar{Q}^{\text{new}}_{jt} = Q^{D*}_{jt} + (1 - s^{\text{sell}}_{jt-1})\bar{Q}^{\text{new}}_{jt-1}, \tag{15}$$

yielding new housing supply:

$$Q^S_{jt}(\boldsymbol{p}_j) = s^{\text{sell}}_{jt}(\boldsymbol{p}_j)\bar{Q}^{\text{new}}_{jt}(\boldsymbol{p}_j). \tag{16}$$

This formulation allows new development to respond dynamically to expected unit values rather than just current prices—capturing how developers internalize inventory dynamics. This competitive framework allows new housing supply to dynamically respond to voucher-induced demand shocks through development and inventory decisions—enabling supply adjustments in counterfactuals where policies generate the time-varying demand patterns observed empirically through changes in voucher quantities and mix.

4.3.2 Resale Housing Supply

Resale Housing Stock. Each market t, a share λ^{res} of the total stock of type $j \in \mathcal{J}^{\text{res}}$ in the city considers selling, defining the resale stock $\bar{Q}^{\text{res}}_{jt}$.

Selling Choice and Resale Housing Supply. Each owner $f \in \mathcal{F}^{\text{res}}$ in stock $\bar{Q}^{\text{res}}_{jt}$ makes a myopic decision: sell at market price or continue occupancy. Owner f sells if:

$$u^{\text{sell}}_{fjt} = \alpha^{\text{res}}_j p_{jt} - \underbrace{(C^O_j + C^O_t + \xi^O_{jt})}_{C^O_{jt}} + \epsilon_{fjt} \geq 0, \tag{17}$$

where $\alpha^{\text{res}}_j p_{jt}$ is the value from selling at market price, C^O_{jt} represents opportunity costs, and ϵ_{fjt} is an idiosyncratic logit shock. Opportunity costs capture the net cost of selling—broker fees, moving expenses, and the loss of occupancy net present value. Type fixed effects C^O_j and time effects C^O_t absorb systematic variation across housing types and market conditions. Unobserved costs ξ^O_{jt} capture type-time specific changes, such as neighborhood amenity improvements that increase the value of staying. In each market t, the share of resale stock deciding to sell is:

$$s^{\text{sell}}_{jt} = \frac{\exp(\bar{u}^{\text{sell}}_{jt})}{1 + \exp(\bar{u}^{\text{sell}}_{jt})}, \tag{18}$$

where $\bar{u}_{jt}^{\text{sell}} = \alpha_j^{\text{res}} p_{jt} - C_{jt}^O$. Resale housing supply is:

$$Q_{jt}^S(p_{jt}) = \bar{Q}_{jt}^{\text{res}} \cdot s_{jt}^{\text{sell}}(p_{jt}). \tag{19}$$

Altough stylized, this static and competitive framework allows for heterogeneous supply elasticities across resale types—allowing resale supply to respond to voucher-induced demand shocks as price increases induce more owners to sell.[26] The main limitation is that supply cannot adjust to changes in relative future prices, and that it abstracts from the joint decision of owners to sell units and buy another one (i.e., housing filtering).

4.4 Housing market equilibrium

Before describing the equilibrium, it remains to formally define the set of potential voucher applicants and housing buyers in each market.

Voucher Demand. Active households $i \in \mathcal{I}_t$ comprise all households that arrived in current or previous markets and haven't made housing choices. Potential applicants $i \in \mathcal{I}_t^E \subseteq \mathcal{I}_t$ are eligible for at least one voucher type. Demand for voucher b is:

$$\mathcal{I}_{bt}^A = \{i \in \mathcal{I}_t^E : b_{it}^* = b\}. \tag{20}$$

Applicants $\mathcal{I}_t^A$ delay housing choice; non-applicants $\mathcal{I}_t^{NA} = \mathcal{I}_t^E \setminus \mathcal{I}_t^A$ choose immediately.

Housing Demand. Aggregate demand for housing type j comprises three groups:

$$Q_{jt}^D(p_{jt}, p_{-jt}) = \underbrace{\sum_{i \in \mathcal{I}_t^{NE}} q_{ijt}^H}_{\text{Non-Eligible}} + \underbrace{\sum_{i \in \mathcal{I}_t^{NA}} q_{ijt}^H}_{\text{Non-Applicants}} + \underbrace{\sum_{b \in \mathcal{B}_t} \sum_{i \in \mathcal{I}_{bt}^B} \mathbb{1}\{j \in \mathcal{J}_{it}\} q_{ijt}^H}_{\text{Voucher Beneficiaries}}, \tag{21}$$

where $\mathcal{I}_t^{NE}$ are non-eligible arrivals, $\mathcal{I}_t^{NA}$ are eligible who don't apply, and $\mathcal{I}_{bt}^B$ are beneficiaries with voucher b scheduled for market t. This decomposition reveals how voucher design shapes market outcomes: the transmission of voucher-induced shock to housing segments depends on selection into the program (extensive margin) and how discounts and restrictions distort beneficiary choices conditional on participation (intensive margin).

4.4.1 Subsidized Homeownership Market Equilibrium.

Equilibrium Definition. *Given voucher policy $\mathcal{B} = \{\mathcal{B}_t\}_{t \in \mathcal{T}}$, an equilibrium consists of a vector of prices $\boldsymbol{p} = \{p_{jt}\}_{j,t}$ and a vector of cutoff scores $\bar{\boldsymbol{r}} = \{\bar{r}_{bt}\}_{b,t}$ such that:*

1. *Households make optimal housing and voucher choices: housing demand is given by (4) and*

[26] Data limitations prevent modeling listing durations or seller transitions. Units in voucher-eligible segments often transact through informal channels where such data is unavailable.

voucher demand by (11).

2. *Owners and Developers behave optimally: New and Resale Owners selling decisions are given by (13) and (18), and total development by (14).*

3. *The housing market clears:*

$$Q^S_{jt}(\boldsymbol{p}_j) = Q^D_{jt}(\boldsymbol{p}_t) \quad \forall j \in \mathcal{J}, t \in \mathcal{T}$$

4. *The voucher allocation clears: the number of applicants for voucher b in period t with scores above the equilibrium cutoff scores equals the number of vouchers available,*

$$A_{bt} = |\{i \in \mathcal{I}^A_{bt} : r_{ibt} \geq \bar{r}_{bt}\}|.$$

Equilibrium Computation. In practice, equilibrium is computed for finite horizon $t \in \{1, \ldots, T\}$ with initial conditions from data (unsold new housing stock, pending applicants) and terminal price beliefs based on average growth rates. See Appendix E for algorithm details.

5. Estimation and Results

5.1 Estimation Sample and Assumptions

In this section, I briefly describe the main assumptions made the data to the model and the estimation sample construction. I provide details, sensitivity checks, and complementary summary statistics in Appendix C.

Markets and Housing Types Definition. I discretize time and housing units into markets and housing types. I set estimation markets $t \in \mathcal{T}^E$ to half-year periods from 2012 to 2018, aligning with DS01 call schedules. Housing units are aggregated into types $j \in \mathcal{J}$ by structure (house or apartment), condition (new or resale), size terciles, and neighborhood. I define neighborhoods by clustering census tracts within counties in two steps. First, I define which counties are worth clustering as those that exceed the median county-level share of total transactions or the median price per square meter variance; otherwise, all census tracts within a county are pooled into a single neighborhood.[27] Second, I cluster census tracts within counties into Low- and High-SES neighborhoods by the share of college-educated residents. I follow Alves et al. (2023) in using the SKATER algorithm (Assunção et al., 2006), which allows to impose the constraint that each neighborhood contains at least 30% of county transactions.[28]

[27] Santiago's counties are very heterogenous in terms of geographic size and how heterogenous they are in terms of SES and housing prices.

[28] More granular housing types better approximate the homogeneous goods assumption but (i) increase parameters since mean utilities are fixed effects, raising incidental parameter concerns; (ii) mechanically reduce market shares,

Housing Types Estimation Sample. I consider housing types that are transacted at least 10 times per market. The estimation sample comprises 211 out of 410 possible housing types, which account for 92% of all transactions.[29] I define the price of a housing type p_{jt} as the average transaction price of all units of type j in market t, and the size X_j as the mean size. Table A.4 shows characteristics of considered housing types relative to the transaction data by Neighborhood Cluster. A regression of unit level transaction prices against product-market fixed effects shows that the defined housing types explain 81.2% of price variation.

Market Size Assumptions. On the demand side, I assume that $\mathcal{I}_t = 70.000$ households arrive each period and begin making choices. On the supply side, I set the stock of new housing types $\bar{Q}_{jt}^{new}$ to the one observed in the new development survey data. For resale housing types, I set the stock of owners of units of each type $\bar{Q}_{jt}^{res}$ to 20% percent of the city stock of each type, taking into account the growth in the stock over time due to new development.

Households Estimation Sample. The voucher applicants sample comprises all households that applied for any DS1 voucher during the estimation period, and received a voucher before 2022. The arrival period t_i^a is set to the market of the first voucher application. The voucher holder sample comprises all households that had an active voucher during the estimation markets. I'll refer to the applicants and users samples as the micro data from now on. Unsubsidized householdsare drawn from the last available CASEN survey for their market of arrival. I draw from households that live in the MR, their DS1 scores and eligibility is predicted as described in Section 2.1 and treated as data. I'll refer to the unsubsidized sample as the macro data from now on.

Housing Choice Market. For households in the voucher holder sample that purchased a housing unit before 2022, the housing choice period t_i^h is set to the market in which the transaction took place. I randomly assign non-users uniformly to one of the four markets after their voucher assignment. Households in the macro data do not apply for a voucher and make a housing choice uppon arrival.

5.2 Demand estimation

Estimation Challenge. Household self-selection into vouchers creates challenges for demand estimation. While voucher-induced variation typically identifies preferences when subsidies depend only on observables the DS1 program presents two problems. Because households self-select based on housing preferences, voucher status is endogenous, preventing direct exploitation of voucher-induced price variation. Additionally, microdata is available only for applicants, creating a sample selected on preferences that standard methods do not accommodate (Nevo, 2001; Petrin, 2002; Berry et al., 2004; Berry and Haile, 2024).

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producing noisier estimates and making discrete choice model convergence harder; and (iii) increase zero-transaction periods, which would require modeling product availability accross periods increasing the model complexity without having economic interpretation (i.e. housing types are abstractions, not actual *products*).

[29] The housing types left out of the estimation sample are units with rare characteristics given their location, such as large houses in apartment dense neighborhoods.

Approach. I jointly estimate housing and voucher choice models via MLE, accounting for preference-based selection into the microdata. The voucher choice model function as a *control* for both selection into the applicant sample and endogeneity of voucher status. The fact that DS1 purchases are matched to the universe of real estate transactions allows for a straightforward likelihood, as double-counting concerns are minimal (Grieco et al., 2025). Once controlled for selection, voucher-induced identified variation can be exploited to identify the demand parameters without requiring supply-side instruments. There are two main sources of identifying variation: (i) within-market price and choice set differences and across-market variation in voucher design, provide identification for housing preference parameters; (ii) across-market variation in the total supply and mix of vouchers shifts equilibrium cutoff scores and applicants' winning probabilities, providing variation for the voucher values.

Estimation proceeds in two steps. First, I recover parameters $\boldsymbol{\theta}^{(1)} = \{\boldsymbol{\alpha}, \boldsymbol{\gamma}_d, \boldsymbol{\beta}_d^{Loc}, \boldsymbol{\beta}_d, \boldsymbol{\nu}, \boldsymbol{\delta}\}$ via SMLE. Second, I recover the common preference parameters $\boldsymbol{\theta}^{(2)} = \{\boldsymbol{\beta}_0, \boldsymbol{\gamma}, \boldsymbol{\xi}\}$ by projecting the estimated mean utilities $\hat{\boldsymbol{\delta}}_{jt}$ onto product and market characteristics. Here I present a simplified version of the estimator, focusing on the intuition and the identification argument. A complete derivation of the estimator and computational implementation is provided in Appendix C.

Selection Corrected Mixed Data Likelihood. For a candidate vector of parameters $\tilde{\boldsymbol{\theta}}^{(1)}$ the Selection Corrected Mixed Data Likelihood Estimator (SCMDLE) log-likelihood is given by:

$$\mathcal{L}^{\text{SCMDLE}}(\tilde{\boldsymbol{\theta}}^{(1)}) = \sum_{i \in \mathcal{I}} \ell_i^{\text{Mic}}(\boldsymbol{z}_i, b_{it^a}^*, j_{it^h}^*; \tilde{\boldsymbol{\theta}}^{(1)}) + \sum_{j \in \mathcal{J}} \ell_{jt}^{\text{Mac}}(I_t^{NB}, s_{jt}^{NB}; \tilde{\boldsymbol{\theta}}^{(1)}), \tag{22}$$

where i are households in the microdata for which we observe their voucher $b_{it^a}^*$ and housing $j_{it_i^h}^*$ choices, as well as their demographics $\boldsymbol{z}_i$ at markets they make choices in.[30] The macrodata contains the aggregate product shares s_{jt}^{NB} and number of unsubsidized households I_t^{NB} for each market. As DS1 transactions are matched to the universe of real estate transactions, the shares and number of unsubsidized households can be computed directly from the data, avoiding double-counting concerns. The micro-likelihood and macro-likelihood contributions are given by:

$$\ell_i^{\text{Mic}}(\boldsymbol{z}_i, b_{it^a}^*, j_{it^h}^*; \tilde{\boldsymbol{\theta}}^{(1)}) = \log\left(\int w_{t^a}^{\text{Mic}}(z_{it^a}, \nu; \tilde{\boldsymbol{\theta}}^{(1)}) q_{ij^*t^h}^H(z_{it_i^h}, b_{it_i^h}, \nu; \tilde{\boldsymbol{\theta}}^{(1)}) dF(\nu)\right), \tag{23}$$

$$\ell_{jt}^{\text{Mac}}(I_t^{NB}, s_{jt}^{NB}; \tilde{\boldsymbol{\theta}}^{(1)}) = I_t^{NB} s_{jt}^{NB} \log \int w_t^{\text{Mac}}(z, \nu; \tilde{\boldsymbol{\theta}}^{(1)}) q_{jt}^H(z, \nu; \tilde{\boldsymbol{\theta}}^{(1)}) dG(z) dF(\nu), \tag{24}$$

where $q_{ij^*t^h}^H$ and q_{jt}^H are the model implied choice probabilities for individual subsidized households and aggregate product shares for unsubsidized households, respectively. If we ignore the w terms, the likelihood is equivalent to a standard MLE estimators for demand models with microdata (Petrin, 2002; Grieco et al., 2025).

[30] In appendix Appendix C, I present the estimator for the multiple application case. Here I focus on the single application case, as is the current implementation of the estimator.

Selection Correction Weights. The selection correction terms are given by:

$$w_{t^a}^{\text{Mic}}(z_{it^a},\nu) = \frac{q^B_{ib^*t^a}(z_{it^a},\nu;\boldsymbol{\theta})}{\int\left(1-q^B_{0t^a}(z_{it^a},\nu';\boldsymbol{\theta})\right)dF(\nu')} \qquad \frac{\text{Voucher Choice}}{\text{Application Probability}}, \tag{25}$$

$$w_t^{\text{Mac}}(z,\nu) = \frac{q^B_{i0t}(z,\nu;\tilde{\boldsymbol{\theta}}^{(1)})}{\int q^B_{0t}(z',\nu';\tilde{\boldsymbol{\theta}}^{(1)})dG(z')dF(\nu')} \qquad \frac{\text{Voucher Choice}}{\text{Non-Application Probability}}. \tag{26}$$

The micro selection correction term emerges from the model-implied probability of observing household i applying for voucher b^* and purchasing housing j^*, conditional on observing i in the microdata. The correction term has a natural interpretation: the numerator matches the joint probability of the observed voucher and housing choices for each value of ν. This voucher choice probability reweights the distribution of unobserved preferences—it reduces the likelihood contribution from housing choices for values of ν that make the observed voucher choice unlikely. The denominator captures the probability that household i with characteristics z_{it^a} applies for any voucher, upweighting households whose observables make them unlikely applicants. Together, w^{Mic} adjusts for selection into voucher status both by unobservables and observables. The macro selection terms balances the same goals, with the difference that controls at the population of eligible non-applicants level instead of the individual level.[31]

Recover common preferences. In the second step, given estimated mean utilities $\hat{\boldsymbol{\delta}}_{jt}$, parameters $\boldsymbol{\theta}^{(2)}$ are recovered via OLS using the parametrization in (2).

Identification. The main identification argument is that after controlling for selection into voucher status and the microdata, individual level variation in prices and choice sets (McFadden, 1972) as well as the panlel-structure of microdata (Berry and Haile, 2024) allow for identification of the demand parameters. Here I briefly disccuss the main sources of variation in the data:

1. **Voucher induced price p_{ijt} and choice sets J_{it} variation:** Besides the standard subsidized vs non-subsidized variation, the DS1 design provides richer dimensions of variation. The voucher menu provides within-market variation, as hypothetically, we observe two identical households with different voucher status facing different prices and choice sets. The changes in the voucher menu design generate across-market variation, as new voucher types are introduced and existing ones are updated.

2. **Voucher Supply induced variation in cutoff scores $\bar{r}_{bt}$ and choice sets $\mathcal{B}_{it}$** As there are no voucher preference parameters being estimated, the previous argument suffices for identification of the housing preference parameters. However, that is conditional on controling for selection on preferences. Loosely speaking, an excluded instrument is often required for selection correction methods. In this model, this would map to shifters to the value of applying for a voucher (9)

[31] Note as eligibility and scores for DS1 vouchers are simulated for the population, they are considered in the demographic distribution $G(z)$. As a result, non-eligible households have $w_t^{\text{Mac}}(z,\nu) = 1$.

that are orthoganal to housing preferences: time to win and voucher choice sets. Across-market variation in total supply and mix of vouchers shift equilibrium cutoff scores which determines time to win. Within a market, two individuals might have identical housing preferences but have different scores due to repeated applications. On top of that, changes to eligibility and scoring rules affect both vouchers choice sets and time to win.

5.3 Demand Estimates

Price Elasticity of Demand. Table A.1 shows the estimated own-price elasticities and willingness to pay for selected housing attributes; Table 1 reports estimated parameters. I estimate a median price elasticity of -1.42, with significant heterogeneity across voucher status. The median elasticity for High voucher recipients is -0.98, while Low voucher recipients exhibit substantially higher price sensitivity at -1.57.

Selection Correction Relevance. Panel A Figure 5 shows the distribution of price, homeownership, and same-county preference parameters. The Low voucher group exhibits the highest price sensitivity with a right-skewed distribution. This pattern highlights the importance of selection correction: despite having significantly higher SES composition than other voucher groups and similar demographics to the eligible population (Section 3), Low voucher recipients are the most price sensitive. This is a result of the selection correction weights increasing the weight of larger values of unobserved preference heterogeneity rationalizing why a household would apply for vouchers when other with similar observable characteristics would not.

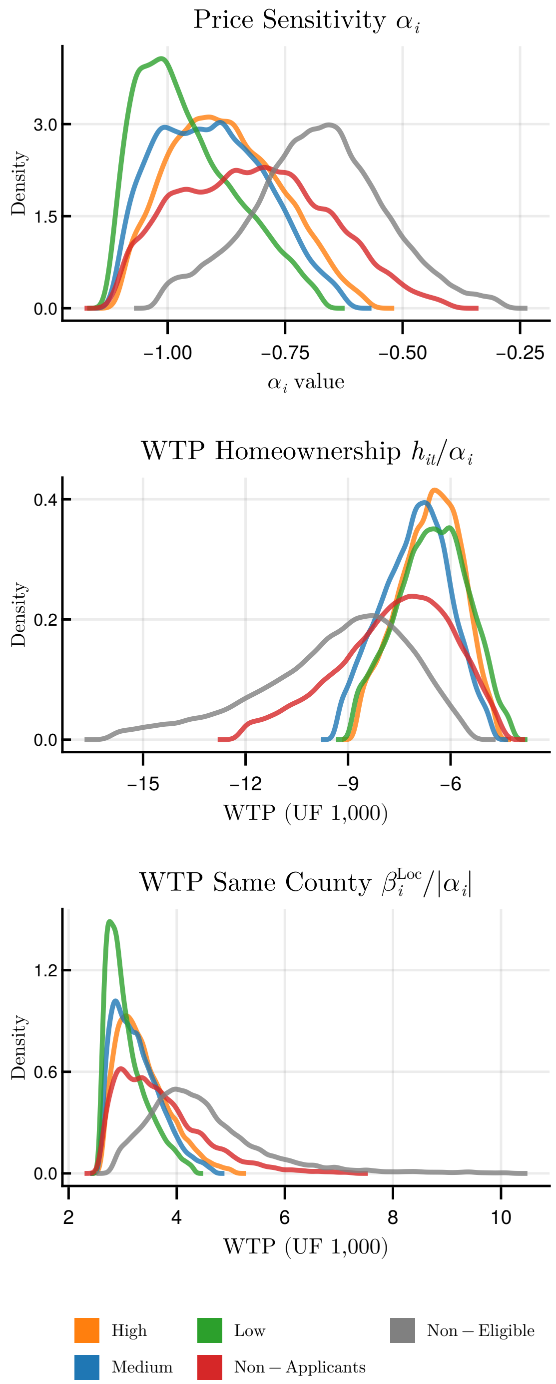
Table 1: Own-Price Elasticities and Willingness to Pay

	Subsidized Households			**Non-Subsidized**		**Overall**
	High Subsidy	Medium Subsidy	Low Subsidy	Non-Applicants	Non-Eligible	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Own-Price Elasticities						
Median price elasticity	-0.98	-1.17	-1.57	-1.68	-1.38	-1.42
	[-1.16, -0.80]	[-1.38, -0.99]	[-1.85, -0.98]	[-3.33, -1.01]	[-2.73, -0.83]	[-2.44, -0.90]
Panel B: Willingness to Pay (1,000 UF)						
Homeownership	-6.6	-7.0	-6.6	-7.6	-9.1	-7.7
	[-7.4, -5.9]	[-7.9, -6.3]	[-7.4, -5.8]	[-9.0, -6.4]	[-11.0, -7.8]	[-9.3, -6.5]
Same County	3.3	3.2	3.0	3.5	4.3	3.6
	[3.0, 3.7]	[2.9, 3.5]	[2.8, 3.3]	[3.1, 4.1]	[3.7, 4.9]	[3.1, 4.3]
House (vs. Apartment)	-0.5	-0.5	-0.4	-0.5	-0.6	-0.5
	[-0.5, -0.4]	[-0.5, -0.4]	[-0.5, -0.4]	[-0.6, -0.4]	[-0.7, -0.5]	[-0.6, -0.4]
New Construction	0.6	0.6	0.5	0.6	0.7	0.6
	[0.5, 0.6]	[0.5, 0.6]	[0.5, 0.6]	[0.5, 0.7]	[0.6, 0.9]	[0.5, 0.7]

Notes: Panel A shows median quantity weighted own-price elasticities. Panel B reports WTP in thousands of UF for selected housing attributes. Columns (1)-(5) range based on voucher type (Subsidized), Non-Applicants correspond to simulated households that are eligigible for at least one voucher, while Non-Eligible are not. Brackets show [25th, 75th] percentile values.

Preferences and Voucher Concentration. The estimates disentangle the role of preferences for housing attributes from the effects of housing prices and price cap constraints on the voucher concentration patterns described in Section 4. Panel B of Table 1 shows that preferences for size, structure type (house vs. apartment), and new construction are largely vertical—all groups exhibit similar WTP for these attributes. The key differences emerge in homeownership and location preferences: subsidized households show higher WTP for homeownership but lower WTP for staying in the same county compared to non-applicants and non-eligible groups. Panel A Figure 5 confirms these preferences are not only different in magnitude but also more concentrated relative to non-subsidized groups. These results clarify the source of voucher concentration patterns: subsidized households prioritize homeownership over location, exhibiting higher willingness to relocate combined with greater price sensitivity. Therefore, the concentration of voucher use in lower-SES neighborhoods and counties of origin results from housing prices and restricted choice sets rather than beneficiaries' preferences to remain in disadvantaged neighborhoods—they are willing to move but price constraints limit their options. The diversion ratios in Panel B Figure 5 support this interpretation, subsidized households are more likely to substitute toward the outside option even while having higher WTP for homeownership and and similar preferences for structure type and vintage.

Panel A: Parameter Distributions



Panel B: Diversion Ratios

(a) Overall diversion ratios

From \ To	**RH**	**RA**	**NH**	**NA**	**Out**
RH	·	0.30	0.01	0.15	0.54
RA	0.39	·	0.01	0.16	0.44
NH	0.12	0.09	·	0.60	0.19
NA	0.19	0.15	0.25	·	0.42

(b) Non-subsidized households

From \ To	**RH**	**RA**	**NH**	**NA**	**Out**
RH	·	0.33	0.01	0.16	0.51
RA	0.39	·	0.01	0.16	0.44
NH	0.12	0.09	·	0.61	0.19
NA	0.18	0.14	0.26	·	0.41

(c) High voucher (DS01)

From \ To	**RH**	**RA**	**NH**	**NA**	**Out**
RH	·	0.17	0.00	0.05	0.78
RA	0.45	·	0.00	0.05	0.51
NH	0.43	0.08	·	0.01	0.48
NA	0.38	0.12	0.00	·	0.49

(d) Medium voucher (DS02)

From \ To	**RH**	**RA**	**NH**	**NA**	**Out**
RH	·	0.16	0.00	0.08	0.76
RA	0.37	·	0.00	0.09	0.54
NH	0.39	0.09	·	0.08	0.43
NA	0.34	0.14	0.00	·	0.53

(e) Low voucher (DS03)

From \ To	**RH**	**RA**	**NH**	**NA**	**Out**
RH	·	0.15	0.01	0.23	0.61
RA	0.28	·	0.00	0.30	0.42
NH	0.33	0.08	·	0.22	0.38
NA	0.28	0.21	0.01	·	0.50

Figure 5: Parameter Distributions and Diversion Ratios

Notes: Panel A shows the distribution of price, homeownership, and Same County estimated preference parameters. Panel B presents the average diversion ratios for household types grouped by structure type and vintage, the row category is removed from the choice set labeled as RH = resale houses, RA = resale apartments, NH = new houses, NA = new apartments, Out = outside option.

5.4 Supply Estimation

5.4.1 Model-Based Voucher Exposure Instruments

Estimation Challenge. The endogeneity concern for estimating housing supply parameters comes from the correlation between equilibrium prices $\boldsymbol{p}_j$ and unobserved maintenance, development, and opportunity costs. While variation in voucher supply over time combined with concentrated voucher use in specific housing segments (documented in Section 2.2) provides demand-side variation, standard methods such as shift-share instruments cannot be applied here because within-city demand substitution violates SUTVA (Alves et al., 2023).

Model-based Voucher Exposure Instruments. Following Alves et al. (2023), I construct demand-side model-based instruments that account for substitution patterns. The key insight is that voucher demand shocks' distribution across housing segments is mediated by beneficiaries' preferences—the demand model captures how each household's voucher changes their choice probabilities across all housing types, given their preferences and market conditions. Formally, the instrument is the change in demand for product j in market t when comparing the subsidized scenario with one where all households making a housing choice are unsubsidized $b_{it} = 0$:

$$\triangle^{\mathrm{DS1}} Q_{jt}(p_{jt}, p_{-jt}) = \sum_{b \in \mathcal{B}_t} \sum_{i \in \mathcal{I}_{bt}^{B}} \mathbb{1}\{j \in \mathcal{J}_{it}\} q_{ijt}^{H}(b_{it}) - q_{ijt}^{H}(0), \tag{27}$$

holding equilibrium prices p_{jt} and households' choice timing t_i^h fixed—a partial equilibrium exercise.[32]

The instrument leverages two sources of variation: (i) the total stock of active vouchers, which cumulates from new and previously introduced vouchers; (ii) the composition of beneficiaries and their substitution patterns, which determine how voucher shocks propagate across segments. Unlike standard shift-share designs that use fixed exposure weights and miss compositional changes, this approach lets exposure vary endogenously through the demand model, capturing how beneficiaries' preferences and cross-segment substitution distribute the aggregate voucher shock across housing types. As a result, the identifying variation comes from cross-temporal variation in voucher assignment without the need of fixing the exposure weights, allowing satisfaction of the SUTVA assumption.

5.4.2 Supply Estimation and Results

Inventory Estimation. For estimating the inventory parameters $\{\alpha^{\mathrm{new}}, C_j^M, C_t^M, \xi_{jt}^M\}$, I exploit the finite dependence of the owner's objective (i.e., selling is a terminal action) and apply a Hotz-Miller

[32] A three-step IV approach (Bayer et al., 2007; Almagro and Domínguez-Iino, 2024) could generate instruments accounting for equilibrium price adjustments from program shutdown. However, this requires computationally expensive calculations and careful consideration of where to assign voucher holders and applicants when both prices and applications adjust in equilibrium. As this affects identification assumptions regarding cross-market spillovers, I leave this extension for future work.

inversion (Hotz and Miller, 1993) to get the following estimating equation:

$$\ln(s^{\text{sell}}_{jt}) - \ln(s^{\text{hold}}_{jt}) - \beta \ln(s^{\text{sell}}_{jt+1}) = -\beta\gamma + \alpha^{\text{new}}(p_{jt} - \beta p_{jt+1}) + C^M_j + C^M_t + \xi^M_{jt} \tag{28}$$

where $\beta = 0.96$ is the calibrated annual discount factor and γ is Euler's constant. The share of the stock of new units that sold each period s^{sell}_{jt} is observed from the transaction and development survey data. The equation captures the owner's trade-off: $p_{jt} - \beta p_{jt+1}$ captures differences in the attractiveness of selling now relative to the discounted option value of selling in the next market, while maintenance costs $C^M_j + C^M_t + \xi^M_{jt}$ make selling today more attractive.

I estimate via 2SLS, instrumenting the price difference term by the difference in the constructed instruments $\triangle^{\text{DS1}} Q_{jt} - \triangle^{\text{DS1}} Q_{jt+1}$ which shifts relative prices due to changes in the exposure to the voucher demand shock. Table A.6 presents OLS and IV estimates of $\hat{\alpha}^{new}$. While OLS leads to a noisy zero coefficient, the IV estimate is significant and positive, implying an upward sloping supply curve.

Development Estimation. For estimating the development cost parameters $\{\psi^0, \psi^0_j, \psi^0_t, \xi^D_{jt}\}$, I recover the value of a new unit $\hat{\Pi}_{jt}$ by solving a fixed point (D.1) using the inventory parameters estimates. From developers' FOC (14) and parametrizing (ψ^0_j, ψ^0_t), the estimating equation is:[33]

$$\ln(Q^{D*}_{jt}) = (\psi^1 + \psi^1_{house} X^{house}_j) \ln(\hat{\Pi}_{jt}) + \tilde{\psi}^0 + \tilde{\psi}^0_j + \tilde{\psi}^0_t + \tilde{\xi}^D_{jt} \tag{29}$$

where Q^{D*}_{jt} is the number of units that begin sales in the new development survey. The parameter of interest is ψ^1_j the supply elasticity of development with respect to units values, which I allow to vary between houses and apartments as land to build houses is more scarce. I instrument initial values with the current and future voucher shock instruments $(\triangle^{\text{DS1}} Q_{jt}, \triangle^{\text{DS1}} Q_{jt+1})$.

Table A.7 presents the estimates of the development elasticity with respect to units values $\{\hat{\psi}^1, \hat{\psi}^1_{house}\}$. Column (8) is the preferred specification, the estimated price elasticity of development is positive and significant, with a point estimate of 6.4 for apartments and 3.7 for houses. It's worth noting that ψ^1 captures the long run elasticity of development, as it is with respect to the net present value of a unit $\hat{\Pi}_{jt}$. In column (4), I report estimates from the same specification, but where the elasticity of development is with respect to current prices p_{jt}. The estimates are lower than the dynamic estimates, 4.2 for apartments and 2.1 for houses, highlighting the relevance of accounting for forward looking developers when estimating the supply of new development.

Resale Estimation. The structure of the resale supply model yields a standard log-shares estimation equation:

$$\ln(s^{\text{sell}}_{jt}) - \ln(s^{\text{hold}}_{jt}) = (\alpha^{\text{res}} + \alpha^{\text{res}}_{house} X^{house}_j) p_{jt} - C^O_j - C^O_t - \xi^O_{jt} \tag{30}$$

[33] I parametrize $\psi^0_j = \exp(\psi^0 + \psi^0_t + \xi^D_{jt})$ and $\psi^1_j = \psi^1 + \psi^1_{house} X^{house}_j$

where s_{jt}^{sell} is the share of units selling constructed as the total transactions over the calibrated share $\lambda^{\text{res}} = 0.2$ of the city stock considered selling in each period.

5.5 Price Elasticity of Housing Supply

Stock vs Flow of Housing. Before presenting the estimates of the price elasticity of housing supply, lets fix ideas on what is being captured by each component of the supply side. The increase in the city stock of housing is defined by new development quantities Q_{jt}^{D*}, whose elasticity is directly captured by $\hat{\psi}^1$. Conditional resale and new segments stock, the resale and new segment owners determine the flow of transactions in each period Q_{jt}^S. Both components matter for the counterfactuals of interest, as equilibrium prices are determined by the supply of both resale and new development segments.

Price Elasticity of Housing Transactions. In the counterfactuals of interest, I'll simulate permanent changes in the design of the voucher policy for which the relevant object is the change in transacted quantities of each housing type. On the new development segment, the supply is determined by (16) which is detemined by changes in stock by new development and the sales decisions of units owners. As both components are forward looking, the supply elasticity of interest corresponds to the long run elasticity of new development. On the resale segment, owners' decisions are myopic so the reaction to a permanent or temporary change in prices is equivalent.

Table 2 reports quantity weighted elasticities of housing transactions for a permanent 1% increase in prices, for new and resale housing. Panel A shows the overall elasticities, the differences are by an order of magnitude, with new development having a elasticity of 2.7 and resale housing having a elasticity of 0.25. Panel B shows decompose by structure type, showing that the large elasticity of new development is driven by apartments. This is expected, as the main cost for development is land, with apartment buildings requiring much less land per unit relative to houses. The relative differences are similar for resale housing, with apartments having a elasticity of 0.36 and houses having a elasticity of 0.21.

Opportunities for Design. Panel C of Table 2 shows the elasticities by a discrete measure of targeting, defined as the housing type being eligible for a voucher for at least one market. The results show negligible differences between groups, both on average and its distribution. As documented in Section **??**, eligible and non-eligible types are strognly correlated with location with eligible units concentrated in lower SES neighborhoods. This result have two important implications. For the determinants of housing supply, this results show that-within a city-the heterogeneity in supply elasticities is driven by physical attributes rather than location. For the design of homeownership vouchers, this suggests room for lowering the price pass-through by policies that target the most elastic segments. I will explore the effects of such policies in the following sections.

Table 2: Quantity weighted supply elasticities

	New Development				**Resale Housing**			
	Mean (SD)	Median	p25	p75	Mean (SD)	Median	p25	p75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overall								
All	2.67 (0.98)	3.12	1.74	3.33	0.25 (0.16)	0.21	0.08	0.43
Panel B: By Structure Type								
Houses	1.25 (0.51)	1.27	1.04	1.47	0.23 (0.11)	0.19	0.05	0.27
Apartments	3.07 (0.65)	3.23	3.04	3.36	0.36 (0.12)	0.31	0.17	1.09
Panel C: By Voucher Targeting								
Targeted HT	2.68 (0.91)	3.12	1.85	3.31	0.19 (0.07)	0.17	0.09	0.32
Non-targeted HT	2.65 (1.07)	3.11	1.64	3.40	0.21 (0.13)	0.18	0.12	0.36

Notes: New development elasticities are simulated using the estimated model; for a 1% increase in prices the unit values are recovered solving a fixed point for the inventory problem, See Appendix D for details. Resale elasticities are obtained in closed form. The sample comprises all housing types in the estimation sample, elasticities are quantity weighted.

6. The Equilibrium Effects of Homeownership Vouchers

I use the estimated model to evaluate the equilibrium effects of the DS1 program on key outcomes relevant for effectiveness: price pass-through, homeownership rates, and consumer surplus. To do so, I compare the simulated housing market equilibrium under the DS1 program $\boldsymbol{\mathcal{B}}^{DS1}$ to a baseline without the policy $\boldsymbol{\mathcal{B}}^{0}$. The baseline serves as an efficient benchmark as there are no frictions in housing demand or supply. The DS1 equilibrium replicates the program as in the data, with departures discussed in the model and demand estimation sections. Relative to the baseline, the DS1 program awards vouchers to households that delay their housing choices to receive them, with equilibrium prices and cutoff scores clearing the market. These simulations hold all market primitives fixed, including households' preferences and the costs of unit owners and developers. Details on the policies, simulation, and outcomes considered in this section are provided in Appendix E.

Equilibrium Effects and Cost Effectiveness. Table 3 compares equilibrium outcomes under the DS1 program relative to the baseline. Overall, the DS1 program increases housing prices by 1.5%, new development by 0.9%, homeownership rates by 1.2%, ammounting to a 0.61 Marginal Value of Public Funds (MVPF), meaning that each dollar of subsidy generates 0.61 in net welfare gains for housing buyers and sellers. The policy significantly increases homeownership rates among beneficiaries; by 41.4% for High, 15.1% for Medium, and 27.2% for Low voucher. Beneficiaries receive USD$445 million in net transfers, around half of the policy cost. However, pecuinary externalities harm the unsubsidized population, reducing homeownership rates by 0.3% amounting to a USD$243.7 million surplus loss. Price increases lead to a USD$303 million gain in producer surplus for sellers, with 99% of the gains received by households selling their units and developers being almost indifferent. Deadweight losses amount to USD$325 million, consistent with an scenario where demand is elastic relative to supply.

The overall MVPF of 0.61 is in line with gains from policies that target adult populations in the US (Hendren and Sprung-Keyser, 2020). However, this is a conservative measure for two reasons. First, it does not consider potential gains from increasing the activity of the development sector or potential tax revenues to the government from increased homeownership. Second, it does not consider gains from homeownership that might not be fully internalized by households, such as increases in consumption smoothing and wealth accumulation (Sodini et al., 2023), or improvements in labor and children's future outcomes (Chetty et al., 2016; Van Dijk, 2019; Currie and Van Parys, 2025).[34] Notably, even without incorporating these additional benefits, DS1 program's MVPF is comparable to Hendren and Sprung-Keyser (2020) estimates for US housing vouchers when accounting for labor market gains (Jacob and Ludwig, 2012). In what follows, I exploit the richness of the model to understand the mechanisms and distributional effects of the policy.

Voucher Concentration, New Development, and Price Effects. Panel B of Table 3 decomposes the effects accross vintage and structure type, and by targeted and non-targeted segments-defined as housing types with baseline prices below the maximum price cap in at least one market. Price increases are localized in the targeted resale segment, where prices increase by 3.9% for houses and 2.9% for apartments.

Figure 6 shows the price (a) and quantity (b) effects of the DS1 program relative to the no-voucher baseline, accoss baseline price segments. The increase in prices is concentrated in the most affordable resale segments. There are two mechanisms at play beyond the voucher price caps and decreasing discount schedules. First, beneficiaries have preferences for the most affordable resale housing segment, as those units are located in their origin counties and they are the most price sensitive. When subsidized, they become less price sensitive, so they do not substitute towards other segments even though prices increase. This compounds with the fact that the resale segment is the least price elastic segment.

On the new development segment, the price increase is significantly smaller, both for targeted new apartments (0.8%) and houses (0.4%). This is driven by the reaction of developers to the demand shock, increasing new development rates of targeted apartments and houses. Figure 6 shows the

[34] While accounting for such effects is beyond the scope of this paper, Fuenzalida et al. (2024) finds that DS1 marginal winners increase children's school attendance, grades, and graduation, though with reduced parental labor market participation. Hendren and Sprung-Keyser (2020) estimates for the MTO voucher experiment Chetty et al. (2016) go to infinite MVPF when accounting for effects on children's future outcomes. I abstract from these effects as a careful evaluation would require not only estimating the effects over the full distribution of voucher winners, but also accounting for spillovers to the non-beneficiary population.

Table 3: Equilibrium Effects of the DS1 Program Relative to the No-Voucher Baseline.

Panel A: Household Outcomes and Characteristics

	Homeownership ($\triangle$%)	Consumer Surplus ($\triangle$%)	Compensating Variation (MM USD)	Household Characteristics: Price Sensitivity (Mean Pctl α_i)	Homeownership Value (Mean Pctl h_i)	Income (Mean Pctl z_i^{Inc})
By Voucher Status:						
High	41.4	55.1	155.2	8.5	43.5	30.0
Medium	15.1	19.9	152.6	15.1	57.1	31.5
Low	27.2	36.9	137.6	17.6	29.7	37.6
Unsubsidized	-0.3	-0.0	-243.7	54.3	51.0	52.0
Overall	1.2	0.0	201.6	—	—	—

Panel B: Housing Market

	Prices: Targeted ($\triangle$%)	Prices: Non-Targeted ($\triangle$%)	Producer Compensating Variation: Targeted (MM USD)	Producer Compensating Variation: Non-Targeted (MM USD)	New Development: Targeted ($\triangle$%)	New Development: Non-Targeted ($\triangle$%)
By Housing Type:						
New Apartments	0.8	0.0	35.7	0.3	2.3	-0.4
New Houses	0.4	-0.0	0.3	-0.0	-0.0	-0.5
Resale Apartments	2.9	0.0	57.2	0.7	—	—
Resale Houses	3.9	0.0	208.7	0.3	—	—
Overall	2.7	0.0	301.8	1.3	2.2	-0.4

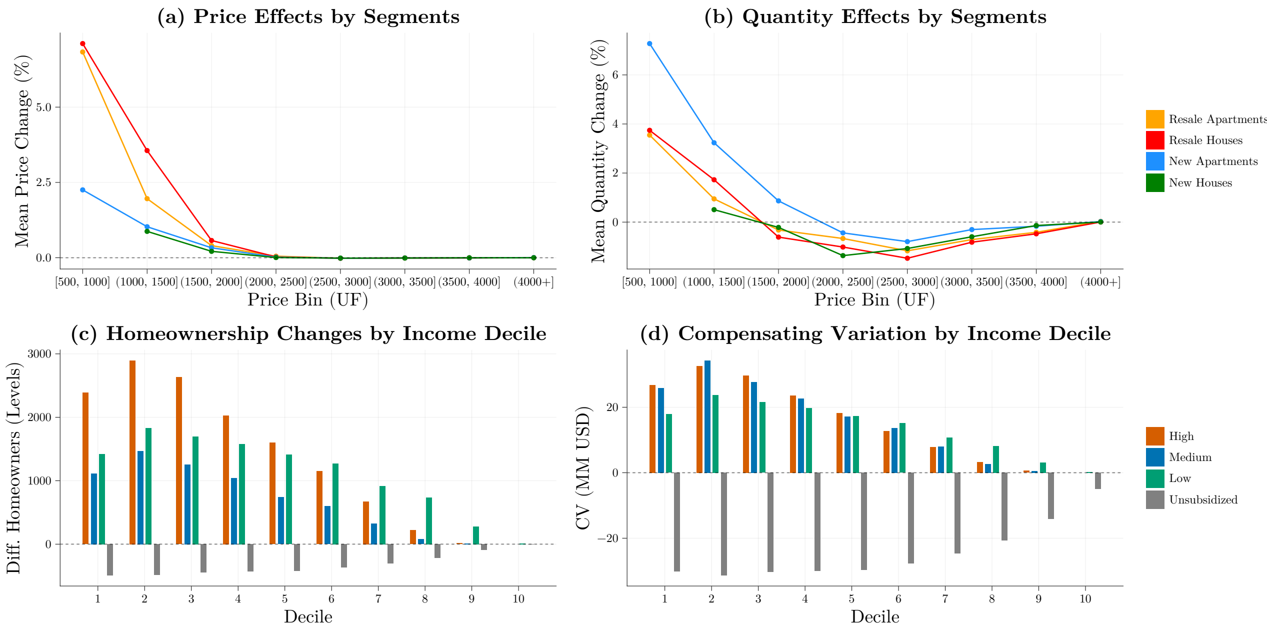
Panel C: Policy Outcomes

	Policy Cost (MM USD)	Deadweight Loss (Share of Cost)	Marginal Value of Public Funds (MVPF): Households	Households + Resale Owners	Total Surplus
Overall	833.5	0.39	0.24	0.56	0.61
High	301.6	—	0.51	—	—
Medium	321.8	—	0.47	—	—
Low	210.1	—	0.65	—	—

Notes: This table presents counterfactual simulations of the DS1 homeownership voucher program under the estimated demand and supply model. Panel A reports household-level outcomes and characteristics by voucher status. All changes denoted by $\triangle$% are percentage changes from the baseline equilibrium. Household characteristics report mean percentiles of the respective distributions. Panel B shows equilibrium effects in targeted segments, defined as housing types that have baseline prices below the maximum price cap for at least one half-year. Changes in prices are quantity-weighted averages. Panel C presents the policy's fiscal cost, deadweight loss as a share of cost, and marginal value of public funds (MVPF), calculated as the ratio of CV to Policy Cost for the respective group. See Appendix E for details on each outcome.

significant incrrease in new development transactions in the most affordable price segments. This increase is not only absorbing subsidized demand, but also capturing demand from non-beneficiaries substituting away from resale units.

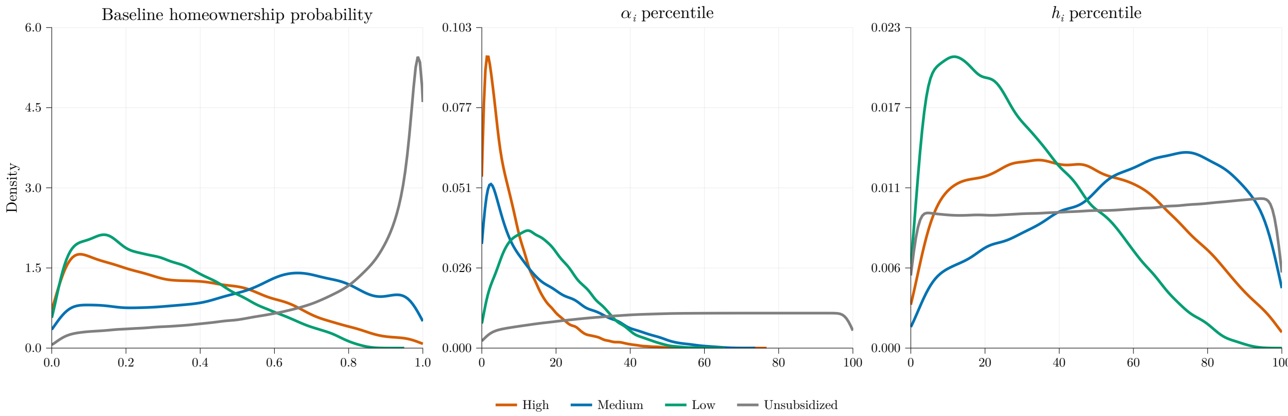
Figure 6: Equilibrium Effects of the DS1 Program Relative to the No-Voucher Baseline.



Voucher Targeting, Pecuniary Externalities, and Homeownership Rates. Figure 6 shows the changes in homeownership rates (c) and compensating variation (d) by voucher status and income deciles. Pecuniary externalities are mostly borne by lower-income unsubsidized households, as price increases are localized in the affordable segments they have preferences for. However, their homeownership rates are not significantly affected, with the policy having net positive effects on homeownership rates accross the income distribution.

How does the policy increase homeownership rates while subsidizing only 12% of potential buyers and significantly increasing prices? Figure 7 shows the distribution of beneficiaries by baseline ownership probability, price sensitivity, and ownership value. The answer is that the policy attracts extramarginal households, those that are less likely to purchase a house without the voucher. This not only explains why the policy has positive effects on overall homeownership rates, but also explains why vouchers have such different effectiveness at transferring resources to households. Panel C of Table 3 shows that the Low voucher is the most effective at transferring resources to beneficiaries, transferring 65 cents per dollar spent while the Medium voucher only transfers 47. Although these are the least generous vouchers and are awarded to higher-SES households relative to the High and Mid vouchers, they attract households that are as unlikely to purchase without assistance as the High voucher beneficiaries. The reason behind this is that it attracts households with a lower value for homeownership and with a similar price sensitivity as the other vouchers' beneficiaries. In the absence of assistance, these households are the most likely to stay as renters.

Figure 7: Targeting of DS1 Program by Baseline Ownership Probablility, Price Sensitivity, and Homeownership Value.



7. Targeting vs. Price Pass-Through in the Design of Vouchers

In order to empirically quantify the trade-off between targeting and price pass-through in the design of vouchers, I simulate budget-balanced variants of the DS01 program that aim to capture the different dimensions of the trade-off:

- **All Low $\mathcal{B}^{Low}$ or High $\mathcal{B}^{High}$ Vouchers.** I simulate budget-balanced variants of the DS01 program that reallocate the entire budget to either the Low or the High voucher while keeping eligibility, scoring, and other features unchanged. This exercise serves two purposes. First, it quantifies the trade-off between targeting and price pass-through. Compared with All-Low, the All-High design has tighter eligibility and provides larger subsidies to lower-SES households, but it also concentrates demand into a smaller housing-market segment, potentially amplifying pass-through effects.

  Second, the All-Low and All-High scenarios allow me to study the value of offering multiple voucher alternatives as in the DS01 design. A menu can improve targeting when households have unobserved preference heterogeneity: the Low voucher attracts less price-sensitive applicants, reserving the High voucher for those who need greater assistance. If most heterogeneity is observable, however, a single High voucher could suffice. Because cost-effectiveness ultimately hinges on price pass-through, DS01 may still dominate if the All-High design amplifies pass-through even while improving observable targeting.

- **Vouchers for New Housing $\mathcal{B}^{New}$.** This policy consists of the DS01 voucher menu with the added restriction that vouchers can be used only to purchase newly built units. Because supply in the new segment is much more price-elastic than in the resale market, channeling demand here should dampen price pass-through and improve cost-effectiveness. However, the composition of subsidized households may change significantly, potentially reducing targeting and effectiveness in raising homeownership rates.[35]

The differences between the DS01 and the All-Low and All-High policies allow for a deeper understanding of the trade-off between targeting and price pass-through, as well as the value of screening through a voucher menu. On the one hand, the All-High policy mechanically improves targeting, as all the resources are used to award the most generous and restrictive vouchers to low-SES households—up to the 40% of the most socially vulnerable households according to the SVS. On the other hand, the All-Low policy offers the least generous and least restrictive vouchers to low- and middle-SES households—up to the 90% of the most vulnerable households.

In the absence of equilibrium price adjustments, the results from the previous section would suggest that the All-High policy would be more effective than the DS01 policy at increasing homeownership rates, as the increase in homeownership rates was driven by the households that were awarded the High voucher. However, considering the equilibrium price adjustments might flip this conclusion, as results also showed that the increase in housing prices was driven by the resale housing segment, which is the preferred housing type of low-income households. Which effect dominates depends on the interaction between households' voucher and housing choices as well as the supply-side response.

Targeting, Price Passthrough, and Policy Effectiveness. Panel A of Table **??** shows that relative to DS01 the All-High policy is almost equally effective at increasing homeownership rates (18.4% vs. 19.2%), almost triples the price pass-through (11.5% vs. 4.4%), and raises both the overall policy cost and the cost per extra homeowner by more than 10%.

Panel B shows that the All-High policy outperforms DS01 only in overall targeting. However, the costs for the non-applicant households are significantly higher, both on the consumer surplus and homeownership rates. This causes prices for resale houses and apartments to almost double relative to the DS01 policy. This is underscored by the increase in the compensating variation necessary to leave the non-applicant households indifferent to the policy, which increases from USD$52.3 million under the DS01 to USD$380.5 million under the All-High policy.

Panel C sheds light on the mechanisms behind these results. Because 86% of vouchers are used in the resale segment, the demand shock is heavily concentrated there. Notably, even though a small fraction of vouchers are used in the new development segment, the price pass-through is similar to that under DS01; this similarity reflects demand-substitution effects.

On the other hand, the All-Low policy less effective than the DS01 policy at increasing homeownership rates (15.4% vs 19.2%), however it reduces the cost per extra homeowner by around 30%. At the same time, it significantly increases upward mobility from 6.3% to 12.2%, reducing the cost per mover by a third relative to the DS01 policy (USD$3,394 vs. USD$4,273). The ex-post cost

[35] This counterfactual is also policy-relevant: similar designs have been implemented in other countries, such as Colombia's *Mi Casa Ya*, which provides means-tested, rationed vouchers exclusively for affordable new housing developments.

of the policy is reduced by almost half.

Panel B sheds light on the mechanisms behind these results, highlighting how greater cost-effectiveness comes at the expense of weaker targeting. The All-Low policy targets households with a price sensitivity below the median of the population, even lower than non-applicant households. This is explained by the fact that a lower subsidy is not enough to attract the most vulnerable households, even though they are prioritized by the scoring rule. The policy also attracts households with a higher value for homeownership. Taken together, the All-Low policy is attracting a significant share of inframarginal households, which explains the reduction in the impact on homeownership rates.

Panel C explains why the price pass-through is lower than in the DS01 policy, as the vouchers are more intensively used in the new development segment. However, the effect on prices is lower, as developers react to the increase in demand by constructing more new apartments and houses relative to the DS01 policy. In particular, the development of new apartments increases by a third relative to the DS01 policy, from 6% to 8%.

The Value of Offering a Voucher Menu. Overall, the DS01 policy strictly dominates the All-High policy in all demand-side outcomes and cost-effectiveness, the All-High policy only performs better in terms of overall targeting. The All-Low policy leads to higher mobility and lower costs per extra homeowner, but at the cost of a lower impact on homeownership rates and a less effective targeting. While I don't rank policies in a single dimension, the DS01 policy achieves similar homeownership rates as the All-High policy at a lower cost, while performing better than the All-Low policy in terms of homeownership rates and targeting.

The value of offering a menu of alternatives to screen households is well understood in economics. For the context of housing vouchers, these results show that multiple alternatives can improve targeting while reducing voucher-induced price pass-through. On top of that, it underscores the relevance of jointly designing multiple kinds of assistance, as households take-up choices depend on all the types of available assistance for them, and their sorting affect the equilibrium effectiveness of each type of assistance.

7.0.1 Heterogenous Supply Price Elasticities and the Opportunities for Policy Design

The previous section highlighted the importance of considering equilibrium price adjustments when designing homeownership vouchers. In the supply estimation, I find significant heterogeneity in the supply price elasticities across housing segments. This result suggest that there is space for a better design, as policymakers could restrict the use of vouchers in segments with a more elastic supply response, leading to a lower price pass-through. However, this might affect the targeting of the policy, as the value of assistance would be reduced for households for preferences for the restricted segments.

In practice, it might be unfeasible to implement choice restrictions based on estimates of supply price elasticities, as it might seem arbitrary to households. However, in practice, some homeownership assistance programs are restricted to new developments, such as the Colombian homeownership subsidy *Mi Casa Ya*. Inspired by this policy and the empirical finding that the new housing segment is significantly more elastic than the resale housing segment, I simulate a policy that consist on the DS01 program adding the restriction that vouchers can only be used to purchase new housing units.

Supply Price Elasticities, Targeting, and Effectiveness. Panel A of Table **??** shows that the DS01 Only New policy outperforms the DS01 policy in all dimensions. It leads to higher homeownership rates (23.4% vs. 19.2%) at less than half the cost per extra homeowner, and to three times more upward mobility (21.1% vs. 6.3%) at a fourth of the cost per mover. The overall cost of the policy is reduced by around 30%.

However, Panel B shows that this comes at the cost of significantly lower targeting, even when compared to the All-Low policy. The DS01 Only New policy attracts households with a lower mean price sensitivity and higher value for homeownership relative to the non-applicant population. With the significant increase in homeownership rates mostly driven by the increase in voucher use, as the combination of lower price sensitivity and reduced out-of-pocket prices makes the subsidized households very unlikely to not purchase a house.

Panel C shows that developers react to the increase in demand by significantly increasing the new construction of apartments (from 6% to 12%) and houses (from 1% to 7%) relative to the DS01 policy. This is what explains the price pass-through being reduced by half relative DS01 policy, as the increase in supply leads to a lower equilibrium price increase. This also explains the effectiveness of the policy in increasing homeownership rates, as the pecuniary externalities on the unsubsidized population are significantly lower than in the DS01 policy.

These results highlight the potential of using supply-side information to design more effective homeownership assistance programs. However, there is no silver bullet, because choice restrictions might significantly weaken policy targeting.

8. Conclusion

Although widely adopted, the effectiveness of vouchers to increase homeownership rates is still debated. Designing effective policies requires understanding both housing segment price equilibrium adjustments and how to screen inframarginal households. Equilibrium price adjustments depend on the supply elasticity of each segment and aggregate demand for them. Targeting and rationing vouchers requires understanding the preferences of intended and unintended beneficiaries to design vouchers and allocation rules that maximize take-up from intended beneficiaries. However, improved targeting correlates beneficiaries' preferences more strongly, concentrating the subsidy shock in their preferred segments and potentially amplifying inflationary effects. The success of a policy at increasing homeownership rates depends on both the composition of beneficiaries and how the housing market adjusts.

In this paper, I have developed a competitive equilibrium model of a homeownership market to provide guidance on designing targeted and rationed voucher policies. First, I use the model to evaluate the aggregate and distributional effects of large-scale voucher policies. I show that targeted vouchers increase homeownership rates while raising prices, with increases in new development—the most elastic segment—playing a key role in buffering inflationary effects. Second, I quantitatively evaluate the trade-off between increasing targeting and reducing price pass-through. Both strictly targeted and loosely targeted policies are dominated by the DS1 policy, which offers voucher alternatives with different means-testing levels. Offering less generous but less restrictive vouchers to higher-SES households enables targeting the most generous vouchers to the poorest households. Finally, I evaluate voucher policies that restrict voucher use to the most elastic housing segments. These policies significantly increase cost-effectiveness by reducing price pass-through, but ultimately target households with preferences for these segments rather than those most in need of assistance.

This analysis of the homeownership market does not investigate potential strategic responses of developers in pricing and development decisions. Future research could incorporate this margin, as developers may respond by building more lower-quality units or capturing assistance rents through price increases. Another abstracted margin is households' understanding and beliefs about the trade-offs involved in applying for vouchers. Access to information on households' beliefs would allow exploration of whether different allocation mechanisms have implications for who receives assistance, potentially improving targeting.

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A Extra Tables and Figures

A.1 Background and Data Sources

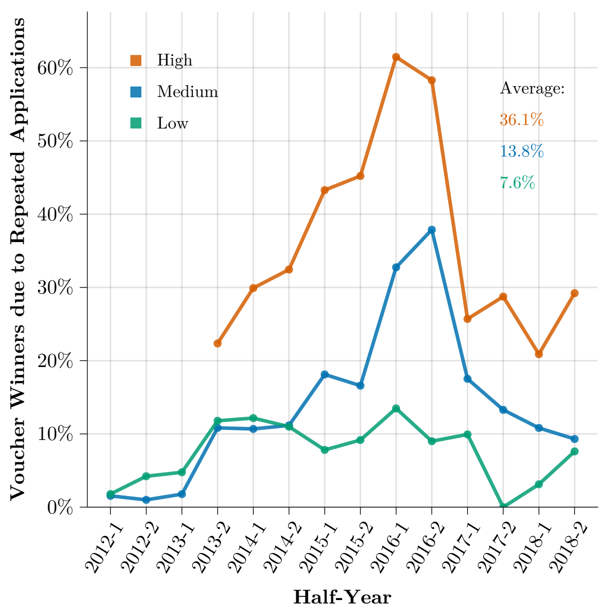
Table A.1: Voucher Use and Policy Costs over Time

Panel A: DS1 Vouchers	**High**			**Medium**			**Low**		
Total Awarded	22606			22117			31150		
Eligible Transactions (%)	11.7			27.4			53.5		
Eligible Transactions Subsidized (%)	21.4			9.9			6.9		
Mean Subsidy Share of Price	78.0			50.5			16.9		
Panel B: Beneficiaries' Choices									
Share Used (%)	60.7			67.6			64.9		
Share Changes County (%)	39.4			43.8			53.7		
	Subsidized	**Unsubsidized**	**Eligible**	**Subsidized**	**Unsubsidized**	**Eligible**	**Subsidized**	**Unsubsidized**	**Eligible**
Price (UF)	670.0	714.3	704.4	873.2	857.6	850.3	1,446.5	1,251.2	1,221.2
	(165.6)	(143.4)	(147.5)	(250.0)	(246.0)	(244.6)	(394.7)	(457.5)	(460.9)
Size (m^2)	44.9	51.2	50.0	48.3	50.7	50.1	50.3	51.1	50.7
	(12.3)	(17.3)	(16.7)	(14.6)	(19.3)	(18.3)	(15.1)	(20.7)	(19.9)
House (%)	63.7	56.6	58.3	69.6	50.9	53.9	47.6	42.7	45.2
	(48.1)	(49.6)	(49.3)	(46.0)	(50.0)	(49.8)	(49.9)	(49.5)	(49.8)
New (%)	0.5	19.6	15.6	14.0	26.6	23.9	48.4	35.9	34.4
	(6.9)	(39.7)	(36.3)	(34.7)	(44.2)	(42.6)	(50.0)	(48.0)	(47.5)
Neighborhood Share College Educated (%)	22.5	23.3	21.1	24.8	29.3	27.1	33.4	40.2	38.2
	(10.8)	(19.9)	(18.9)	(11.2)	(22.7)	(21.8)	(15.7)	(24.7)	(24.7)
Total Transactions	13,721	50,168	64,056	14,953	119,036	150,394	20,211	249,316	293,571

Notes: Variable construction detailed in Appendix B. Eligible transactions are defined as transactions in Santiago below each voucher's price cap at the time of signing the contract. The share of college educated households correspond to the census tract level.

A.2 Descriptive Results

Figure A.1: Voucher Winners due to Repeated Applications



Notes: This figure shows the share of winners by voucher and half-year whose score would have been below the cutoff score without the extra application score.

Table A.2: Transaction Characteristics Subsidized vs Eligible

	Unit Price (UF)			Size (m²)			House			New Construction			Share College Ed.		
	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low
Subsidized transaction	-19.83***	74.14***	173.60***	-2.45***	-1.78***	-0.17	-0.07***	0.04***	0.05***	-0.09***	-0.02**	0.11***	-0.04***	-0.02***	-0.01***
	(4.36)	(3.98)	(7.78)	(0.23)	(0.25)	(0.31)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Observations	64,052	150,391	293,568	64,052	150,391	293,568	64,052	150,391	293,568	64,052	150,391	293,568	64,052	150,391	293,568
Adjusted R^2	0.234	0.295	0.354	0.162	0.124	0.155	0.326	0.448	0.560	0.501	0.496	0.488	0.573	0.655	0.689
Control mean	713.45	850.63	1207.35	50.92	50.22	50.69	0.57	0.52	0.45	0.18	0.25	0.33	0.23	0.28	0.38
Fixed Effects															
Market-County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Price				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓
House	✓	✓	✓	✓	✓	✓				✓	✓	✓	✓	✓	✓
New	✓	✓	✓	✓	✓	✓	✓	✓	✓				✓	✓	✓
Sh. College	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			

Notes:

Table A.3: Demographics Regression

	Dependent Variable							
	Used Voucher	Unit Price (UF)	Size (m^2)	House	New Construction	Change County	Dist. City Center (km)	Sh. College Ed.
High								
Income Percentile (std.)	-0.012* (0.006)	45.266*** (2.662)	-0.098 (0.256)	-0.006 (0.009)	0.001 (0.002)	-0.001 (0.009)	-0.086 (0.107)	-0.000 (0.002)
Family Size	-0.025*** (0.003)	3.474*** (1.331)	-0.292** (0.124)	0.014*** (0.005)	-0.000 (0.001)	0.005 (0.004)	0.194*** (0.056)	-0.000 (0.001)
Has Children	0.018 (0.014)	22.331*** (6.025)	-0.722 (0.542)	0.043** (0.020)	-0.003 (0.003)	-0.043** (0.019)	-0.334 (0.234)	-0.001 (0.004)
Age (std.)	-0.039*** (0.003)	0.785 (1.478)	0.321** (0.131)	0.021*** (0.005)	-0.001 (0.001)	-0.020*** (0.005)	-0.217*** (0.060)	0.001 (0.001)
Observations	22,563	11,272	11,272	11,272	11,272	11,272	11,272	11,272
Adjusted R^2	0.080	0.386	0.046	0.099	0.013	0.228	0.439	0.421
Mean Dep. Var.	60.7	669.9	44.9	63.7	0.5	39.4	16.0	22.5
Medium								
Income Percentile (std.)	-0.024*** (0.006)	88.682*** (3.889)	-0.014 (0.312)	0.027*** (0.008)	0.007 (0.005)	-0.020** (0.009)	-0.291*** (0.104)	-0.001 (0.002)
Family Size	-0.022*** (0.004)	35.772*** (2.331)	-0.043 (0.187)	0.039*** (0.005)	-0.009*** (0.003)	-0.015*** (0.005)	0.090 (0.062)	-0.002** (0.001)
Has Children	-0.011 (0.011)	48.379*** (6.460)	0.486 (0.437)	0.021 (0.013)	-0.017* (0.009)	-0.054*** (0.015)	0.056 (0.177)	-0.009*** (0.003)
Age (std.)	-0.030*** (0.004)	-19.462*** (2.165)	0.558*** (0.152)	0.005 (0.004)	-0.009*** (0.003)	-0.016*** (0.005)	-0.261*** (0.059)	0.001 (0.001)
Observations	20,030	11,451	11,451	11,451	11,451	11,451	11,451	11,451
Adjusted R^2	0.082	0.407	0.042	0.272	0.347	0.213	0.416	0.329
Mean Dep. Var.	66.6	880.8	48.3	70.0	13.0	43.7	14.5	24.7
Low								
Income Percentile (std.)	0.015** (0.007)	263.721*** (6.867)	-0.318 (0.397)	-0.012* (0.007)	-0.022*** (0.007)	-0.020** (0.009)	-0.351*** (0.104)	0.011*** (0.002)
Family Size	-0.018*** (0.004)	83.127*** (4.176)	-0.204 (0.211)	0.049*** (0.005)	-0.017*** (0.005)	-0.019*** (0.006)	0.174** (0.070)	-0.002* (0.001)
Has Children	-0.019** (0.008)	45.273*** (7.311)	-0.071 (0.323)	0.011 (0.008)	-0.009 (0.008)	-0.020* (0.011)	0.790*** (0.125)	-0.022*** (0.003)
Age (std.)	-0.053*** (0.003)	-62.198*** (3.171)	0.464*** (0.148)	-0.013*** (0.004)	-0.015*** (0.004)	0.000 (0.005)	-0.156*** (0.052)	-0.003** (0.001)
Observations	28,639	16,391	16,391	16,391	16,391	16,391	16,391	16,391
Adjusted R^2	0.034	0.374	0.096	0.541	0.528	0.176	0.525	0.443
Mean Dep. Var.	64.4	1457.3	50.1	47.5	48.4	53.8	11.6	33.1
Controls								
Price			✓	✓	✓	✓	✓	✓
Size		✓		✓	✓	✓	✓	✓
House		✓	✓		✓	✓	✓	✓
New		✓	✓	✓		✓	✓	✓
County Origin FE	✓	✓	✓	✓	✓	✓	✓	✓
Award Date FE	✓							
Award × Purchase Date FE		✓	✓	✓	✓	✓	✓	✓

Note: Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

A.3 Estimation Sample

Table A.4: Housing Types Comparison

	Considered	Transactions	% Diff
Number of Observations			
Overall	505,220	549,057	8.7
High SES Cluster	192,717	207,965	7.9
County Cluster	119,460	136,772	14.5
Low SES Cluster	193,043	204,320	5.8
Price (UF)			
Overall	3104	3284	5.8
High SES Cluster	4212	4401	4.5
County Cluster	1677	1849	10.2
Low SES Cluster	2881	3109	7.9
Size (m^2)			
Overall	68.8	69.0	0.3
High SES Cluster	78.8	78.9	0.0
County Cluster	58.5	59.5	1.8
Low SES Cluster	65.1	65.3	0.3
House (%)			
Overall	42.3	41.4	-2.0
High SES Cluster	41.2	40.8	-0.9
County Cluster	53.3	49.8	-6.6
Low SES Cluster	36.6	36.5	-0.2
New (%)			
Overall	35.0	34.6	-1.0
High SES Cluster	38.3	38.5	0.4
County Cluster	35.0	33.3	-4.8
Low SES Cluster	31.5	31.5	0.0

Notes: Table compares housing types considered in estimation (weighted by transactions per type) with actual transaction data for estimation markets (2012-2018). % Diff calculated as (Transactions - Considered) / Considered $\times$ 100.

A.4 Demand Estimation Results

Table A.5: Demand Estimates

	Common	**Demographic Interactions**			
		Income	Age	Family Size	Children
Panel A: Utility Parameters					
Price (UF100) α	-13.95	0.01	0.91	0.60	-0.19
	(2.09)	(0.00)	(0.18)	(0.12)	(0.04)
House β^{House}	-2.95	0.13	-0.65	-0.20	3.45
	(0.00)	(0.05)	(0.19)	(0.08)	(1.21)
New β^{New}	3.59	3.71	-1.39	-3.77	2.20
	(1.01)	(1.22)	(0.46)	(1.24)	(0.73)
Size (10 m^2) β^{Size}	3.19	-0.00	0.07	-0.04	-0.19
	(0.80)	(0.00)	(0.02)	(0.02)	(0.06)
Same County β^{Loc}	20.80	-0.63	0.17	0.33	4.20
	(3.74)	(0.14)	(0.04)	(0.07)	(0.92)
Homeownership γ_0, γ_d	-38.94	-0.93	-0.34	0.90	-5.59
	(5.84)	(0.19)	(0.07)	(0.18)	(1.12)
Panel B: Unobserved Heterogeneity					
Price σ_α	0.02				
	(0.00)				
Homeownership σ_γ	1.27				
	(0.45)				

Notes: Common coefficients for housing attributes (House, New, Size) come from the second-stage, standard errors are clustered by housing type. All other coefficient come from the first-stage, standard errors computed using the Fisher information matrix. All Non-price parameters are expressed in 100 UF units (scaled by $10/|\alpha_0|$) for interpretability. Income corresponds to 100UF annual income, age to decades, family size to number of members, and children to binary indicator.

A.5 Supply Estimation Results

Table A.6: Inventory Estimates

	OLS	IV
	(1)	(2)
Price dynamic (UF$100)	-0.004	0.189**
	(0.005)	(0.082)
Housing Type FE	✓	✓
Market FE	✓	✓
Observations	761	761
F-Stat	-	17.69

Notes: Estimates from 2SLS regression equation (28) using ($\triangle^{\text{DS1}}Q_{jt} - \triangle^{\text{DS1}}Q_{jt+1}$) as instruments for the price difference term. The sample consist of 63 housing types across 14 markets, shares of sales are the ration of observed transactions over the total stock in the development survey data. Standard errors in parentheses are clustered at the housing type level.

Table A.7: Development Estimates

	OLS		IV		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Price (UF$100)	-0.574**	-0.122	3.615**	4.246**				
	(0.191)	(0.222)	(1.148)	(1.413)				
Log Price (UF$100) x House		-1.099**		-2.116**				
		(0.161)		(0.525)				
Log $\hat{\Pi}$					-0.433	0.038	5.521*	6.370*
					(0.484)	(0.546)	(1.214)	(2.857)
Log $\hat{\Pi}$ x House						-1.085*		-2.670**
						(0.443)		(1.018)
Housing Type FE	✓	✓	✓	✓	✓	✓	✓	✓
Market FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	761	761	761	761	761	761	761	761
F-Stat	-	-	21.79	19.12	-	-	20.91	18.41

Standard errors in parentheses are clustered at the housing type level. * $p < .1$, * $p < .05$, ** $p < .01$

Table A.8: Used Housing Supply Estimates

	OLS		IV	
	(1)	(2)	(3)	(4)
Price (UF$100)	-0.003*	0.009**	0.005*	0.028**
	(0.001)	(0.002)	(0.003)	(0.004)
Price (UF$100) x House		-0.009**		-0.08**
		(0.002)		(0.006)
Housing Type FE	✓	✓	✓	✓
Market FE	✓	✓	✓	✓
Observations	2030	2030	2030	2030
F-Stat	-	-	137.90	117.01

Standard errors in parentheses

* $p < .1$, * $p < .05$, ** $p < .01$

B Data Appendix

B.1 The DS1 voucher menu

Generosity and Choice Restrictions.

Table A.9: DS1 Menu Updates and Assigned Markets

	Discount Schedule	Price Cap	Update date	Half-Year Assigned
Low				
	$\max\{100, \min\{800 - 0.5p, 300\}\}$	2,000	May 2012	[2012–1, 2015–2]
	$\max\{125, \min\{725 - 0.375p, 350\}\}$	2,000	December 2015	[2016–1, 2016–2]
	$\max\{125, \min\{725 - 0.375p, 350\}\}$	2,200	2016	[2017–1, 2018–2]
Medium				
	$\min\{800 - 0.5p, 500\}$	1,000	May 2012	[2012–1, 2013–2]
	$\min\{800 - 0.5p, 500\}$	1,200	August 2013	[2014–1, 2015–2]
	$\min\{725 - 0.375p, 500\}$	1,400	December 2015	[2016–2, 2018–2]
High				
	$\min\{800 - 0.5p, 500\}$	800	August 2013	[2014–1, 2015–2]
	500	1000	December 2015	[2016–2, 2018–2]

Aggregation Assumptions.

Table A.10: DS1 Calls and Winners Aggregation

Call Number	Call Open Date	Assigned Half-Year of Application	First Purchase Date	Assigned Half-Year of Voucher Award
2012–1	03/22/2012	2012–1	08/09/2012	2012–2
2012–2	06/28/2012	2012–1	11/08/2012	2012–2
2012–3	11/05/2012	2012–2	03/21/2013	2013–1
2013–1	03/25/2013	2013–1	08/14/2013	2013–2
2013–2	07/01/2013	2013–1	12/05/2013	2013–2
2013–3	08/01/2013	2013–2	12/12/2013	2014–1
2013–4	09/02/2013	2013–2	02/20/2014	2014–1
2013–5	10/02/2013	2013–2	03/06/2014	2014–1
2014–1	03/18/2014	2014–1	08/13/2014	2014–2
2014–2	07/08/2014	2014–2	11/20/2014	2015–1
2014–3	11/06/2014	2014–2	03/26/2015	2015–1
2015–1	05/18/2015	2015–1	09/04/2015	2015–2
2015–2	11/10/2015	2015–2	04/07/2016	2016–1
2016–1	04/18/2016	2016–1	09/22/2016	2016–2
2016–2	11/03/2016	2016–2	04/06/2017	2017–1
2017–1	05/15/2017	2017–1	09/28/2017	2017–2
2017–2	09/01/2017	2017–2	01/18/2018	2018–1
2018–1	04/09/2018	2018–1	09/27/2018	2018–2
2018–2	11/07/2018	2018–2	03/21/2019	2019–1

C Demand Estimation Appendix

C.1 Sample definition and assumptions

[Update Tables]

C.2 Selection Corrected Mixed Data Likelihood Estimator

C.2.1 Intuition from the ideal case

To build intuition, let's assume that microdata is available for all households. That is, we observe every household that arrives to the homeownership market, their sequence of voucher and housing choices $(\boldsymbol{b}_i^*, j_{it_i^h}^*)$, and their demographics $\boldsymbol{z}_i = \{z_{it}\}_{t \in [t_i^a, t_i^h]}$.[36]

Each household i arrives in period t_i^a and begins making choices. Each period t, eligible households that have not received a voucher nor made a housing choice, decide whether to apply for a voucher $b \in \mathcal{B}_{it}$ or not $b = 0$. Households that decide to not apply for a voucher make a housing choice at $t_i^h = t_i^a$, and households that are awarded a voucher make a housing choice in period $t_i^h > t_i^a$. Then, for each applicant household i, I observe the sequence of voucher applications $\boldsymbol{b}_i^* = \{b_{it}^*\}_{t \in T_i^B}$ where $T_i^B = \{t_i^a, ..., t_i^w\}$ is the set of periods between arrival and winning a voucher.[37] For non-applicant households, I only observe one voucher choice $b_{it^a}^* = 0$. For all households, I observe one housing choice $j_{it_i^h}^*$ in the period they make a housing choice t_i^h, which is either the period of arrival t_i^a or the period in which they are assigned to use the voucher.

The relevant probability for the likelihood is the probability of observing a sequence of choices $(\boldsymbol{b}_i^*, j_{it_i^h}^*)$ given the observed characteristics $\boldsymbol{z}_i$ and voucher status b_{it^h}:

$$\mathbb{P}_{\nu_i, \boldsymbol{\epsilon}_i^B, \epsilon_i^H}((\{b_{it}^*(z_{it}, \nu_i, \boldsymbol{\epsilon}_{it}^B)\}_{t \in T_i^B}, j_{it_i^h}^*(z_{it_i^h}, b_{it_i^h}, \nu_i, \boldsymbol{\epsilon}_{it}^H) | \boldsymbol{z}_i, b_{it^h}, T_i^B, t_i^h). \tag{C.1}$$

where the subscripts of the probability denote the unobserved parameters for which I will need to integrate over. Note that the *actual* probability of observing such a sequence includes the winning probabilities (i.e., repeated applications) and the probability of being assigned to use a voucher in period t_i^h (i.e., exogenous period of housing choice). I restrict attention to the probability given (T_i^B, t_i^h), as winning probabilities and housing assignment probabilities do not depend on the preference parameters so they will integrate out of the likelihood.

Given the model assumptions, the application and housing choice probabilities are conditionally independent. That is, conditional on households preferences, there is no correlation between the voucher and housing choices (i.e., there is no systematic individual preferences for a voucher, and

[36] In the model, I assume that households do not internalize the evolution of z_{it} over time, so this can be treated as exogenous.

[37] Adding exogenous departure is straightforward, currently, the idiosyncratic tastes for vouchers make departure of the system happen randomly or by changes in preferences or voucher design.

voucher status does not change households preferences beyond discounts and choice restrictions). Therefore, the probability of observing a sequence of choices $(\boldsymbol{b}_i^*, j_{it_i^h}^*)$ in periods (T_i^B, t_i^h) is given by the product of the voucher choices and the housing choice probabilities:

$$\left(\prod_{t \in T_i^B} \mathbb{P}_{\nu_i, \boldsymbol{\epsilon}_{it}^B}(b_{it}^*(z_{it}, \nu_i, \epsilon_{it}^B; \boldsymbol{\theta}))\right) \times \mathbb{P}_{\nu_i, \boldsymbol{\epsilon}_{it_i^h}^H}(j_{it_i^h}^*(z_{it_i^h}, \nu_i, \boldsymbol{\epsilon}_{it_i^h}^H, b_{it_i^h}; \boldsymbol{\theta}))$$

Let $\boldsymbol{\theta} = \{\boldsymbol{\alpha}, \boldsymbol{\beta}_d^c, \boldsymbol{\gamma}_d^c, \boldsymbol{\sigma}, \boldsymbol{\delta}\}$ be the vector of parameters of interest, note that the mean utilities δ_{jt} are treated as parameters. The individual contribution to the likelihood at parameters $\boldsymbol{\theta}$ is given by:

$$\mathcal{L}_i(\boldsymbol{\theta}) = \int \underbrace{\left(\prod_{t \in T_i^B} q_{ib^*t}^B(z_{it}, \nu; \boldsymbol{\theta})\right)}_{\text{Voucher choices in } T_i^B} \times \underbrace{q_{ij^*t^h}^H(z_{it_i^h}, b_{it_i^h}, \nu; \boldsymbol{\theta})}_{\text{Housing choice in } t_i^h} dF(\nu)$$

where q^B and q^H are the model implied choice probabilities (11) and (4) respectively, and b^* and j^* indicate the observed voucher and housing choices.

Voucher Choice Model as Weight for the Distribution of Unobserved Characteristics. The key insight is that the voucher choice probabilities *control* for the endogeneity of the voucher status b_{it^h}. Note that in the model, vouchers have no intrinsic value, as a result, there is no parameters in q^B that are not in q^H. We can think of the product of the voucher choice probabilities as *weights* for the distribution $F(\nu)$ of unobserved characteristics. To fix ideas, imagine there are only two alternatives: one voucher and no voucher, and we have two identical i up to their unobserved characteristics ν_i and with different voucher status. If we were only matching the housing choice probabilities, we would integrate over the same distribution $F(\nu)$ for both households. However, when matching the voucher choice probabilities, the likelihood would penalize values of ν for which it is unlikely that each household ends up with their respective voucher status. As a result, the likelihood would integrate over a different weighted distribution $F(\nu)$ for each household.

Identifying variation. Now that we are controlling for the endogeneity of the voucher status b_{it^h}, we can use the variation they induce in prices and choice sets, as now we can say that conditional on demographics and unobserved preferences, with a large sample we will observe identical individuals with differential voucher status. The policy induces the following variation that allows for identification of the parameters:

- **Individual price and choice sets variation:** Vouchers provide exogenous variation in the housing prices and choice sets of each household. As a result, identification of the price sensitivity parameters follow the standard (McFadden, 1972) argument. This is the standard identification argument in education (Neilson, 2013; Bodéré, 2023) and health care (Tebaldi, 2025) settings where vouchers provide variation in prices at the individual level. Intuitively, once the endogeneity of the voucher status is controlled for, the vouchers work as a *perfect* instrument in the sense that they deterministically shift prices and choice sets.

- **Voucher value and choice set variation:** The voucher application model only relies on housing preferences and the calibrated discount factor ρ. While the previous argument is enough for identification of the housing preference parameters, it is useful to note that the voucher application model provides extra identifying variation. Given that we are estimating housing preference parameters, variation in voucher choice sets $\mathcal{B}_{it}$ due to the eligibility rules, and different values V^B_{ibt} due to differences in their scores r_{ibt} which in combination with the equilibrium cutoff scores $\bar{r}_{bt}$ determine the probability of winning a voucher, provide extra identifying variation. Intuitively, we have two identical individuals that only vary in their eligibility and scores, which are orthogonal to housing preferences, and therefore face different voucher values or choice sets. Loosely speaking, this kind of variation is what an excluded instrument provides in two-step selection correction methods.

- **Policy Changes:** Finally, while the previous arguments are enough to identify the parameters, there is extra identifying variation across markets due to policy changes. Changes in eligibility, scoring rules, the number of vouchers available, and the generosity and price cap of each voucher, induce variation across markets for the voucher choice problem. For example, when a new DS1 is introduced in 2006, ineligible households in 2005 could be eligible in 2006, and eligible households in 2005 could decide to not apply and wait for the better 2006 voucher.[38]

C.2.2 Incorporating unobserved data structures

If all households in the micro data arrive in period t^a, apply for a voucher, and subsequently are awarded the voucher in period t^w and make a housing choice in period t^h, we would observe $\boldsymbol{z}_i = \{z_{it}\}_{t\in[t_i^a,t_i^h]}$, the sequence of voucher applications $\boldsymbol{b}_i^* = \{b^*_{it}\}_{t\in T_i^B}$, and the housing choice $(j^*_{it_i^h}, t_i^h)$. However, since I cannot match applicant households over time, and I only observe applicants' demographics at the point of application, I only observe a snapshot of the voucher and housing choices. Specifically, for each applicant household i I only observe the *chosen* voucher at the period of application $b^*_{it_i^a}$, as opposed to the full sequence of voucher choices $\boldsymbol{b}_i^*$. To leverage the variation of the voucher choice, I must adapt the likelihood to account for this limitation.[39]

Micro likelihood.- Recall that the micro data only contains households that applied for a voucher. The relevant probability for the likelihood is the probability of observing a sequence of choices $(\boldsymbol{b}_i^*, j^*_{it_i^h})$

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[38] Note that changes across markets are less relevant for identification, as the mean utility parameters δ_{jt} capture year and city level fixed effects. Loosely speaking, while withing market variation helps identify the price sensitivities, across market variation does not. However, in my case, across market variation also affect the voucher choice problem, and, as we shall see, this affects the likelihood (i.e., identification) of the mean utilities and, as a result, also the price sensitivities.

[39] While no being able to match households over time and not observing the full sequence of voucher choices is a limitation, in the next sections I show that these limitations are not a problem for identification of the parameters, and just add computational and econometric complexity to the estimation.

given the household applied for a voucher upon arrival:

$$\mathbb{P}_{\nu_i,\boldsymbol{\epsilon}_i^B,\boldsymbol{\epsilon}_{ith}^H}(\{\boldsymbol{b}_i^*(z_{it},\nu_i,\boldsymbol{\epsilon}_{it}^B)\}_{t\in T_i^B}, j_{it_i^h}^*(z_{it_i^h},\nu_i,\boldsymbol{\epsilon}_{it^h}^H)|b_{it^a}^*(z_{it^a},\nu_i,\boldsymbol{\epsilon}_{it^a}^B)\neq 0) \tag{C.2}$$

where the term $b_{it^a}^*(z_{it^a},\nu_i,\boldsymbol{\epsilon}_{it^a}^B)\neq 0$ conditions the probability on the household i applying for a voucher upon arrival. We can rewrite this probability using Bayes rule and the model implied choice probabilities:

$$\begin{aligned}
&= \frac{\mathbb{P}_{\nu_i,\boldsymbol{\epsilon}_i^B,\boldsymbol{\epsilon}_{ith}^H}(\{\boldsymbol{b}_i^*(z_{it},\nu_i,\boldsymbol{\epsilon}_{it}^B)\}_{t\in T_i^B}, j_{it_i^h}^*(z_{it_i^h},\nu_i,\boldsymbol{\epsilon}_{ith}^H)|b_{it^a}^*(z_{it^a},\nu_i,\boldsymbol{\epsilon}_{it^a}^B)=0)}{\mathbb{P}_{\nu_i,\boldsymbol{\epsilon}_i^B,\boldsymbol{\epsilon}_{ith}^H}(b_{it^a}^*(z_{it^a},\nu_i,\boldsymbol{\epsilon}_{it^a}^B)=0)}\\
&= \frac{\int\left(\prod_{t\in T_i^B} q_{ib^*t}^B(z_{it},\nu;\boldsymbol{\theta})\right)\times\left(q_{ij^*th}^H(z_{it_i^h},\nu_i,\boldsymbol{\epsilon}_{ith}^H)\right)dF(\nu)}{\int 1-q_{0t^a}^B(z_{it^a},\nu;\boldsymbol{\theta})dF(\nu)}.
\end{aligned}$$

Where the first equality follows from the fact that $\mathbb{P}(b_{it^a}^* = 0|\{\boldsymbol{b}_i^*(z_{it},\nu_i,\boldsymbol{\epsilon}_{it}^B)\}_{t\in T_i^B}) = 1$ for all households in the microdata, and the second from conditional independence and the model implied choice probabilities. The numerator contains the probabilities of the observed voucher and housing choices, while the denominator is a selection correction term that adjusts for the probability that household i applies for a voucher upon arrival (i.e., selects into the microdata).

Given observed choices $(\boldsymbol{b}_i^*, j_{it_i^h}^*)$, the individual contribution to the likelihood is given by:

$$\mathcal{L}_i^{\text{Mic}}(\boldsymbol{z}_i,\boldsymbol{\theta}) = \int w_{t^a}^{\text{Mic}}(z_{it^a},\nu)q_{ijt^h}^H(z_{it_i^h},b_{it_i^h},\nu;\boldsymbol{\theta})dF(\nu), \tag{C.3}$$

where the selection correction term is

$$w_{t^a}^{\text{Mic}}(z_{it^a},\nu) = \frac{\left(\prod_{t\in T_i^B} q_{ib^*t}^B(z_{it},\nu;\boldsymbol{\theta})\right)}{\int 1-q_{0t^a}^B(z_{it^a},\nu';\boldsymbol{\theta})dF(\nu')},$$

and $dF(\nu)$ is the distribution of unobserved characteristics. Note that the likelihood consists of matching the observed housing choices while controlling for the voucher choices and selection into the microdata by $w_{t^a}(z_{it^a},\nu)$. This adjustment is online—as opposed to two-step selection correction methods—as it depends on the unobserved characteristics ν and the parameters $\boldsymbol{\theta}$. The selection adjusted micro log-likelihood is given by:

$$\ell^{\text{Mic}}(\boldsymbol{z},\boldsymbol{\theta}) = \sum_{i\in\mathcal{I}} \log \mathcal{L}_i^{\text{Mic}}(\boldsymbol{z}_i,\boldsymbol{\theta})$$

Macro likelihood. Households outside the micro-sample are the ones that decide to not apply for a voucher, either because they are not eligible or they decide to not apply. Since all households in the macro data make a voucher and housing choice in the period of arrival, I drop the t^a subscript. Since I do not observe demographics of these households, it is necessary to integrate over the distribution of observables $G(\boldsymbol{z})$ and unobservables $F(\boldsymbol{\nu})$. In this case, given the large market assumption, the housing choice probabilities equal the share of each housing type among the unsubsidized population:

$$\begin{aligned}\mathbb{P}_{z_{it},\nu_i,\epsilon^B_{it},\epsilon^H_{it}}(b^*_{it}(z_{it},\nu_i,\epsilon^B_{it}) \cap j^*_{it}(z_{it},\nu_i,\epsilon^H_{it}) | b^*_{it^a}(z_{it^a},\nu_i,\epsilon^B_{it^a}) = 0) = \\ = \frac{\mathbb{P}_{z_{it},\nu_i,\epsilon^B_{it},\epsilon^H_{it}}(b^*_{it^a}(z_{it^a},\nu_i,\epsilon^B_{it^a}) \cap j^*_{it}(z_{it},\nu_i,\epsilon^H_{it}))}{\mathbb{P}_{z_{it},\nu_i,\epsilon^B_{it}}(b^*_{it^a}(z_{it^a},\nu_i,\epsilon^B_{it^a}) = 0)} \\ = \frac{\int q^B_{i0t}(z,\nu;\boldsymbol{\theta}) q^H_{ijt}(z,\nu;\boldsymbol{\theta}) dG(z) dF(\nu)}{\int q^B_{0t}(z,\nu;\boldsymbol{\theta}) dG(z) dF(\nu)}\end{aligned}$$

where the first equality follows from Bayes' rule and the fact that $\mathbb{P}(b^*_{it} = 0 | j^*_{it}, \boldsymbol{\theta}) = 1$ for all households in the macro data (i.e., all individuals out of the microdata did not apply for a voucher). The second equality comes from the model implied choice probabilities. Note that eligibility is determined by $\boldsymbol{z}$, so ineligible households have $q^B_{0t}(z,\nu;\boldsymbol{\theta}) = 1$.

Now we can write the macro likelihood, which will penalize the model from not matching the observed shares for jt among the unsubsidized population. The contribution to the macro log-likelihood of product j in market t is given by:

$$\ell^{\mathrm{Mac}}_{jt}(I^{NB}_t, s^{NB}_{jt}, \boldsymbol{\theta}) = I^{NB}_t s^{NB}_{jt} \log \int w^{\mathrm{Mac}}_t(z,\nu) q^H_{jt}(\boldsymbol{\theta}) dG(z) dF(\nu) \tag{C.4}$$

where

$$w^{\mathrm{Mac}}_t(z,\nu) = \frac{q^B_{i0t}(z,\nu;\boldsymbol{\theta})}{\int q^B_{0t}(z',\nu';\boldsymbol{\theta}) dG(z') dF(\nu')},$$

I^{NB}_t is the number of unsubsidized households making a housing choice in market t, and s^{NB}_{jt} is the observed share of unsubsidized households buying housing type j in market t. Given the market size assumption (i.e., the number of households arriving each period), I^{NB}_t is just equal to that minus the number of households that applied for a voucher for the first time in that period. Given that I match the subsidized transactions to the universe of real estate transactions, s^{NB}_{jt} is observed.

The macro log-likelihood is given by:

$$\ell^{\mathrm{Mac}}(\boldsymbol{I}^{NB}, \boldsymbol{s}^{NB}, \boldsymbol{\theta}) = \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{J}} \ell^{\mathrm{Mac}}_{jt}(I^{NB}_t, s^{NB}_{jt}, \boldsymbol{\theta})$$

Selection Corrected Mixed Data Likelihood. The final step is to combine the micro and macro likelihoods. The goal is to recover the parameters $\boldsymbol{\theta} = \{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\xi}, \boldsymbol{\sigma}\}$.

In the first step, I recover $\theta^1 = \{\boldsymbol{\alpha}, \boldsymbol{\beta}^c_d, \boldsymbol{\gamma}^c_d, \boldsymbol{\sigma}, \boldsymbol{\delta}\}$ by maximizing the selection corrected mixed data log-likelihood:

$$\log \hat{L}(\boldsymbol{\theta}) = \ell^{\mathrm{Mic}}(\boldsymbol{z}, \boldsymbol{\theta}) + \ell^{\mathrm{Mac}}(\boldsymbol{I}^{NB}, \boldsymbol{s}^{NB}, \boldsymbol{\theta}) \tag{C.5}$$

In a second step, given the estimated parameters $\hat{\boldsymbol{\theta}}^1$, I recover the parameters of interest $\boldsymbol{\theta}^2 = \{\beta_0, \gamma_0, \boldsymbol{\xi}\}$ running the following OLS regression:

$$\hat{\delta}_{jt} = \gamma_0 + \gamma_t + \boldsymbol{\beta}^0 X_j + \xi_{jt}$$

where $\delta_{0t} = 0$ and ξ_{jt} are normally distributed errors, which are treated as parameters.

C.3 Computational Implementation

This appendix details the computational implementation of the Mixed Data Likelihood Estimator (MDLE) and the Selection-Corrected extension (SCMDLE), building on the estimator described in Section 6 and fully derived in Appendix AE. For details on the econometric properties of the MDLE I refer the reader to Grieco et al. (2025).

Utility Parametrization. Let $\mathcal{D} = \{\text{Inc}, \text{Age}, \text{Fam}, \text{Children}\}$ index households' demographics z_i^d. Let $\mathcal{C} = \{\text{House}, \text{Size}, \text{New}\}$ index housing types characteristics X_{jt}^c. Two product characteristics that vary at the (i, j, t) level, prices p_{jbt} and location match $\mathbb{1}(z_i^{\text{Loc}} = X_{jt}^{\text{Loc}})$. The structural preference parameters $\{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\beta}^{\text{Loc}}, \boldsymbol{\gamma}, \boldsymbol{\sigma}, \boldsymbol{\xi}\}$ are:

- Price sensitivity (4): $\boldsymbol{\alpha} = \{\alpha_0, \alpha_{\text{Inc}}, \alpha_{\text{Age}}, \alpha_{\text{Fam}}\}$.
- Housing characteristics (15): $\boldsymbol{\beta} = \{\beta_0^c, \boldsymbol{\beta}_d^c\}$.
- Location match parameters (4): $\boldsymbol{\beta}^{\text{Loc}} = \{\beta_0^{\text{Loc}}, \boldsymbol{\beta}_d^{\text{Loc}}\}$.
- Homeownership parameters (4): $\boldsymbol{\gamma} = \{\gamma_0, \boldsymbol{\gamma}_d, \boldsymbol{\gamma}_t\}$.
- Common unobserved preferences ($|J| \times |T| = 2,954$): $\boldsymbol{\xi} = \{\xi_{jt}\}_{j,t}$.
- Random coefficient standard deviations (2): $\boldsymbol{\sigma} = \{\sigma^p, \sigma^h\}$ (correlation implemented, need to update notation)

As standard, I reparametrize deterministic utility pooling the observed and unobserved common preferences in fixed effects δ_{jt}. Also, as standard in models with (i, j) characteristics, I keep the common prices and location preference parameters separate. The main difference relative to standard demand estimation is that α_0 is estimated in the first stage and identified by voucher induced variation in prices and choice sets, instead of using supply-side exclusion restrictions. The deterministic utility component is:

$$\bar{u}_{ijt} = \left(\alpha_0 + \sum_{d \in \mathcal{D}} \alpha_d z_i^d + \sigma^p \nu_i^p\right) p_{jbt} + \sum_{c \in \mathcal{C}} \left(\sum_{d \in \mathcal{D} \setminus \{0\}} \beta_d^c z_i^d\right) X_{jt}^c \tag{C.6}$$

$$+ \left(\sum_{d \in \mathcal{D}} \beta_d^{\text{Loc}} z_i^d\right) \mathbb{1}(z_i^{\text{Loc}} = X_{jt}^{\text{Loc}}) + \left(\gamma_0 + \sum_{d \in \mathcal{D}} \gamma_d z_i^d + \sigma^h \nu_i^h\right) + \delta_{jt}. \tag{C.7}$$

Let $\boldsymbol{\theta} = \{\boldsymbol{\alpha}, \boldsymbol{\beta}_d^c, \boldsymbol{\beta}^{\text{Loc}}, \gamma_d, \boldsymbol{\sigma}, \boldsymbol{\delta}\}$ denote the parameters of interest for the first step.

Numerical Integration: Unobserved heterogeneity parameters require numerical integration. I follow Grieco et al. (2025) best practices and use Gaussian quadrature for the micro likelihood and Monte Carlo simulation for the macro likelihood. For the micro component, I use 11-point Gaussian quadrature for each random coefficient, wich implies $R = 221$ nodes. Let $r \in \{1, ..., R\}$ index quadrature nodes for (ν_r^p, ν_r^h) and their respective weights w_r. Housing and voucher choice probabilities are numerically integrated as:

$$q^H_{ijt_i^h}(\boldsymbol{z}_i, b_{it^h}; \boldsymbol{\theta}) = \int q^H_{ijt_i^h}(\boldsymbol{z}_i, b_{it^h}, \boldsymbol{\nu}; \boldsymbol{\theta}) dF(\boldsymbol{\nu}) \approx \sum_{r=1}^{R} w_r q^H_{rijt_i^h}(\boldsymbol{z}_i, b_{it^h}, \boldsymbol{\nu}_r; \boldsymbol{\theta}) \tag{C.8}$$

$$q^B_{ibt_i^a}(\boldsymbol{z}_i; \boldsymbol{\theta}) = \int q^B_{ibt_i^a}(\boldsymbol{z}_i, \boldsymbol{\nu}; \boldsymbol{\theta}) dF(\boldsymbol{\nu}) \approx \sum_{r=1}^{R} w_r q^B_{ribt_i^a}(\boldsymbol{z}_i, \boldsymbol{\nu}_r; \boldsymbol{\theta}) \tag{C.9}$$

For the macro component, I use use Monte Carlo integration with $S_t = 10.000$ simulated households per market. Let s index each simulated household, whose observables are drawn from CASEN (regional population weights available and updated in each version) and unobservables $\boldsymbol{\nu}_s$ from $\mathcal{N}(0, 1)$. The voucher and housing choice probabilities are numerically integrated as:

$$q^H_{jt}(b_0; \boldsymbol{\theta}) = \int\int q^H_{jt}(\boldsymbol{z}, b_0, \boldsymbol{\nu}; \boldsymbol{\theta}) dG(\boldsymbol{z}) dF(\boldsymbol{\nu}) \approx \frac{1}{S_t} \sum_{s \in S_t} q^H_{sjt}(\boldsymbol{z}_s, b_0, \boldsymbol{\nu}_s; \boldsymbol{\theta}) \tag{C.10}$$

$$q^B_{bt}(\boldsymbol{\theta}) = \int\int q^B_{bt}(\boldsymbol{z}, \boldsymbol{\nu}; \boldsymbol{\theta}) dG(\boldsymbol{z}) dF(\boldsymbol{\nu}) \approx \frac{1}{S_t} \sum_{s \in S_t} q^B_{sbt}(\boldsymbol{z}_s, \boldsymbol{\nu}_s; \boldsymbol{\theta}) \tag{C.11}$$

GPU Numerical Integration and Numerical Stability. In standard demand estimation, the gradient and hessian sparse structure allows for an inner- and outer-loop optimization approach that significantly reduces the computational burden. The fact that households apply for vochers and purchase houses in different markets doesn't allow for this approach, as the micro likelihood contribution of each individual i depends on the mean utility parameters δ_{jt} of the market where they make choices. This makes the gradient and hessian of the SCMDLE estimator less sparse, and require keeping track of arrays at the integration nodes level for the micro component.

To overcome this, I run estimation at the GPU instead of the CPU which allows for efficient computation of large arrays at the cost of sacrificing numerical precision and stability during optimization (i.e., using Float32 instead of Float64 precision). As this is not a contribution of this paper, I'll skip details that mostly boils down to applying best practices from Conlon and Gortmaker (2020) adapted to a Float32 arquitecture: instead of computing $\log(\max(p, \epsilon))$ setting the machine epsilon tolerance $\epsilon^{\text{Float64}} = 1 \times 10^{-300}$ set it at $\epsilon^{\text{Float32}} = 1 \times 10^{-40}$. Note that this irrelevant at the true parameters (i.e., the minumum observed share is of the order of 1×10^{-5}), it only threatens numerical stability during optimization. The speed and memory advantages of using the GPU allows to keep track of the full gradient and hessian objects, lowering the numerical instability concerns in estimation by using hessian based optimization methods.

Estimation Procedure. In order to avoid starting parameters that might lead to a large share of clipped probabilities, I follow the following procedure:

1. **Logit Demand Regression.** I get initial $\alpha_0^{(1)}$ and $\delta_{jt}^{(1)}$ by running a log-shares regression: $\log\left(\frac{s_{jt}}{s_{0t}}\right) = \alpha_0^{(1)} * p_{jt} + \delta_{jt}^{(1)}$ using market prices and aggregate shares, with $\delta_{jt}^{(1)}$ being the residuals.
2. **Set and update of random guess.** I begin with a random guess for the rest of the parameters in the range $[-0.01, 0.01]$ and update it with the following steps:
   (a) **Update random guess.** Estimate the MDLE model without random coefficients, keeping $\delta_{jt}^{(1)}$ fixed.
   (b) **Estimate MDLE without random coefficients.** I use the current guess of the parameters as starting values and estimate the MDLE model without random coefficients (allows inner-outer loop optimization).
3. **MDLE Estimation.** Use the previous step guess and random coefficients initialized at $\sigma_p = \sigma_h = 0.01$ as starting values to estimate the full MDLE model $\hat{\boldsymbol{\theta}}^{\text{MDLE}}$ (allows inner-outer loop optimization).
4. **Selection-Corrected MDLE Estimation.** Use $\hat{\boldsymbol{\theta}}^{(MDLE)}$ as starting values and estimate the SCMDLE model to get the final estimates $\hat{\boldsymbol{\theta}}^{\text{SCMDLE}}$.

C.3.1 MDLE Numerical Log-Likelihood

I begin by presenting the MDLE numerical log-likelihood and its gradient and hessian contributions. Recall that the mean price sensitivity parameter α_0 is not identified in the MDLE, so the parameters in this section should not be interpreted as such.

MDLE Numerical Log-Likelihood. The MDLE estimator is equivalent to the SCMDLE estimator with selection weights equal to one. Formally, the MDLE numerical log-likelihood is:

$$\mathcal{L}^{\text{MDLE}}(\boldsymbol{\theta}) = \sum_{i \in \mathcal{I}^B} \ell_i^{\text{Mic}}(\boldsymbol{\theta}) + \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \ell_{jt}^{\text{Mac}}(\boldsymbol{\theta}) \tag{C.12}$$

$$\ell_i^{\text{Mic}}(\boldsymbol{\theta}) = \log\left(\max\left\{q^H_{ij^*bt_i^h}(\boldsymbol{z}_i; \boldsymbol{\theta}), \epsilon\right\}\right) \tag{C.13}$$

$$\ell_{jt}^{\text{Mac}}(\boldsymbol{\theta}) = I_t^{NB} s_{jt}^{NB} \log\left(\max\left\{q^H_{jt}(\boldsymbol{\theta}), \epsilon\right\}\right). \tag{C.14}$$

The machine epsilon tolerance is set to $\epsilon = 1 \times 10^{-40}$, the minimum value that Float32 arquitectures can handle without underflow. For a given candidate parameter vector $\tilde{\boldsymbol{\theta}}$, if an individual i or product j are not in the numerically stable range $q < \epsilon$ their gradient and hessian contributions are set to zero. In order to ease exposition I'll abuse notation and ignore this considerations.

Gradient Contributions. Let the score $g^H_{(o)jtk}$ of the log-choice probability for product j in market t with respect to parameter θ_k at level of observation $o \in \{(r,i),(i),(s,j),(j)\}$ be:

$$g^H_{(o)jtk} = \frac{\partial \log q^H_{(o)jt}}{\partial \theta_k} = \frac{\partial \bar{u}_{(o)jt}}{\partial \theta_k} - \sum_{j' \in \mathcal{J}_{(o)bt}} q^H_{(o)j't} \frac{\partial \bar{u}_{(o)j't}}{\partial \theta_k}, \tag{C.15}$$

where $\mathcal{J}_{(o)bt}$ is the respective choice set for (o). The MDLE gradient element for each parameter θ_k is:

$$\frac{\partial \mathcal{L}^{\text{MDLE}}}{\partial \theta_k} = \sum_{i \in \mathcal{I}} \frac{\partial \ell_i^{\text{Mic}}}{\partial \theta_k} + \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \frac{\partial \ell_{jt}^{\text{Mac}}}{\partial \theta_k}. \tag{C.16}$$

With each macro and micro contribution being:

$$\frac{\partial \ell_i^{\text{Mic}}(\boldsymbol{\theta})}{\partial \theta_k} = \frac{1}{q^H_{ij^*t^h}} \sum_{r=1}^{R} w_r q^H_{rij^*t^h} g^H_{rij^*tk} \tag{C.17}$$

$$\frac{\partial \ell_{jt}^{\text{Mac}}(\boldsymbol{\theta})}{\partial \theta_k} = \frac{I_t^{NB} s_{jt}^{NB}}{q^H_{jt}} \frac{1}{S_t} \sum_{s \in S_t} q^H_{sjt} g^H_{sjtk} \tag{C.18}$$

Hessian Contributions. The Hessian also have the standard close formula for logit probabilities (i.e., $\frac{\partial^2 \log(q^H_{(o)jt})}{\partial \theta_{k_1} \partial \theta_{k_2}} = \frac{\partial g^H_{(o)jtk_1}}{\partial \theta_{k_2}}$) with linear utilities (i.e., $\frac{\partial^2 \bar{u}_{(o)jt}}{\partial \theta_{k_1} \partial \theta_{k_2}} = 0$). Let the cross-derivative of the log choice probability for housing type j in market t with respect to parameters θ_{k_1} and θ_{k_2} at level of observation o be:

$$h^H_{(o)jtk_1k_2} = \frac{\partial^2 \log q^H_{(o)jt}}{\partial \theta_{k_1} \partial \theta_{k_2}} = \frac{\partial g^H_{(o)jtk_1}}{\partial \theta_{k_2}} = - \sum_{j' \in \mathcal{J}_{(o)bt}} q^H_{(o)j't} g^H_{(o)j'tk_1} g^H_{(o)j'tk_2}. \tag{C.19}$$

The MDLE Hessian element $(\theta_{k_1}, \theta_{k_2})$ is:

$$\frac{\partial^2 \mathcal{L}^{\text{MDLE}}}{\partial \theta_{k_1} \partial \theta_{k_2}} = \sum_{i \in \mathcal{I}} \frac{\partial^2 \ell_i^{\text{Mic}}}{\partial \theta_{k_1} \partial \theta_{k_2}} + \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \frac{\partial^2 \ell_{jt}^{\text{Mac}}}{\partial \theta_{k_1} \partial \theta_{k_2}} \tag{C.20}$$

With each macro and micro contribution being:

$$\frac{\partial^2 \ell_i^{\text{Mic}}}{\partial \theta_{k_1} \partial \theta_{k_2}} = \frac{1}{q^H_{ij^*t^h}} \left(\sum_{r=1}^{R} w_r q^H_{rij^*t^h} \left[g^H_{rij^*t^hk_2} g^H_{rij^*t^hk_1} + h^H_{rij^*t^hk_1k_2} \right] \right) - g_{ij^*t^hk_1} g_{ij^*t^hk_2} \tag{C.21}$$

$$\frac{\partial^2 \ell_{jt}^{\text{Mac}}}{\partial \theta_{k_1} \partial \theta_{k_2}} = \frac{I_t^{NB} s_{jt}^{NB}}{\sum_{s \in S_t} q^H_{sjt}} \left[\sum_{s \in S_t} q^H_{sjt} (h^H_{sjtk_1k_2} + g^H_{sjtk_1} g^H_{sjtk_2}) - g^H_{jtk_1} g^H_{jtk_2} \right] \tag{C.22}$$

C.3.2 SCMDLE Numerical Log-Likelihood

[update notation]

D Supply Estimation Appendix

D.1 Supply Estimation Details

D.1.1 New Housing Supply Derivations and Estimation

Inventory Problem Estimation. Starting from the inventory management problem in equation (12), where selling is a terminal action, I apply the Hotz-Miller inversion. Under the perfect foresight assumption, the expected value function and the share equation can be expressed as:

$$\mathbb{E}_\omega \Pi_{jt+1} = \gamma + \exp(\bar{\pi}^{\text{sell}}_{jt+1}) + \ln(s^{\text{sell}}_{jt+1}) \text{ and } s^{\text{sell}}_{jt} = \frac{\exp(\bar{\pi}^{\text{sell}}_{jt})}{\exp(\bar{\pi}^{\text{sell}}_{jt}) + \exp(-C^M_{jt} + \beta(\gamma + \exp(\bar{\pi}^{\text{sell}}_{jt+1}) + \ln(s^{\text{sell}}_{jt+1})))} \tag{D.1}$$

where γ is Euler's constant. Taking logs and rearranging yields the estimating equation:

$$\ln(s^{\text{sell}}_{jt}) - \ln(s^{\text{hold}}_{jt}) - \beta \ln(s^{\text{sell}}_{jt+1}) = -\beta\gamma + \alpha^{\text{new}}(p_{jt} - \beta p_{jt+1}) + C^M_j + C^M_t + \xi^M_{jt} \tag{D.2}$$

where $s^{\text{hold}}_{jt} = 1 - s^{\text{sell}}_{jt}$ and the β is calibrated to an annual discount factor of 0.96. The cost parameters C^M_j and C^M_t are product and time fixed effects, respectively.

Recovering Expected Profits. With estimated parameters $\{\hat{\alpha}^{\text{new}}, \hat{C}^M_j, \hat{C}^M_t, \hat{\xi}^M_{jt}\}$, I recover expected profits $\hat{\Pi}_{jt}$ through solving the fixed point problem in equation (D.1) as:

$$\Pi_{jt} = \max\{\alpha^{\text{new}} p_{jt}, -C^M_{jt} + \beta \mathbb{E}_\omega \Pi_{jt+1}\} + \gamma + \ln(s^{\text{sell}}_{jt}) \tag{D.3}$$

An assumption on prices and mantainance costs for $t > T$ is needed to recover the expected profits. For prices, I set (p_{jT+1}, p_{jT+2}) as observed in the data for 2019 and set a growth rate for the last four markets to compute the prices for $t > T + 2$. As the median time in the market for a unit is around two markets (one year), the results are not sensitive to the choice of the growth rate. For mantainance costs, I assume that they grow at the average growth rate from the last four markets.

Development Cost Estimation. Treating recovered profits $\hat{\mathbf{\Pi}}$ as data, I parametrize the development cost function from equation (14):

$$\begin{aligned} \psi^0_j &= \exp(\psi^0 + \psi^0_t + \psi^0_j + \xi^D_{jt}) \\ \psi^1_j &= \psi^1 + \psi^1_{house} X^{house}_j \end{aligned}$$

where $\{\psi^0_j, \psi^0_t\}$ are fixed effects, ξ^D_{jt} is an unobserved cost shock, and elasticity varies between houses and apartments. Taking logs from the developer's FOC (14) and substituting the parametrization:

$$\begin{aligned} \ln(Q^{D*}_{jt}) &= \psi^1_j \ln(\psi^0_j) + \psi^1_j \ln(\hat{\Pi}_{jt}) \\ &= \psi^1_j(\psi^0 + \psi^0_t + \psi^0_j + \xi^D_{jt}) + \psi^1_j \ln(\hat{\Pi}_{jt}) \end{aligned}$$

Defining $\tilde{x} = \psi_j^1 x$ for any parameter x:

$$\ln(Q_{jt}^{D*}) = (\psi^1 + \psi_{house}^1 X_j^{house}) \ln(\hat{\Pi}_{jt}) + \tilde{\psi}^0 + \tilde{\psi}_j^0 + \tilde{\psi}_t^0 + \tilde{\xi}_{jt}^D \tag{D.4}$$

D.1.2 Resale Housing Supply

Starting from the selling decision in equation (18), taking the log odds ratio and substituting the parametrizations yields the estimating equation:

$$\ln(s_{jt}^{\text{sell}}) - \ln(s_{jt}^{\text{hold}}) = (\alpha^{\text{res}} + \alpha_{house}^{\text{res}} X_j^{house}) p_{jt} - C_j^O - C_t^O - \xi_{jt}^O \tag{D.5}$$

Table A.11: Summary of data and calibrated parameters for supply estimation

Type	Parameter	Description	Data Source
New Housing	s_{jt}^{sell}	Total transactions over stock in survey for	transaction data; survey data
	Q_{jt}^{D*}	units beginning sales in market t	New development survey data
	Stock evolution	Tracked using equation (15), set initial stock to observed stock in 2012-1 that began sales bedore	New development survey data
Resale Housing	s_{jt}^{sell}	Transactions divided by assumed resale stock $\bar{Q}_{jt}^{\text{res}}$	Transaction data
	$\bar{Q}_{jt}^{\text{res}}$	$\lambda^{\text{res}} = 0.3$ of total city stock	Santiago Housing Stock data
	Stock evolution	Initial stock set to 2011 values, new housing sales add to the stock one year later	Santiago Housing Stock data

D.1.3 Instruments Construction

[Updating Tables]

E Counterfactuals Appendix

E.0.1 Counterfactual Policies and Outcomes

I simulate housing market equilibria under a set of voucher policies $\boldsymbol{\mathcal{B}}$, over the study period $t \in \mathcal{T}^c$, which spans half-year intervals from 2012 to 2018. A policy $\boldsymbol{\mathcal{B}}$ specifies, for each period t, the set of available voucher types $b \in \mathcal{B}_t$, each characterized by: the number of vouchers awarded A_{bt}, generosity d_{bt}, price cap $\bar{p}_{bt}$, scoring rule r_{bt}, and eligibility criteria e_{bt}. For each policy, I solve for the equilibrium housing prices $\{p_{jt}\}_{j \in J, t \in \mathcal{T}^c}$ and voucher cutoff scores $\{\bar{r}_{bt}\}_{b \in \mathcal{B}_t, t \in \mathcal{T}^c}$, under which households make application and housing choices, developers choose construction levels, and owners decide whether to sell their units. I consider following counterfactual policies:

1. **No Vouchers $\boldsymbol{\mathcal{B}}^0$.** This baseline counterfactual eliminates all vouchers, so households and firms make choices based solely on equilibrium housing prices. Households make no application choices, and make a housing choice at the arrival period t_i^a.

2. **DS01 Vouchers $\boldsymbol{\mathcal{B}}^{DS01}$.** This policy replicates the DS01 program as described in the data and estimation appendix. Departures from the actual program follow the same assumptions discussed in the data and estimation appendix.

3. **All Low $\boldsymbol{\mathcal{B}}^{Low}$ or High $\boldsymbol{\mathcal{B}}^{High}$ Vouchers.** I simulate budget-balanced variants of the DS01 program that reallocate the entire budget to either the Low or the High voucher while keeping eligibility, scoring, and other features unchanged. Basically, this means changing the number of vouchers of each type awarded in each period A_{bt} and having only one type of voucher available in each period.

4. **Vouchers for New Housing $\boldsymbol{\mathcal{B}}^{New}$.** This policy consists of the DS01 voucher menu with the added restriction that vouchers can be used only to purchase newly built units. All other voucher features remain the same, equilibrium cutoffs vary due to selection of applicants.

Budget Balance. I construct budget balanced policies using the same methodology used by the MHU: the cost of each voucher is the mean discount from 500UF to the price cap of the voucher $\int_{500}^{\bar{p}_{bt}} d_{bt}(p)dp$. For each counterfactual policy I determine the number of vouchers to be awarded A_{bt} by dividing the total budget by the mean cost of the voucher.

Equilibrium Outcomes. I consider the following outcomes of interest:

1. **Homeownership Rates:** I define homeownership rates as the probability that household i purchases a housing unit in the city when making a housing choice with voucher b_{it^h},

$$q_{it^h}^{\text{own}}(\boldsymbol{\mathcal{B}}) = 1 - q_{i0t^h}^{H}(\boldsymbol{p}_{t^h}, b_{it^h}). \tag{E.1}$$

The total homeownership rate is given by $Q^{own}(\boldsymbol{\mathcal{B}}) = \sum_{t\in\mathcal{T}^c}\sum_{i\in\mathcal{I}} q^{\text{own}}_{it^h}(\boldsymbol{\mathcal{B}})$. Note that for each i the homeownership probability under different policies depends on its voucher status b_{it^h} and the market in which makes a housing choice t^h as equilibrum prices and preferences (i.e., δ_{jt}) change accross markets.

2. **Price Pass-through:** I define price pass-through as the share-weighted percentage change in prices relative to the baseline:

$$\triangle PP(\boldsymbol{\mathcal{B}}, \boldsymbol{\mathcal{B}}^0) = \sum_{t\in\mathcal{T}^c}\sum_{j\in\mathcal{J}} s_{jt}(\mathcal{B})\frac{p_{jt}(\boldsymbol{\mathcal{B}}) - p_{jt}(\boldsymbol{\mathcal{B}}^0)}{p_{jt}(\boldsymbol{\mathcal{B}}^0)}, \tag{E.2}$$

where $s_{jt}(\mathcal{B})$ are transactions shares under the policy $\mathcal{B}$. Note that this departs frrom the standard standard single-product price pass-through measures (Weyl and Fabinger, 2013), as there are multiple housing types, whose prices and quantities shift in each equilibrium. This captures the price gap sellers receive relative to the baseline, although not the difference in prices that each household pays.

3. **Consumer Surplus and Compensating Variation:** Besides being a direct measure of consumer welfare, CS is useful to evaluate how much of the policy costs is transfered to households rather than owners due to price adjustments. I slightly depart from the standard definition of CS to account for the cost on beneficiaries from delaying their housing choice. The CS of household i, arriving in t^a and making a housing choice in t^h as:

$$CS_{it^h}(\boldsymbol{\mathcal{B}}) = \frac{1}{\alpha_i}\rho^{t^h - t^a}\log\left(1 + \sum_{j\in\mathcal{J}_{it^h}}\exp(u_{ijt^h}(b_{it^h}))\right). \tag{E.3}$$

The compensating variation for each household i is the transfer that would leave them indifferent between the prices under each policy $CV_i(\boldsymbol{\mathcal{B}}) = CS_{it^h}(\boldsymbol{\mathcal{B}}) - CS_{it^a}(\boldsymbol{\mathcal{B}}^0)$.

4. **Beneficiaries' Targeting.** I measure the policy targeting by the price sensitivity α_i and the value of homeownership h_i of beneficiaries and non-beneficiaries. These are the dimensions of households' preferences that are not observable to the government, and as described previously the ones that are most relevant for households becoming owners. I report them as percentiles relative to the population distribution, higher values of $|\alpha_i|$ and h_i means higher price sensitivity and higher value of homeownership. I also decompose both into observable $(\alpha_i(\boldsymbol{z}_i), h_i(\boldsymbol{z}_i))$ and unobservable (ν_i^p, ν_i^h) components.

5. **Targeted Housing Types.** For ease of exposition, I will focus on the effects of the policies of housing types that are *targeted* by each policy. While all housing types are affected by the voucher policies due to demand substitution effects, I focus the exposition on the impacts for housing types that are most affected by each policy, as presenting all housing types would be cumbersome.

6. **Producer Surplus and New Development.** The producer surplus of each housing type j is:

$$PS_j(\boldsymbol{\mathcal{B}}) = \begin{cases} \sum_{t\in\mathcal{T}^c} \int_0^{Q_{jt}^{D*}(\boldsymbol{\mathcal{B}})} \Pi_{jt}(\boldsymbol{\mathcal{B}}) - c_{jt}^D(Q)dQ & \text{if } j \in \mathcal{J}^{\text{new}} \\ \sum_{t\in\mathcal{T}^c} \bar{Q}_{jt}^{\text{res}} \log\left(1 + \bar{u}_{jt}^{\text{sell}}(\boldsymbol{\mathcal{B}})\right) & \text{if } j \in \mathcal{J}^{\text{res}} \end{cases}.$$

The producer surplus for new housing types $j \in \mathcal{J}^{\text{new}}$ corresponds to developers' profits from selling $Q_{jt}^{D*}(\boldsymbol{\mathcal{B}})$ at price $\Pi_{jt}(\boldsymbol{\mathcal{B}})$ and marginal cost $c_{jt}^D(Q)$. For resale housing types $j \in \mathcal{J}^{\text{res}}$, it corresponds to the inclusive value of the selling decision for the exogenous share of owners that consider selling their unit in each period $\bar{Q}_{jt}^{\text{res}}$. All values are rescaled to dollar terms.

I also consider the total new development units $Q^{new} = \sum_{t\in\mathcal{T}^c}\sum_{j\in\mathcal{J}^{\text{new}}} Q_{jt}^{D*}$ as an outcome of interest.

7. **Cost Effectiveness.** I measure the cost-effectiveness of the policy as the ratio of the compensating variation to the cost of the policy.[40] The cost of each voucher is the expected transfer to each beneficiary:

$$C_b = \sum_{i\in\mathcal{I}_{bt}^B}\sum_{j\in\mathcal{J}_{it^h}} q_{ijt^h}^H(b_{it}) d_{bt_i^h}(p_{jt_i^h}) \tag{E.4}$$

So the cost-effectiveness of the policy is given by

$$CE(\mathcal{B}) = \frac{\sum_{i\in\mathcal{I}} CV_i(\boldsymbol{\mathcal{B}})}{\sum_{b\in\mathcal{B}} C_b}. \tag{E.5}$$

E.1 Counterfactual Equilibrium Simulations

Markets and Housing Types. I compute the equilibrium of the housing market for the 14 periods observed in the data $t \in \mathcal{T}^c = \{1, \ldots, T\}$, which are half-year periods from 2012 to 2018. I keep the housing types used in estimation, see Appendix B for details.

Voucher Policies. In each counterfactual, the voucher menu is fixed $\boldsymbol{\mathcal{B}} = \{\mathcal{B}_t\}_{t\in\mathcal{T}^c}$.

Households. I draw 980k households $i \in \mathcal{I}^c$, with 70k households arriving each period.[41] For each household I draw the following objects:

- **Observable Characteristics and Predicted Eligibility:** I draw the observable characteristics $\boldsymbol{z}_{it}$ from the CASEN survey, each household's characteristrics are drawn from the last available CASEN (2011, 2013, 2015, 2017) at their time of arrival t_i^a. I also draw the predicted elegibility score e_{it} and initial score r_{it} (See Appendix B), I treat both as data.

[40] Once the MHU awards a voucher, they are accounted as expected expenses from their annual budget. If a voucher expires, it is counted as an unrealized expense and returns to the central government budget.

[41] As in the estimation, this number is choosen to roughly match the assumption of 30% of households choosing the outside option $j = 0$.

- **Unobserved Preferences:** I draw $(\nu_i^p, \nu_i^h) \sim N(0, \hat{\Sigma})$ where $\hat{\Sigma}$ is the estimated covariance matrix of the preference shocks.
- **Time to use:** I draw the time to use the voucher uniformly $t_i^u \in \{1, 2, 3, 4\}$ and keep it fixed across counterfactuals. If i is awarded a voucher in t, their get assigned to make a housing choice in $t_i^h = t_i^u$.
- **Idiosyncratic Preferences:** For each household, I draw $\{\boldsymbol{\epsilon}_{it}^B\}_{t \geq t_i^a}$ and $\boldsymbol{\epsilon}_i^H$ iid from a Type I Extreme Value distribution. I draw this $S = 500$ times (number of equilibrium computations per counterfactual) and keep it fixed across counterfactuals.

I keep the previously arrived households $t_i^a < 1$ that are active from the voucher data. This includes households that were awarded a voucher in 2011 and have not used it by 2012, and households that applied to a voucher in the second half of 2011 and were not awarded a voucher.

Housing Stock. For new housing stock, I fix the initial stock of housing as the observed stock in the data $\bar{\boldsymbol{Q}}_0$, all the new units built in $t < 1$ that are not sold in $t = 1$.

For used housing, I fix the total stock of used housing $\bar{Q}_{jt}$ to the 30% of the total housing stock in 2011. The stock of used housing increases by new development, each new unit sold in t is added to the stock of used housing one year later $t + 2$.

Unobserved Preferences. I treat the unobserved preferences $\hat{\xi}_{jt}$ and costs $\{\hat{\xi}_{jt}^M, \hat{\xi}_{jt}^C, \hat{\xi}_{jt}^O\}$ fixed across counterfactuals. Mantainance costs for $t > T$ are sampled from the distribution of mantainance costs in the data.

Mantainance Costs. In estimation, developers have perfect foresight of future mantainance costs. I compute the average growth rate of mantainance costs for each housing type $\triangle_j^c$, and set costs to $C_{j\tau} = (1 + g^c)^\tau C_{jT}$ for all $\tau \geq T$.

Beliefs. I keeep the estimation assumptions for beliefs over prices and cutoff scores over the study period. For prices $p_{jt_{\tau \geq T}}$, I assume that households and firms believe that prices will grow at the average growth rate of prices $\triangle_j^p$ in the last four periods, which is computed at each guess of the equilibrium prices $\boldsymbol{p}$.

E.2 Equilibrium Computation

Algorithm: Finding the equlilibium of the model requires computing equilibrium prices $\boldsymbol{p} = \{p_{jt}\}_{j \in \mathcal{J}, t \in \mathcal{T}^c}$ and cutoff scores $\bar{\boldsymbol{r}} = \{\bar{r}_{bt}\}_{b \in \mathcal{B}, t \in \mathcal{T}^c}$, for each counterfactual policy $\mathcal{B}$. I do so by a nested fixed-point algorithm, solving for the $\bar{\boldsymbol{r}}$ at each guess of the price vector $\boldsymbol{p}$. The algorithm proceeds as follows:

1. Make an initial guess for the equilibrium prices $\boldsymbol{p}^0 = \{p_{jt}\}_{j \in \mathcal{J}, t \in \mathcal{T}^c}$ and cutoff scores $\bar{\boldsymbol{r}}^0 = \{\bar{r}_{bt}\}_{b \in \mathcal{B}, t \in \mathcal{T}^c}$.

2. At each iteration k, I inherit $(\boldsymbol{p}^{k-1}, \bar{\boldsymbol{r}}^{k-1})$. I compute the mean growth rate of prices $\triangle_j^k$. I then update the guess according to the following steps:

   (a) **Equilibrium cutoff scores:** Keeping $\boldsymbol{p}^{k-1}$ fixed, initialize a guess $\bar{\boldsymbol{r}}^0 = \bar{\boldsymbol{r}}^{k-1}$. The inner loop is run for each $t \in \mathcal{T}^c$. At each iteration g for time t, I inherit $(\bar{\boldsymbol{r}}^{g-1}, \mathcal{I}_t^E)$ and update cutoff scores as follows:[42]

      i. Get optimal voucher choice b_{it}^* given by (10) for all eligible households $i \in \mathcal{I}_t^E$.

      ii. The set of winners of each voucher are the applicants with scores above the cutoff $\mathcal{I}_{bt}^W = \{i \in \mathcal{I}_{bt}^A : r_{ibt} \geq \bar{r}_{bt}^{g-1}\}$.

         - If $|\mathcal{I}_{bt}^W| = A_{bt}$ for all $b \in \mathcal{B}_t$, then set $\bar{r}_{bt}^g = \bar{r}_{bt}^{g-1}$. If $t < T^c$, update $\mathcal{I}_{t+1}^E$ and continue to $t+1$, else exit the loop.
         - Else, update the cutoff scores for each voucher type b as follows:

$$\bar{r}_{bt}^g = \begin{cases} A_{bt}\text{-th highest score of } \mathcal{I}_{bt}^W & \text{if } |\mathcal{I}_{bt}^W| > A_{bt} \\ 0.9\bar{r}_{bt}^{g-1} & \text{if } |\mathcal{I}_{bt}^W| < A_{bt} \\ \bar{r}_{bt}^{g-1} & \text{if } |\mathcal{I}_{bt}^W| = A_{bt}, \end{cases}$$

         and go to the next iteration.

      set $\bar{\boldsymbol{r}}^k = \bar{\boldsymbol{r}}^g$ once the inner loop is exited.

   (b) **Housing Market Equilibrium:** Given $\bar{\boldsymbol{r}}^k$, set voucher status b_{it} and $t_i^h = t + t_i^u$ for all households $i \in \mathcal{I}^W(\bar{\boldsymbol{r}}^k)$. Given $\boldsymbol{p}^{k-1}$,

      i. **New Housing Supply:** Solve the fixed point problem for new housing inventory $\{\mathbb{E}\Pi_{jt}, s_{jt}^{sell}\}_{j\in\mathcal{J}^{\text{new}}, t\in\mathcal{T}^c}$. Compute optimal development and new housing stock $\{Q_{jt}^{D*}, \bar{Q}_{jt}^{\text{new}}\}_{j\in\mathcal{J}^{\text{new}}, t\in\mathcal{T}^c}$. Supply $Q_{jt}^S(\boldsymbol{p}_j^{k-1})$ is given by (16).

      ii. **Used housing supply:** Supply $Q_{jt}^S(\boldsymbol{p}_{jt}^{k-1})$ is given by (19).

      iii. **Housing Demand:** Given the sets $\{\mathcal{I}_t^B, \mathcal{I}_t^{NA}, \mathcal{I}_t^{NE}\}$ demand $Q_{jt}^D(\boldsymbol{p}_{jt}^{k-1})$is given by (21).

      iv. **Update price guess:** Compute excess demand matrix $\boldsymbol{z} = [Q_{jt}^D - Q_{jt}^S]_{j\in\mathcal{J}\times t\in\mathcal{T}^c}$,

         - If $||\boldsymbol{z}||_\infty < \epsilon^p$, then set $(\boldsymbol{p}, \bar{\boldsymbol{r}}) = (\boldsymbol{p}^{k-1}, \bar{\boldsymbol{r}}^k)$.
         - Else, update the price guess $\boldsymbol{p}^k$: $p_{jt}^k = p_{jt}^{k-1} + \delta_p z_{jt}$.

[42] Note that $\mathcal{I}_t^E$ depends on $(\mathcal{I}_{t-1}^E, \bar{\boldsymbol{r}}_{t-1})$.

F Extra Derivations