High-End Housing and Gentrification: Evidence from a San Francisco Lottery

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Abstract

In major cities throughout the United States and around the world, contentious debates over housing policy frequently focus on the extent to which high-end housing developments are a cause of gentrification. In this paper, we contribute novel empirical evidence to this debate by studying a unique lottery in the city of San Francisco that allowed a limited number of property owners to convert their buildings into high-end condominiums. Relying solely on exogenous variation from the lottery, we study the long-run effects of these developments on local home prices, demographics, and new business entry. Compared to losing lottery applicants, winners are vastly more likely to invest in alterations and renovations in their properties, to see their property values increase, to rent their properties to new tenants, and to sell them to new owners. The home values of adjacent buildings also increase. At the neighborhood level, conversions lead to higher resident incomes, home values, and rental prices, while also increasing the shares of the population that are White, young, college-educated, and working in information and professional services. Over time, new establishments specializing in education and professional services enter the neighborhood. We discuss economic interpretations of these results in the broader context of a local housing market where demand is high and supply is sharply constrained.

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1 Introduction

Policymakers in cities across the United States and around the world are grappling with how best to address surging rents and home prices. Since the 1990s, a steady influx of high-income workers to major cities has led to rapid increases in home prices, changes in demographic characteristics, and shifts in the composition of local businesses --- a process commonly referred to as gentrification.

In response to these trends, many economists and policymakers have advocated relaxing regulatory barriers that restrict market-rate housing developments in expensive cities (e.g., Furman, 2015; Glaeser, 2017; Hsieh and Moretti, 2017, 2019). Yet despite its popularity among economists, this policy prescription has proven highly controversial among the broader public. From the perspective of many observers, market-rate housing development seems to make problems worse: luxury condominiums sprout up in low-income neighborhoods, high-income residents continue to stream in, and local price growth continues unabated. Rather than taming the excesses of gentrification, opponents argue that market-rate housing developments cause and exacerbate it.

In this paper, we provide new evidence about the extent to which high-end, market-rate housing developments are a cause of gentrification. Empirical strategies to answer this question must address a fundamental econometric concern: Precisely because high-end developments are most likely to occur in neighborhoods with strong housing demand, comparisons between locations with and without such developments will overstate their role in driving neighborhood change. The econometric challenge is thus to isolate the causal effect of high-end developments independently from local shocks that may simultaneously induce neighborhood change.

To overcome this challenge, we study a unique administrative lottery in the city of San Francisco that permitted a limited number of property owners to legally convert buildings into high-end condominiums. In 1979, San Francisco banned condominium conversions due to widespread public concern about their effects on local home prices and the supply of rentable units. However, in response to growing cross-pressure from opponents of the ban, city officials in 1981 struck a compromise: Each year the city would run a lottery allowing a maximum of 200 winning units to convert their properties into condominiums.

Beyond the econometric appeal of the lottery, our focus on San Francisco and on condominiums is motivated by their central place in national debates about gentrification and housing policy. As we will discuss in greater detail, San Francisco has been a poster city of skyrocketing home prices and demographic change in recent decades, providing an ideal empirical setting for this research. At the same time, condominiums are front-and-center in controversies about housing policy not only in San Francisco, but in cities across the United States and around the globe. As a legal structure designed to facilitate ownership of units within multi-family buildings, condominiums are often attractive to high-income workers with preferences for living in dense urban areas. Condominiums are also generally exempt from rent control and tenant eviction protections that apply to other multi-family buildings, further fueling concerns about displacement of low-income residents.

To shed new light on these controversies, we study the long-run effects of lottery-induced condominium conversions in San Francisco on local home prices, demographics, and new business entry. To do so, we use annual lottery data from 2001 to 2013, including applicant information from both lottery winners and losers. We supplement the lottery panel with a rich and detailed suite of data sources and outcomes: address-level data on evictions, building permits, building characteristics, assessed home values, property sales, and homeowner-occupied status from the San Francisco Assessor's Office; block-level data on new business and establishment entry from SF Open Data; and tract- and block-level demographic and employment data from the U.S. Census Bureau.

Our empirical strategy combines exogenous variation from the lottery with a stacked difference-in-differences design to estimate the causal effects of condominium conversions on key outcomes. This framework allows us to assess the validity of the research design using balance tests; to combine information across lotteries; to consider treatment dynamics over a 15 year period; and to move seamlessly from estimating the intention-to-treat (ITT) effect of winning the lottery to the local average treatment effect (LATE) of converting to a condominium.

Lottery winners and losers are statistically indistinguishable on key outcomes and characteristics as far back as 12 years before the lottery, implying the lottery was successfully randomized. After the lottery, we find that winners invest in costly new alterations and renovations to their properties, and on average see their home values increase by 44% 15 years later. Condominium converters see their home values increase by 52% over the same horizon. Lottery winners shift towards renting their units, and hold their properties in the near-term before selling at higher rates in the long-run.

A central controversy in policy debates focuses on the extent to which new condominium supply affects nearby home and rental prices. To address this question, we turn towards estimating price spillovers on nearby properties. Our empirical design offers a convenient setting for estimating these effects, by comparing nearby properties of lottery winners to nearby properties of lottery losers. We augment our main empirical specification with controls for the probability of having nearby lottery winners at various distances. This procedure addresses endogeneity concerns stemming from the fact that being close to a lottery winner is, in part, a function of location; the location is, in turn, potentially correlated with unobservable characteristics or shocks determining home values (Borusyak and Hull, 2023). Following a condominium conversion, we find that home values for parcels nearby lottery winners increase by 10%.

The finding that nearby home values increase is suggestive that condominium conversions may play a larger role in neighborhood change. To further explore this possibility, we adapt our lottery design to exploit exogenous variation in neighborhood-level exposure to condominium conversions. Over a horizon spanning approximately 15 to 20 years, we find that an additional lottery winner increases home values, rents, the population of high-income residents, and shares of the population that are White and college-educated. Data on the local workforce indicates that, on average, these residents are younger, earn more, are more likely to work in information, finance, professional services, or arts and entertainment, and are less likely to work in retail trade, health care, or transportation and warehousing. Using data on new business formation, we also find that lotteries lead to increases in establishments specializing in education, real estate, and professional services.

Heterogeneity analyses suggest that the local effects of condominium conversions are larger in neighborhoods with initially lower shares of the population that are White and college graduates. These results are consistent with a wealth of qualitative research in sociology arguing that demographic characteristics such as income, race, and education are key mediators of gentrification in American cities (Zukin, 1987; Lees et al., 2013; Freeman, 2005). Counterfactuals suggest that the increase in the local supply of condominiums over the past twenty years can explain a modest but important role in gentrification in San Francisco. Overall, the results imply that supply-side housing policies play a significantly larger role in gentrification than has been previously documented in the existing literature.

Our study contributes to a growing body of research on the determinants of housing prices and gentrification in cities. Existing studies have emphasized that demand for low-income neighborhoods reflects changes in employment and amenity opportunities in the city core (Diamond, 2016; Almagro and Dominguez-Iino, 2021; Couture et al., 2019). At the same time, a budding and complementary literature has examined the role of supply-side drivers of local home price appreciation, like new construction (Asquith et al., 2019; Pennington, 2021). A key feature of our setting is that condominium conversions hold the *quantity* of housing units fixed while changing housing *quality*. In this sense, our research is a complement to studies that have considered the effects of foreclosures on neighborhoods (Lin et al., 2009; Campbell et al., 2011; Gerardi et al., 2015), although we study the effects of a positive shock to housing quality rather than a negative one. Policy debate further focuses on how the quality and price of housing responds to urban development policies such as zoning, rent control, and eviction protections (Autor et al., 2015; Diamond et al., 2019).[1] Our paper contributes to frontier research that uses highly credible empirical variation, detailed data, and detailed analysis of counterfactuals to study the impacts of key urban policies on local home prices and demographics.

To our knowledge, Boustan et al. (2019) is the only other paper to consider the role of condominiums in urban change. Boustan et al. (2019) instrument for city-level variation in condominium density with regulatory changes governing conversions. They find no relationship between condominiums and resident income, education, or race. However, their work leaves open the possibility that condominiums could affect the distribution of individuals and incomes within the city. In our study, we focus on the experience of one city — San Francisco — but provide credible estimates of the within-city housing and neighborhood effects of condominium conversions. Our work is closely related to Diamond et al. (2019) and Pennington (2021), both of which consider the setting of San Francisco, and study the local effects of rent-control and new construction, respectively.

[1]Of particular interest to this paper, both Autor et al. (2015) and Diamond et al. (2019) study rent control and find that condominiums and condominium conversions play an important role in driving policy outcomes.

The rest of the paper is organized as follows. Section 2 discusses the history of condominium conversions and our institutional setting. Section 3 discusses the data, and section 4 discusses how we implement the lottery design in a regression framework. Section 5 presents our estimates of the effect of winning the lottery on winning and nearby parcels. Section 6 studies the impacts of condominium conversions on neighborhood outcomes, finding a significant effect on demographic outcomes normally associated with gentrification. Section 7 concludes.

2 Background and Setting

2.1 Changes in Demographics and Housing Markets in San Francisco and Other Major U.S. Cities

San Francisco provides an ideal setting for an empirical study of gentrification and housing supply, for two reasons.

First, like many major American cities, San Francisco has undergone dramatic demographic changes since the 1990s (Couture and Handbury, 2023). Panel A of Figure 1 plots time series for San Francisco, selected major American cities, and the U.S. national average in rental prices, median family incomes, the share of the population that is college-educated, and the share of the population that is Black or Hispanic. All values are indexed to 100 in 1990. Relative to the national average, San Francisco, New York, Washington DC, Los Angeles, and Boston have seen meteoric growth in rents, median family income, and the share of the population that is college-educated over the last three decades. Moreover, while the country as a whole became increasingly racially diverse over this period, the share of the population that is Black or Hispanic declined in San Francisco and other major U.S. cities.

Second, Panel B shows that San Francisco, like other major cities, has failed to increase the per capita supply of housing at a pace consistent with the national average. In a market with scarce housing, changes to the existing stock of units, like condominium conversions, may play an outsized role in shaping broader demographic trends.

2.2 The Rise of Condominiums

A condominium is a legal form of ownership for housing units, often thought of as apartments, within a multi-unit building. An individual owns the unit itself, while common spaces (such as elevators, hallways, stairwells, and yards), building infrastructure (such as heating and water pipes), and the land under the building are jointly owned by residents. In the U.S., laws governing this ownership structure were first passed in Puerto Rico in 1958. The Federal Housing Administration began to insure mortages on condominiums as part of the National Housing Act of 1961 (Kerr, 1963). Over the next few years, states passed their own laws authorizing condominiums en masse. By 1969, all U.S. states had passed such statutes (Boustan et al., 2019).

Condominiums can be added to the local housing supply either through new construction or by converting existing units. In the 1970s, city lawmakers became concerned that conversions were drastically reducing supply in the rental housing market, leading to higher prices and displacing renters. In response, several cities passed ordinances to limit or prohibit this behavior (Boustan et al., 2019).[2] Public debates over condominium developments and conversions have recently reemerged. For example, in response to growing public concern, New York state legislators passed a law in 2019 requiring approval from current tenants to convert a building into condominiums.[3] Following passage of the law, conversions in New York City declined sharply by 80%.[4]

Although city policymakers and the public fiercely debate whether condominiums are an important causal driver of gentrification, there is no doubt that the rise of condominiums has at the very least coincided with large demographic shifts across U.S. cities. Figure 2 documents stark patterns in the descriptive evidence. Across the four panels, the x-axes show the 1980 to 2010 percentage point change in the share of owner-occupied units that are categorized as condominiums. The y-axes show the same 30-year change in home values (panel A), rents (panel B), median family income (panel C), and the share of the population that is college-educated (panel D). The scatter points correspond to Meropolitan Statistical Areas, and their size is proportional to their 2010 population.

As shown in Figure 2 the introduction of condominiums generated substantial changes in

[2]The timing of these laws serve as an instrumental variable for city condominium density in Boustan et al. 2019.
[3]Wall Street Journal. "New York Condo Conversions Near the End, a Casualty of Rent Reform." 2019.
[4]The Real Deal. "Rental-to-condo Conversions Drop 80% After 2019 Rent Law: Report." 2021.

cities' housing supply over this period: a 5-10 percentage point increase in the condominium share (shown on the x-axes) is common for large cities. Moreover, changes in the condominium share are strongly correlated with changes in demographics. A 1 percentage point increase in the condominium share is associated with a 5.5 percentage point increase in home values over the 1980 to 2010 period. Similarly, a 1 percentage point increase in the condominium share is associated with a 3.3 percentage point increase in rents, a 1.7 percentage point increase in median family incomes, and a 0.6 percentage point increase in the college share.[5]

This evidence, while suggestive, is insufficient to prove that condominiums *cause* demographic change. Reverse causality is a plausible alternate hypothesis, as is the hypothesis that both trends are driven by external shocks, such as changes in local housing or labor demand. In light of this ambiguity, a primary contribution of this paper is to leverage a unique natural policy experiment to empirically identify the causal effect of condominium conversions on neighborhood change.

2.3 San Francisco Lottery

By 1979, condominium conversions were commonplace in the Bay Area, doubling each year since 1975. For approximately 15% of Bay Area municipalities, conversions comprised 10% or more of the existing rental stock (Ichino, 1979). Following several high-profile conversions that lead to the eviction of long-term tenants, San Francisco city officials moved to regulate the practice.[6] New regulations were designed to "prevent the displacement of existing tenants," "reduce the impact of conversions on nonpurchasing tenants who may be required to relocate," and "prevent the effective loss of the City's low or moderate income housing stock" (San Francisco Board of Supervisors, 2004). Starting in 1981, the City prohibited conversions for buildings with more than six units. Buildings with fewer than six units could still convert, but owners were required to apply and win the right to do so through a lottery process.[7] These buildings had to be Tenancy-in-Commons (TICs), a cooperative legal form in which the property is jointly owned. Because of the unusual owner arrangement, difficulty in mortgage financing, and

[5] A.1 further shows that shows that condominium growth was strongest in cities with the most stringent land use and zoning policies (Panel A), and that condominiums are associated with even larger home value appreciation in more heavily regulated cities (Panel B).

[6] Discussions over condominium conversions were regularly in the newspaper: "Condos Put Squeeze on Rentals" (San Francisco Chronicle, December 1977), "S.F. Problem That's Hard to Live With" (San Francisco Chronicle, March 1979).

[7] Sirkin-Law. "Summary of San Francisco Condominium Conversion Rules." 2022.

tenant protections, TICs are often an intermediate step as their owners pursue converting to a condominium.[8]

City officials in San Francisco limited the total number of units eligible to convert by lottery each year to 200 units. A lottery applicant is an entire building. The lottery consists of two separate applicant pools vying for 100 units of eligible conversions: Pool A and Pool B. Pool A contains applicants who applied to (and lost) three or more prior lotteries, and imposes some restrictions on tenant eviction history, ownership, and occupancy. Prior to 2006, a simple lottery was run among Pool A applicants if the the number of units in Pool A exceeded 100 units. Any unallocated units were added to Pool B. From 2006 until 2013, applicants were grouped and ranked by the number of times they had previously lost the lottery. If the first group included fewer than 100 units, all lottery applicants were allowed to convert. Any remaining units were allocated to the second group, and so on, until the final group's total number of units was larger than the remaining number of units available in Pool A. At that point, those units were randomly allocated among that group's applicants. In Pool B, each applicant receives additional tickets equal in number to the times they have previously lost the lottery. Tickets were then drawn randomly until 100 units were deemed eligible for conversion.[9] Prior to 2006, the number of tickets was limited to be at most five (San Francisco Board of Supervisors, 2005).

Lottery tickets were priced at $250 each, but upon winning, the conversion application required additional fees. Inspection plus application fees, on average, totaled approximately $13,000. For some 5-6 unit buildings, an additional charge of $1,700 was levied by the state of California. A mandatory engineering survey of the building imposed at least $8,000 more.[10]

After a growing backlog of lottery applicants, San Francisco halted the lottery program in 2013. City officials replaced it with the Expedited Conversion Program (ECP) beginning in 2015. Under this new program, TICs satisfying certain ownership and occupancy requirements would be eligible to convert. Buildings that had been owned continuously for longer would be eligible first. A new Expedited Conversion Fee of $22,500 per unit would also be charged.[11] Buildings with renters are required to offer a lifetime lease upon conversion; due to legal challenges, the city

[8] KQED. "San Francisco Inches Toward Deal on 'Tenants in Common' Condo Conversions." 2013.
[9] Sirkin-Law. "San Francisco's Condo Conversion Lottery System." 2022.
[10] Cost estimates from: Sirkin-Law. "San Francisco's Condo Conversion Lottery System." 2022.
[11] GMH - Real Estate Law. "Condominium Conversion in San Francisco." 2019.

stopped accepting conversion applications from buildings with renters in 2017.

2.4 Application Behavior

We now summarize descriptive patterns in lottery applications. Figure A.2 describes how the probability of winning the lottery and reapplying to the lottery varies with the number of tickets recieved for the lottery. By design, the probability of winning the lottery increases with the number of tickets. Given high demand for the lottery, the probability of winning is still low (<30%) even after applying five times before. If a building had applied seven times previously, and consequently was awarded eight lottery tickets, the probability of winning was close to 90%. Reapplication rates increase in the number of tickets a building recieves.

Figure A.3 plots how the probability of applying and winning varies with whether a building had applied any given number of years prior. To illustrate the plot's interpretation, the light blue coefficient above the x-axis value of three indicates how much more likely an individual is to apply if they had applied three years ago. The dark blue coefficients indicate the individual's probability of winning the lottery. The plot shows that most applicants lose the lottery and then reapply. Approximately 12% of applicants win in a given lottery year, and 82% reapply the following year. This implies that over 90% of lottery losers reapply. Applicants dynamically selecting into lotteries is thus a minor concern in our setting, given that reapplication rates are so high. Second, over 60% of applicants had won a lottery within seven years.

This latter point is confirmed in Figure A.4, which plots the probability of being a lottery winner (shown on the y-axis) if the building lost the lottery a given number of years prior (where the number of years prior is shown on the x-axis). For example, a coefficient of 45% for an x-axis value of seven indicates that 45% of losers eventually won the lottery within seven years. Overall, the figure shows that many lottery losers reapply and become lottery winners soon after. As a result, simple comparisons in outcomes between lottery winners and losers are likely to downwardly bias the effect of condominium conversions, since many losers ultimately convert. This fact motivates the regression design we discuss in Section 4.

3 Data

Our primary outcome of interest is home values, for which we use the assessed value of land and structures for a parcel as given in the San Francisco Assessor's Office annual files. We further merge information about parcel-level building permits and evictions, as well as information about lottery applicants and winners. For neighborhood outcomes, we rely on data from the ACS and business registrations.

3.1 Sources

Our main data come from four main sources, most available through `data.sfgov.org`.

Property Tax Rolls (1999 - 2021) : The San Francisco Office of the Assessor-Recorder makes the years 2007 through 2021 publicly available through their website. To this, we merge in years 1999 through 2006 provided to us directly by the assessor's office. This dataset contains information about the property location, type and construction type, number of bathrooms, bedrooms, rooms, stories, and units, local zoning, property area, whether the property is homeowner-occupied, most recent sale, and assessed value of land and improvements (structures).

Building Permits (1983 - 2021): This dataset contains information on the parcel number, date, estimated cost, and type of building permits.

Evictions (1997 - 2021): This dataset contains each eviction in the city of San Francisco, with its location, file date, and the reason for the eviction.

Lottery Information (2001 - 2013): Lottery information on the applicants, the number of tickets they were assigned, and the winners was provided as part of a public records request. Importantly, the number of tickets allows us to infer whether an applicant was in Pool A or Pool B of the lottery.

Census & ACS Data (2000, 2013-2019): We use American Community Survey (ACS) census block group-level data for years 2013 to 2019 for the city of San Francisco. These data contain information about demographics, income, home values, rents, and education. We also use tract-level outcomes from the 2000 census, concorded to 2010 census tracts by the Neighborhood Change Database.

LODES Data (2002-2019): We use LEHD Origin-Destination Employment Statistics (LODES) data at the census block level for years 2002 to 2019 for the city of San Francisco, aggregated at the census block-group level. This dataset contains information about local residents and workers, such as the number of workers in various age, earnings, and sector categories.

Business Registrations (2000 - 2019): The Office of the Treasurer and Tax Collector contains information on business registrations, including their location, sector, date of registration, and whether the business is still active or not. We aggregate this data to the census block group level, and tabulate counts of establishments in different sectors. We tally new establishments as well as the stock of active ones.

3.2 Summary Statistics

Our lottery data begins in 2001 and continues until the lottery ended in 2013. Figure 3 presents time series for the number of applicants (right axis) and the number of winners (left axis) for each lottery in our sample. The number of winners remains flat at 60 to 65 per year. Each winner on average is a 3-4 unit building, leading to cumulative totals of approximately 200 units per year. Over the study period, the number of applicants nearly doubled. This dramatic increase ensured that winners were randomized even amongst pool A applicants for most years.

Figure 4 plots our estimate of an applicant's probability of winning, based on rules stipulated in city ordinances, and the empirical probability that the applicants actually won. The plot shows that we are able to replicate the lottery's randomization procedure, with the line of fit precisely on the 45 degree line. The years 2001, 2006, 2010, and 2012 saw a sizeable fraction of applicants guaranteed winning in pool A — that is, these applicants had probability "1" of winning. These buildings accounted for 93 of the total 812 winners we observe. Our results on lottery winners, which fully match on the lottery propensity score, will effectively ignore variation from these applicants.

Figure 5 maps the geographic distribution of lottery applicants and winners. Neighborhoods like North Panhandle, Haight Ashbury, Duboce Triangle, and the Mission saw high demand for conversions as well as many lottery winners. Russian Hill had many applicants but few winners. Inner Sunset had few applicants but a surprising number of winners. This random geographic variation will be central to estimating the neighborhood effects of condominium conversion in Section 6. Our main set of findings will rely on locations with or near to lottery applicants. Consequently, neighborhoods like Outer Parkside and South of Market will be largely excluded from the analysis.

Summary statistics for winning and losing applications are presented in Table 1. The calculations are for two years prior to an application. Applicant buildings have around 15 rooms and 1300 sq. ft. per unit. The average assessed home value was nearly 1 million dollars for winners. Column (5) calculates the difference between building characteristics for winners and losers after controlling for lottery p-score and year fixed effects, and column (7) has the corresponding p-value. Reassuringly, no building characteristics are significantly different between lottery winners and losers prior to their application.

4 Design

Our setting provides a unique randomized experiment for studying the effects of condominium conversions on building home values, investment, sales, and renting behavior. Framing this design within an econometric framework provides some complications however, driven largely by repeated applications of losing properties and multiple event times. We now discuss our data structure and framework for estimating the relevant treatment effects.

4.1 Simple Lottery Design

We begin by discussing a regression implementation of the simple lottery design before generalizing to our setting. Let y_{it} denote assessed home value, one of our key outcomes, for parcel i in year t. Let $\tau_t(k)$ indicate whether year t is k years from the lottery and ν_i indicate whether parcel i wins the lottery.

Applicants have unequal probabilities of winning the lottery according to how many tickets they purchase and the ticket composition of other applicants. The number of tickets that can be purchased depends on how many previous times an applicant has lost. Comparisons between lottery winners and losers may give misleading estimates of the effect of condominium conversions if, for example, applicants with the greatest expected housing price appreciation apply more frequently. Controlling for the probability of winning the lottery ensures that we rely on random variation generated by the lottery, rather than endogenous selection into the lottery. As such, we include $\chi_i(p)$ fixed effects, which indicate whether parcel i had probability p (from support set $\mathcal{P}$) of winning the lottery.

We model home values using the following equation:

$$y_{it} = \sum_{k \neq -1} \beta_k^{ITT} \tau_t(k) \nu_i + \sum_k \sum_{p \in \mathcal{P}} \gamma_{pk} \tau_t(k) \chi_i(p) + \varepsilon_{it} \tag{1}$$

The second summation term ensures that comparisons are made between parcels with the same probability of winning the lottery.[12] Following Abdulkadiroğlu et al. (2017), this type of full propensity-score matching ensures that the coefficients β_k^{ITT} capture a convex-weighted average of the causal effects of winning in a building's specific lottery-strata. The coefficients β_k^{ITT} map out the full set of intention-to-treat (ITT) effects — that is, the effect of winning on home values k years before or after the lottery. Years prior to lottery implementation serve as balance tests, allowing an evaluation of whether within a lottery-strata, outcomes are similar prior to the lottery. Throughout, we cluster standard errors at the level of lottery applicant.

The ITT effects provide a transparent assessment of the lottery design. However, we are primarily interested in the effect on home values from parcel i converting to a condominium at time t. We therefore augment the above design to an instrumental-variables setting, where we instrument for whether a parcel ever converts to a condominium after the lottery (given by κ_i) with whether a building won the conversion lottery.[13] The second-stage equation that relates home values to condominium status is given by the following equation:

$$y_{it} = \sum_{k \geq 0} \beta_k^{IV} \tau_t(k) \kappa_i + \sum_k \sum_{p \in \mathcal{P}} \gamma_{pk} \tau_t(k) \chi_i(p) + \varepsilon_{it} \tag{2}$$

[12] The probability of winning a lottery is the same for all applicants who purchase the same number of tickets in a given lottery; consequently, specifications with lottery by ticket fixed effects produce identical regression results.

[13] We instrument for this variable, rather than if a parcel is currently a condominium, so that we do not need to keep track of two sets of event times: one for lottery application and one for conversion.

We instrument for condominium conversion with winning the lottery at each event time in the following first-stage regressions:

$$\tau_t(k)\kappa_i = \sum_{k\geq 0} \beta_k^{FS} \tau_t(k)\nu_i + \sum_k \sum_{p\in\mathcal{P}} \gamma'_{pk}\tau_t(k)\chi_i(p) + \varepsilon'_{it} \tag{3}$$

We use this instrumental variables (IV) approach to assess how the magnitude and significance of the effects change when treatment is defined as a condominium conversion, rather than winning the lottery. Thus, we estimate and report β_k^{IV} for years after the lottery is implemented.

Intuitively, this empirical strategy is an instrumented difference-in-differences design comparing the outcomes of applicant lottery winners and losers with the same ex-ante probability of winning. The lottery design ensures independence of the instrument, but in this setting, only mean-independence of the potential outcomes and treatment assignment with respect to the lottery is required (Hudson et al., 2017). Testing for parallel-trends in the fully-interacted ITT specification offers a diagnostic to assess this assumption.

The exclusion restriction requires that winning or losing the lottery does not directly affect home values — that is, it requires that the lottery can only affect home values through the condominium conversion itself. This is a natural assumption since the lottery's sole purpose is to allow or prohibit condominium conversions. Monotonicity is guaranteed in this setting, as is one-sided non-compliance — regulation for these buildings prohibited condominium conversions except through the lottery while it was active. In Section 5, we show that the first-stage is strong, with more than 80% of winning properties converting. Consequently, the coefficient β_k^{IV} can be interpretted as the causal effect of converting to a condominium on home values at time k after the lottery (Imbens and Angrist, 1994).

4.2 Dynamic Lottery Design

Parcels that lost the lottery but had the same probability of winning are a natural control group for lottery winners. We now extend the above framework to a setting with repeated lotteries and where losing parcels continue to apply. We also rely on recent research on difference-in-differences designs with heterogeneity in treatment timing in order to implement our econometric analysis.

We first create thirteen (one for each lottery) simple lottery designs, composed of each applicant for each lottery year from 2001 to 2013. We then stack these observations according to each lottery m. The $\tau_{mt}(k)$ denotes whether year t for lottery m is k years since the lottery was run. The ν_{im} is an indicator for whether the parcel won that lottery. The $\chi_{im}(p)$ are indicators that the parcel in a given lottery had probability p of winning. Our new outcome y_{imt} denotes assessed home value for parcel i in lottery m in year t.

Parcels have histories duplicated according to how many times they have applied. Consistent with Cengiz et al. (2019) and Baker et al. (2021), we construct a clean set of controls by only including observations for control parcels that are yet to convert to a condominium. This ensures that we do not compare outcomes of previous winners and later winners, which would naturally bias down the effects of converting. [14]

The ITT version of our main specification is as follows.

$$y_{imt} = \sum_{k \neq -1} \beta_k^{ITT} \tau_{mt}(k) \nu_{im} + \sum_k \sum_m \sum_{p \in \mathcal{P}} \gamma_{pmk} \tau_{mt}(k) \chi_{im}(p) + x'_{imt} \zeta + \alpha_{im} + \eta_t + \varepsilon_{imt} \tag{4}$$

While not necessary for a causal interpretation of the coefficients β_k^{ITT}, we include parcel by lottery fixed effects α_{im} in our main specification, for two reasons. First, the fixed effects reduce residual variation in the errors, which increases precision. Second, we drop observations for lottery losers that ultimately convert to a condominium. This occurs if lottery losers convert through the Expedited Conversion Program (implemented in 2013 and discussed in Section 2) or win in a subsequent lottery. The parcel fixed effects help address (i) possible selection bias among losing parcels that later convert, and (ii) an unbalanced sample stemming from different event-time coverage for each lottery. The fact that most losing applicants reapply, as shown in Section 2.4, lessens the first concern. Nevertheless, we consider several robustness exercises to explore these issues in Section 5. With parcel-lottery fixed effects, the coefficients β_k^{ITT}can be interpretted as a convex-weighted average of the underlying treatment effects for each lottery (Sun and Abraham, 2020).

While we do not include them in our main specification, we allow for additional controls x_{imt}, like neighborhood trends. These controls may adjust for random imbalances between lottery

[14]If we were interested in the effect of winning the lottery, it would be reasonable to include observations from later winners in the control group, as those are downstream effects from losing the lottery. A dynamic approach like Cellini et al. (2010) could also be used to estimate the desired treatment effects. We perform this as a robustness exercise in Section 5.3.

winners and losers, and allow us to assess the importance of sample attrition in the control group later in event time. We consider how robust our results are to their inclusion in Section 5. Additionally, an attractive feature of the dynamic setting is that it allows us to disentangle event-time effects from calendar-time effects, given by η_t, and to control for them separately.

This design corresponds to the "stacked" difference-in-differences design of Cengiz et al. (2019) and Baker et al. (2021). While other approaches to multiple event timings have been suggested (Borusyak et al., 2021; Callaway and SantAnna, 2020), the stacked difference-in-differences design offers greater transparency and most naturally accomodates our IV and spillovers analyses.

The LATE implementation estimates the following second-stage regression.

$$y_{imt} = \sum_{k \geq 0} \beta_k^{IV} \tau_{mt}(k)\kappa_{im} + \sum_k \sum_m \sum_{p \in \mathcal{P}} \gamma_{pmk} \tau_{mt}(k)\chi_{im}(p) + x'_{imt}\zeta + \alpha_{im} + \eta_t + \varepsilon_{it} \tag{5}$$

We instrument for winning the lottery and eventually converting to a condominium κ_{im} with winning the lottery through the following first-stage regressions.

$$\tau_{mt}(k)\kappa_{im} = \sum_{k \geq 0} \beta_k^{FS} \tau_{mt}(k) v_{im} + \sum_k \sum_m \sum_{p \in \mathcal{P}} \gamma'_{pmk} \tau_{mt}(k)\chi_{im}(p) + x'_{imt}\zeta' + \alpha'_{im} + \eta'_t + \varepsilon'_{it} \tag{6}$$

As in the ITT specification, attrition in our control group due to the Expedited Conversion Program and later lottery winners might raise concerns over the independence of the instrument. However, the IV difference-in-differences relaxes the necessary assumptions to maintain a causal interpretation. We report coefficients β_k^{IV} for event times after the lottery was conducted. We cluster errors at the applicant level. This is particularly important to account for dependence across lotteries, since applicant histories appear multiple times in the data according to how many lotteries they have entered.

4.3 Spillovers Design

Evaluating the effects of condominium conversions on nearby home values is complicated by two features of our setting. First, treatment will depend on the number of winners at various distances. Second, while winning the lottery may be random, being located near a winner is likely not. For example, parcels in the city center are more likely to be close to winners than parcels on the periphery, and being closer to the city center is likely correlated with unobservable shocks that determine home values. We extend our approach in the previous section to account for these facts.

We consider all residential parcels j within a fixed distance of any lottery applicant. For lottery m, we calculate the number of winning applicants within distance band d given by $\tilde{\nu}_{jm}(d)$. Through repeated simulations of the lottery, we also calculate the probabilities for each distance band that any nearby lottery applicant wins and stack them into the vector $\tilde{\chi}_{jm}$. The ITT version of our main spillovers specification is as follows.

$$y_{jmt} = \sum_{d} \sum_{k \neq -1} \beta_{dk}^{ITT} \tau_{mt}(k) 1(\tilde{\nu}_{jm}(d) > 0) + \sum_{d} \sum_{k} \sum_{m} \tau_{mt}(k) f(\tilde{\chi}_{jm}, \gamma_{dmk}) + x'_{jmt}\zeta + \alpha_{jm} + \eta_t + \varepsilon_{jmt} \tag{7}$$

In our main specification, f captures all linear terms of the coordinates of $\tilde{\chi}_{jm}$. The vector γ_{dmk} contains the coefficients on the terms in the function f. These parametric controls adjust for the fact that buildings near lottery applicants and winners are unlikely to be comparable with buildings that were not near lottery applicants and winners. This is the same insight as in Borusyak and Hull (2023), ensuring that we still rely on lottery variation to estimate the spillover effects while controlling for endogeneity due to a parcel's location. We focus on having any lottery winner a certain distance away as the treatment.[15] The parameters of interest β_{dk}^{ITT} map the full set of spillover dynamics for each distance band d. Parcels are included as controls until their nearby applicants convert to a condominium, if ever. We map parcels to their closest applicant, and cluster errors at that location.

The IV model is estimated in the same way as before. We instrument whether the nearby winner ever converts to a condominium after the lottery with whether the nearby parcel wins the lottery. We estimate these coefficients for all event times greater than zero.

5 Results

In this section, we leverage the lottery design to estimate the causal impact of condominum conversions on winning and nearby properties. We find that winning property owners see large increases in assessed home values. Owners renovate their properties, rent them out, and

[15]The vast majority of parcels are at most near one winner.

eventually sell them several years after the lottery. We also find large and highly localized price spillovers on nearby properties. Homes within 25 meters of a winner increase in value by 10% after 15 years, with this effect becoming insignificant at further distances.

5.1 First-Stage: Effects of Winning the Lottery on Condominium Conversions

We first document that lottery winners overwhelmingly convert their properties into condominiums. Figure 6 plots the β_k^{ITT} and β_k^{IV} coefficients from Equations 4 and 5, respectively, along with their associated 95% confidence intervals. In both specificiations, the outcome is an indicator equal to one if the property is legally registered as a condominium, and zero otherwise.

The β_k^{ITT} coefficients in Figure 6 trace the dynamic treatment effects of winning the lottery over time. In years prior to the lottery, winning and losing applicants are equally (un)likely to convert to condominiums. This is unsurprising, since conversions are legally prohibited unless property owners win the lottery. After the lottery, winning property owners are generally unable to immediately convert their properties into condominiums, since the process for preparing and approving applications is costly and takes time. However, over time, the share of conversions steadily increases. Approximately 20% of winners convert their properties within the first full year, and 60% convert within 3 years. At longer time horizons, the conversion rate surpasses 80% within 10 years, and stabilizes at around 82% within 15 years, which is the end of our sample horizon. That the vast majority of lottery winners eventually convert is again unsurprising, since the sole purpose of the lottery is to obtain legal permission to do so.[16] In Appendix Figure A.5, we show that neighborhoods with a one standard deviation higher population in year 2000 see lottery winners convert at a 5 pp higher rate. However, the propensity for lottery winners to convert their properties is statistically similar across other initial neighborhood characteristics.

In Figure 6, the endogenous variables in the IV model are time-invariant indicators equal to one if the property ever converts to a condominium in our sample period interacted with indicators for each year since the lottery. In the figure, the β_k^{IV} coefficients are informative of the share of lottery-induced compliers who have converted within k years from the lottery. For example, three

[16] For a neglible share of observations (less than 2%), we observe properties classifed as condominiums prior to implementation of the lottery. One possible explanation for this fact is that, several years before the lottery, property owners may have converted in the opposite direction (that is, they changed from condominiums to another legal form), and then applied to the lottery in order to change back. Another perhaps more likely possibility is measurement error in the administrative data.

years after the lottery, the $\beta^{IV}_{k=3}$coefficient of 0.74 = (0.61/0.82) implies that 74% of lottery winners that will ever convert have already done so. By construction, this share converges to 1 by the end of our sample period.

Overall, the high condominium conversion rates in Figure 6 provide compelling evidence of an economically and statistically strong first-stage in our instrumental variables design.

5.2 Effects on Winning Properties

We now study the effects of the lottery on winning properties. The panels in Figure 7 plot the $\beta^{ITT}_{k}$and β^{IV}_{k} coefficients from Equations 4 and 5 for a suite of key outcomes: property values and building and renovation permits. Across all the outcomes, the panels show that winning and losing properties were on common trends prior to the lottery, consistent with effective random assignment from the lottery and with the balance tests presented in Table 1.

Panel A of Figure 7 shows that, over time, winning properties increase dramatically in value relative to losing properties. Within 15 years, the IV estimates indicate that condominium conversions on average cause property values to appreciate by 52%. Since the average property in the sample is worth approximately $1 million, this implies that condominium conversion was on average worth more than $500,000 during our sample period.

Panels B, C, and D of Figure 7 document the effects of winning the lottery on permits for alterations and renovations (Panel B), the inverse hyperbolic sine transformation of the estimated cost of these renovations (Panel C), and their cumulative value, summed from 1999 forwards (Panel D). The number of permits and their value increase sharply in the two years immediately after the lottery, as winning owners make new investments and improvements in their properties. These improvements likely explain part of the increase in property values documented in Panel A. Permit effects are entirely concentrated within the first two years, after which they decline to levels below the level for lottery losers. Panel D demonstrates that the overall value of alterations and renovations for winning owners remain 54% above losing owners through the study period.

The panels in Figure 8 plot the $\beta^{ITT}_{k}$and β^{IV}_{k} coefficients from Equations 4 and 5 for a second set of outcomes: tenant evictions, homeownership, and property sales. Panel A shows that winning properties are more likely to be occupied by a homeowner in the year following the lottery. This implies that the winning property owners are more likely to live in their units when they are making renovations and alterations. However, these owners then quickly move out of the units after the first full year, and instead rent the properties to new tenants. The owners are likely to benefit from higher rental prices, both because condominiums are not subject to rent control and because renters are willing to pay more for the recently renovated (and presumably higher quality) units. Three years after the lottery, the IV estimates imply that lottery-induced converted units are 43 percentage points more likely to be occupied by renters compared to losing lottery units. The magnitude of this effect steadily attenuates as units are sold to new homeowners over time, such that winning units are 19 percentage points more likely to be occupied by renters 15 years after the lottery.

Panel B of Figure 8 traces the effects of winning and converting on property sales, defined as an indicator equal to one if any unit in the parcel is sold.[17] Winning property owners are modestly less likely than losing applicants to sell their units in the years immediately following the lottery — this result is consistent with the finding that owners are more likely to be renovating and renting their properties during these years. However, 7 years after the lottery, winning applicants that convert are on average 3 percentage points more likely to sell their properties than losing applicants. Within 15 years, this effect increases modestly to 5 percentage points.

Lastly, contrary to the concerns of many policymakers and voters, Panel C reveals that condominium conversions do not cause a statistically discernable change in eviction rates. However, we caution that this result does not necessarily imply there is no turnover or displacement of tenants, since in some cases owners may induce tenants to move out without resorting to the legal eviction process.

In the Appendix, we explore whether the effects of condominium conversions on property values vary with neighborhood or property characteristics. Appendix Figure A.6 shows that average property appreciation of winning properties is larger in neighborhoods with initially high poverty rates and low income levels. Otherwise, conversion-driven appreciation does not vary systematically with initial neighborhood characteristics. Appendix Figure A.7 shows that a one standard deviation increase in the year the building was built leads to 10% lower long-run appreciation from converting. The fact that appreciation is larger for older buildings is consistent

[17]The comparison of lottery winners vs. losers is apples-to-apples because units of condominiums can be sold (winners) as can units of tenancy-in-commons (losers; see section 2 for more details).

with significant value-added from alterations and renovations.

5.3 Robustness

The results in the prior section are identified from exogenous variation from the lottery. Consistent with successful randomization of the lottery, the regression results previously shown in Figures 7 and 8 indicate that winning and losing properties are balanced on a rich set of outcomes as far back as twelve years prior to the lottery. Nevertheless, comparisons of winning and losing properties may yield biased estimates of treatment effects if losing applicants are later able to convert via subsequent lotteries, or via the ECP conversion process introduced in 2015. If selection into these conversions is driven by time-varying factors (and so, not accounted for in the property-by-lottery fixed effects in Equation 4), then the results could be biased. For example, if properties with higher expected price growth from converting reapply at a greater rate, our estimates of the causal effects of condominium conversions would be biased downwards.

We implement additional robustness checks to assess this possibility. First, if this form of selection were salient, we would expect lottery winners who had applied repeatedly to subsequently experience greater home value appreciation. To test this hypothesis empirically, we study whether home value appreciation for condominium converters eight years after the lottery varies with the number of times they previously applied.[18] Against the hypothesis, Figure A.8 shows that repeat applicants do not demonstrate statistically distinguishable home value appreciation relative to properties that won the lottery on their first attempt. Moreover, when we restrict the sample to using only never-winners as the control group, as in Figure A.9, the results are highly similar. These findings mitigate concerns about selection bias through reapplications.

In a second exercise to evaluate the importance of endogenous reapplications, we implement a version of the main specificiation including progressively granular neighborhood trends. Controlling for these trends would likely be important if properties with stronger price appreciation are more likely to reapply. Table 2 shows the $\beta^{IV}_{k=15}$ coefficients from these regressions, where the outcome is property values — these coefficients indicate the causal effect of condominium conversions on assessed home values 15 years after the lottery. Column 1 reports the baseline results, Column 2 includes neighborhood-by-year fixed effects, Column 3

[18] We focus on an eight-year horizon so that all lotteries are included in the estimation.

includes census tract-by-year fixed effects, and Column 4 contains census block-group-by-year fixed effects.[19] Reassuringly, across specifications the 15 year home value appreciation remains statistically significant and quantitatively unchanged by these additional controls.

In a final set of exercises, we include the entire set of histories of losing applicants, not just those that have yet to convert. Since we are primarily interested in the effects of converting to a condominium, we adjust comparisons between winning and losing properties for the fact that losing properties may eventually convert. In the Appendix, we describe two instrumental variable designs to do so. Both estimates are quantitatively similar to our main set of results.

5.4 Spillover Effects on Nearby Properties

We now use the econometric design described in Section 4.3 to evaluate the spillover effects of condominium conversions on nearby properties. Panel A of Figure 9 plots the β_k^{ITT} and β_k^{IV} coefficients from estimating Equation 7, where the outcome is the assessed value of homes within a 25-meter radius from the winning property. The 25-meter bandwidth typically includes 3 to 6 properties that are either immediately adjacent to the winning property, across or behind the street, or two to three doors down. Before the lottery, price trends are similar for homes nearby winning and losing applicants, as expected from random treatment assignment. After the lottery, homes located nearby the winners do not immediately increase in value, but do increase beginning approximately 8 years later. This timing is consistent with the treatment dynamics we observed for property sales in Figure 7. Within 15 years of the lottery, these nearby home prices appreciate by 10% (s.e.=4.7%) relative to homes nearby losing lottery applicants. Appendix Table A.4 shows that this result is qualitatively similar when including controls for local time trends by neighborhood, census tract, or census block group.

Panel B of Figure 9 shows results from the same estimation for different bandwidths: the outcome in Panel B is the assessed value of homes within 25- to 50-meter and 50- to 75- meter bandwidths from the winning property, with the β_k^{ITT} coefficients plotted for both distances. These parcels are typically on the same block as the winning property, but further down the street.[20] The figure shows that property values near lottery winners were trending similarly to property

[19] The definition of a neighborhood comes from the San Francisco's Assessor's Office. There are 55 neighborhoods in our sample of lottery applicants.

[20] A city block in San Francisco is about 65 meters wide and 91 meters long.

values near lottery losers in the 12 years leading up to the lottery. This is true for both the 25-50 meter and 50-75 meter distance bands. After the lottery, properties near winners 25-50 meters away see slight but insignificant property value appreciation before tending towards zero at longer horizons; properties near winners 50-75 meters see small property values declines (on the order of 3%) before tending towards zero at longer horizons as well. The latter result suggests that in the short-run, positive price spillovers from conversions are mitigated by competition with other high-end properties nearby. In both bandwidths, we do not find compelling evidence of spillovers on property values in the long-run.

The evidence from Figure 9 thus suggests that the spillover effects of condominium conversions are highly localized. Properties within 25 meters of a condominium conversion appreciate in value, while those farther away see no long-run appreciation . This empirical pattern is informative of the mechanisms that may be driving the spillovers. First, nearby properties might appreciate due to an aesthetic externality from the improved and renovated condominiums, which fades at further distances. Second, nearby properties might appreciate due to a form of behavioral benchmarking, whereby prospective home buyers face imperfect information in the real estate market and so use information about highly local properties as a signal of underlying value. Third, to the extent that local demographic characteristics affect home values, changes in the composition of residents living in the converted condominiums may also play a role. We explore these issues in greater detail in the following section.

6 Neighborhood Effects

We now turn to addressing whether conversions lead to changes in demographic or economic outcomes in affected neighborhoods. In the previous section we documented that conversions have a large effect on the prices of winning properties, and induce substantial turnover in resident composition as owners move in, move out, rent, and eventually sell their properties. We also documented that conversions increase the prices of adjacent buildings. However, directly affected properties comprise only a small share of the neighborhood housing stock – approximately 2.4% of local residential units, on average. Thus, if conversions have a broad-based effect on neighborhood-wide home prices and demographics, they must have spillover effects on the surrounding area.

Condominium conversions could play a role in broader neighborhood-level gentrification through a series of self-reinforcing mechanisms. First, the new, higher-income condominium residents may increase demand for local goods and services, putting upward pressure on local prices and changing the composition of local businesses. Second, the changing quality and prices of local goods and services -– as well as the changing composition of the residents themselves — may in turn affect which residents find the neighborhood attractive. For example, low-income residents may not value the new neighborhood amenities given the prices, whereas high-income residents may find the neighborhood increasingly desirable. Demographic homophily, racism, and network effects may also play an important role in residential sorting patterns, as has been documented extensively in existing research.[21] As more high-income residents enter the neighborhood, the pattern reinforces itself, fueling broader neighborhood change.

Below we explore to what extent condominium conversions in San Francisco caused neighborhood-wide gentrification, and evaluate whether the evidence is consistent with these mechanisms.

6.1 Neighborhood Design

To study neighborhood outcomes, we first adapt our lottery design to a setting in which a cross-section of census block groups are impacted by the cumulative number of lottery winners from 2001 to 2013. We focus on the long-run, aggregate effect of condominium conversions on census block group outcomes. In addition to being a natural time horizon for studying a slow-moving process such as gentrification, census block group data is largely only available after 2013. Consequently, we focus on neighborhood outcomes from 2013 to 2019 and combine information across all lotteries. Census block groups are the smallest geographic unit for which the Census and the American Community Survey (ACS) release information.[22] Being a small, contiguous set of city blocks, they are an intuitive definition of a neighborhood.

[21] For example, immigrants are more likely to move to neighborhoods with other immigrants that share their ethnicity (Abramitzky and Boustan, 2017). In general, to the extent that social and information networks are segregated by education, class, and/or race, this is also likely to affect sorting (Jackson, 2021; DiMaggio and Garip, 2012). For a treatment of the history of racism and segregation in housing markets, see Rothstein (2017).

[22] While their size varies, they correspond to a median of nine city blocks (and most between six and ten blocks) in San Francisco. In our sample, census block groups have a median of 1400 individuals and 600 residential units in 2019.

To estimate the effect of a continuous treatment (conversions) on neighborhood outcomes, we rely on generalized propensity score methods (Imbens, 2000; Hirano and Imbens, 2004). In particular, let y_{gt} be an outcome for census block group g in year t. The variable ν_g denotes the number of lottery winners from all of the thirteen lotteries in our sample and $p_g(\nu_g)$ denotes the probability that the census block group had ν_g winners, given the lottery design.[23] The $p_g(\nu_g)$ captures a neighborhood's demand for the lottery, and by extension, demand for condominium conversions. Once adequately controlled for, we can leverage random variation in condominium conversions through the number of actual winners in the lottery.

We follow the Hirano and Imbens (2004) multi-step procedure in two parts. First, we model neighborhood outcomes as arising from a quadratic in the actual number of conversion lottery winners and the probability of having that number of winners, as follows:

$$y_{gt} = \gamma_0\nu_g + \gamma_1\nu_g^2 + \gamma_2 p_g(\nu_g) + \gamma_3 p_g(\nu_g)^2 + \gamma_4 p_g(\nu_g)\nu_g + x_g'\zeta + \varepsilon_{gt} \tag{8}$$

The x_g denote additional controls. In our main specification, we include all relevant outcomes in the earliest year as controls i.e. $x_g = \mathbf{y}_{g,2000}$ for demographic and business data and $x_g = \mathbf{y}_{g,2002}$ for age, earnings, and sectoral population shares. For outcomes available from the ACS, this information is only available at the tract level.[24] For outcomes of establishment counts from business registrations data and resident and workforce composition from LODES, this information is available at the census block group level. These controls serve multiple purposes. First, our estimate of the generalized propensity score does not fully capture dynamic behavior among lottery applicants. We have argued elsewhere that this is not a substantial concern in our context, and including the baseline controls further mitigates any potential for imbalance. Second, the controls improve the precision of our estimates. Third, by assessing changes relative to a base period, they maintain the flavor of our difference-in-differences designs in Section 5.

In the second step, we use Equation 8 to map out the entire dose-response function

[23] These probabilities are calculated as follows. For each lottery, we permute winners according to the lottery probabilities. We then repeat this process across a large number of simulations. We then calculate $p_g(\nu)$ as the fraction of the simulations in which census block group g recieved ν winners.

[24] Census tract outcomes in the year 2000 using 2010 boundaries come from the Neighborhood Change Database. We have all outcomes for census tracts in 2000 with the exception of the lower and upper quartiles of rent and home values. We simply control for the median home value and the median rent in 2000. The percentage of the population that is hispanic also does not appear in our census tract data, so we calculate it as 100 minus the percent of the population that is White, Asian, or Black. For consistency, we also use this definition in our census block group data.

$\hat{\mathbb{E}}[y_{gt}|\nu, p_g(\nu)]$. The dose-response function can be used to estimate the marginal change in neighborhood outcomes from one additional lottery winner at every level of the treatment and for every block group. These differences can be averaged over all G block groups to get an overall effect as follows:

$$\hat{\beta} = \frac{1}{G} \sum_{g} \sum_{\nu > 0} p_g(\nu - 1) \cdot \left(\hat{\mathbb{E}}[y_{gt}|\nu, p_g(\nu)] - \hat{\mathbb{E}}[y_{gt}|\nu - 1, p_g(\nu - 1)] \right) \tag{9}$$

Standard errors are calculated by bootstrapping the entire procedure, clustering on neighborhoods. We run this regression only for census block groups that had at least one lottery application over the study period. There are six census block groups (out of 326 that had at least one lottery applicant) with 10 or more lottery winners. The linear specification in lottery winners is sensitive to their inclusion; the quadratic specifcation in the main specification above is far more stable.

6.2 Results

Table 3 presents our estimates of the effects of an additional lottery winner on demographic change in neighborhoods. All outcomes are scaled so that the coefficients can be interpretted as a percentage point (pp) change.

We estimate that an additional condominium lottery winner increases median household income by 2.47pp and the share of the population with a college degree by 0.87pp (both significant at the 10% level). Lower quartile rents are unchanged, but median and upper quartile rents increase by 2.57pp and 2.18pp, respectively. Consistent with the previous results for assessed property value effects and spillovers, neighborhood home values increase by more than 2pp across quartiles. Population demographics change significantly as well. The White population increases by 1.57pp, while the Asian population declines by 1.46pp.

We next consider whether the composition of local residents or workers responded to the condominium conversions. We use the LODES data to construct shares of the resident population and local workforce that are younger than 30, between 30 and 54, and older than 55; as well as shares of the population that are making less than $15k annually, between $15k and $40k annually, and greater than $40k annually. Table 4 reports these estimates for the age and earnings categories.

The shares of young and middle-aged residents increase by 0.34pp and 0.29pp, respetively. The local workforce also gets younger, as the share of workers under the age of 30 increases by 1.14pp and the share of workers over the age of 55 decreases by 1.37pp. Both residents and workers earn more, with the share earning more than $40k increasing by 0.92pp and 1.09pp, respectively.

To understand which industries are driving these changes, we also construct shares of the population that work in any of 18 sectors, defined by two digit NAICS codes, and excluding Agriculture and Mining. Table 5 reports estimates from Equation 9 for these outcomes. The results show that resident shares significantly increase by 0.29pp in Information, by 0.36pp in Professional, Scientific, and Technical services, by 0.06pp in Arts and Entertainment, and by 0.07pp in Finance and Insurance. By contrast, residents are less likely to work in Health Care, Retail Trade, or Transport and Warehousing. The evidence on workers is generally less precise, with the exceptions of a sharp decline in local employment in Health Care and Public Administration, and an uptick in the Arts and Entertainment industry.

We now consider whether the count and sectoral composition of businesses in these neighborhoods changed as a result of condominium conversions. Our main outcomes will be the total number of new establishments and the total stock of active establishments, broken down by sector. We consider eight large sector groups: Food, Retail, Education, Arts and Entertainment, Professional Services, Manufacturing, Real Estate, and Construction. Many of the neighborhoods in our sample are residential, so our variables contain a large number of zeros. For this reason, we take the inverse hyperbolic sine transformation, and multiply the outcome by 100 so that coefficients can be interpretted as percentage point changes. However, we stress that the extensive margin response is important for interpretting the magnitude of the effects.

These results are contained in Table 7. Panel A uses counts of new establishments for the first four sector groups as outcomes. Panel B uses total counts of active establishments for those same sector groups as outcomes. Panel C and Panel D are structured similarly for the other four sector groups. We find that an additional lottery winner induces a 6.41pp decline in total food establishments (significant at the 10% level) and a 9.93pp decline in total construction establishments. Education, real estate, and professional services establishments increase by 7.70pp, 2.20pp, and 5.10pp respectively. We find no effect for the retail, arts, and manufacturing sectors.

The story that emerges is consistent with condominium conversions inducing gentrifcation in neighborhoods. White, college-educated, high-income individuals move in. Asian individuals move out. Consistent with our findings in Section 5, home values increase. The fact that rents increase is consistent with condominiums being rent de-controlled, and also consistent with pass-through from increased home values to rents. Residents are younger, earn more, and are more likely to work in information and professional services. New establishments in the education sector enter to meet increasing local demand. We also find that some professional service and real estate businesses move in as the neighborhood gentrifies. All of these neighborhood changes likely magnify and reinforce one another.

6.3 Heterogeneity

The effects of condominium conversions on demographic outcomes may vary with pre-lottery neighborhood characteristics. To assess this possibility, we estimate a fully-interacted version of Equation 8 with census tract covariates in 2000. All covariates are normalized to have mean zero and standard deviation one. We then augment the estimand in Equation 9 to estimate the additional effect of a lottery winner on a neighborhod one standard deviation from the mean of covariate x. The new estimand is given below. As before, standard errors are calculated by bootstrapping the entire procedure.

$$\hat{\beta}_x = \frac{1}{G}\sum_g \sum_{\nu>0} p_g(\nu-1)\cdot\Bigg(\big(\hat{\mathbb{E}}[y_{gt}|\nu, p_g(\nu), x=1] - \hat{\mathbb{E}}[y_{gt}|\nu-1, p_g(\nu-1), x=1]\big) \\ -\big(\hat{\mathbb{E}}[y_{gt}|\nu, p_g(\nu), x=0] - \hat{\mathbb{E}}[y_{gt}|\nu-1, p_g(\nu-1), x=0]\big)\Bigg) \tag{10}$$

These estimates are plotted in Figure 10 for each of ten baseline covariates: percentages of the population that are White, Asian, Hispanic, Black, college-educted, living in poverty, and the logs of the population, median household income, median home values, and rents. For outcomes, we focus on the the share of residents that are high-income in the LODES data. Not only is this an important variable for tracking neighborhood change, but superior measurement affords us greater precision in assessing sources of heterogeneity. Given the modest number of census tracts in our sample (n=123), confidence intervals are plotted at the 90% level.

Panels A and B of Figure 10 provide suggestive evidence that the neighborhood-level effects of condominum conversions on the share of high-income residents are larger in areas with initially higher shares of the population that are white and college-educated. This heterogeneity aligns with the findings from Section 5, in that the buildings of lottery winners appreciate more in neighborhoods that are initially more impoverished. In turn, these buildings are more likely to attract high-income renters and home-buyers. In the long-run, neighborhoods that are initially more distressed see larger demopgrahic change as a result of condominium conversions. The results are consistent with the hypothesis that demographic characteristics such as income, race, and education are key mediators of gentrification in US cities.

6.4 Counterfactual

In this section, we perform a simple quantification to estimate the extent to which condominiums contributed to the overall demographic changes documented in Figure 1 for San Francisco over this period. The quantification extrapolates our results to estimate the effects of increased condominium supply not only from the lottery, but also due to other conversions or new developments. To the extent that the effects of new developments are larger than from lottery-induced conversions, our estimates should be interpretted as conservative. As a first step, we estimate the total number of lottery conversions that would have needed to occur in each neighborhood to explain the share of condominiums in total local housing units. We then combine these estimates with our treatment effects to obtain predictions about the counterfactual effects of condominum supply on neighborhood demographics.

We perform this analysis for the 326 census block groups that ever had a lottery applicant. By focusing on the same sample used in our main estimation, we mitigate concerns about condominiums reallocating residents across areas. However, we cannot rule out the possibility that high-income residents are moving from areas that never saw demand for condominium conversions into areas that did. Moreover, to avoid extrapolating our results far beyond the support of our data, we allow for convexity in treatment effects by using the full quadratic specification from Equation 8. We also cap the number of conversions for a neighborhood at 10, beyond which the marginal estimated treatment effects are quantitatively close to zero.

The results of the conterfactual analysis are presented in Figure 11. The total, unnconditional 20-year changes in the college share, log median rents, and log median home values are plotted in Columns 1, 3, and 5, respectively. Consistent with Figure 1, San Francisco has seen a rapid rise in each of these outcomes. The college-educated share increased 25pp, home values increased 89pp, and rents increased 72pp over this period. The counterfactual analysis suggests that, as a percentage of the total change, condominiums can explain 6.1% of the rise in the college share, 8.2% of the rise in log rents, and 5.3% of the rise in log home values. These results suggest that condominiums have played a small but important role in city-wide gentrification in San Francisco.

7 Conclusion

The rise of condominiums is reshaping the housing stock of cities across the United States. At first blush, condominium conversions may appear to represent a simple change in the legal ownership structure of existing buildings. However, conversions in fact go beyond legal semantics, and bundle several other treatments with potentially far-reaching consequences for local housing markets. Following conversion, condominium units are no longer subject to rent control, face less stringent evictions protections, and are more liquid on the real estate market. High-income residents often find such units attractive, and are willing to pay premium prices for them. In San Francisco, we find that conversions induce property owners to renovate and upgrade units, further causing home values to appreciate. Consequently, nearby parcels become more attractive. In the long-run, the neighborhood gentrifies: rents and home values increase; more educated, higher-income, and white individuals move in; the sectoral composition of residents, workers, and local businesses changes; and demographic minorities move out.

We highlight four main takeaways from this research.

First, the results provide clear evidence that high-end housing is not merely a *consequence* of gentrification, but also a *cause*. Participants in housing policy debates sometimes contend that gentrification is fundamentally a response to local labor demand shocks, and thus would occur even in the absence of high-end housing development.[25] Our results show that high-end housing developments do in fact generate substantial changes in neighborhood outcomes typically associated with gentrification.

Second, while much existing supply-side research emphasizes the importance of housing unit

[25] See, for example, Noah Smith, "Luxury construction causes high rents like umbrellas cause rain." April 22, 2023. https://www.noahpinion.blog/p/luxury-construction-causes-high-rents. See also Boustan et al. (2023), "Condominium development does not lead to gentrification." *Journal of Urban Economics: Insights.*

quantities in driving local neighborhood change (see Baum-Snow 2023 for a review), our research underscores the complementary significance of housing *quality*. In our empirical setting, the overall quantity of units is held approximately constant in the quasi-experimental lottery design. Even so, the results show that, relative to other multi-unit buildings, condominium developments in San Francisco induce substantially different neighborhood outcomes over a 15-year period. In alternate contexts, this lesson about housing quality is likely to have generalizable implications; to name just one example, it is likely relevant in urban policy debates about the share of new construction that is legally mandated to be offered at or below market prices, and at correspondingly varying quality levels.

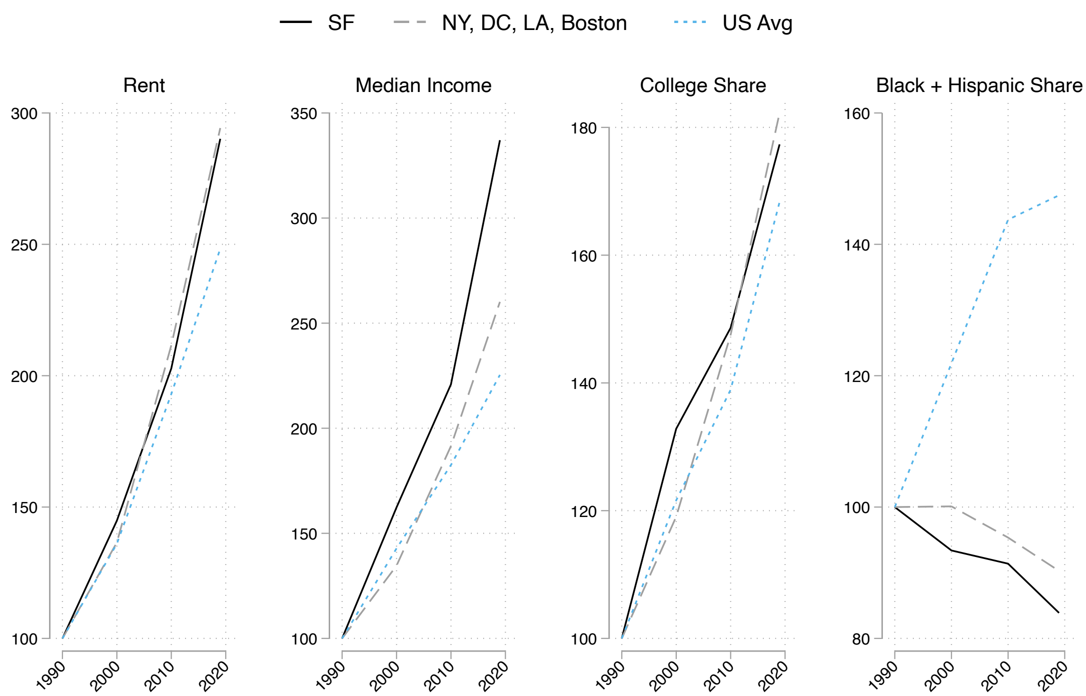
Third, this research highlights the heterogeneous distributional implications of a widespread housing policy regulation, namely, laws governing the local supply of condominiums. Although our results do not yield any particular conclusions about aggregate social welfare, they do call attention to the fact that different demographic groups — as defined by income, education, race, age, or industry — are likely to be affected very differently by changes in the local housing stock. Voters and policymakers may wish to proceed with clear eyes about these impacts.

Lastly, we return to the fact that housing supply in many major U.S. cities, and particularly in San Francisco, has failed to keep pace with housing demand in recent decades. This context is crucial, since in housing markets with limited new construction, policies affecting how the existing housing stock is renovated, used, sold, and rented are likely to be particularly consequential. A corresponding implication, however, is that our empirical results are difficult to extrapolate to housing markets where the aggregate supply of housing units is more elastic. In markets with elastic housing supply, it is possible that the effects of condominiums on local prices and demographics may be more muted. We view this is as a valuable topic for future research.

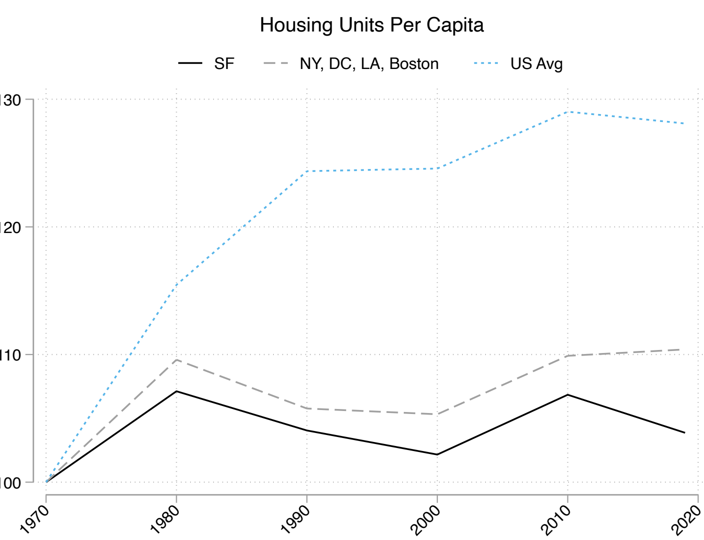
Figures

Figure 1: Gentrification in San Francisco and Other U.S. Cities

Panel A: Rents and Demographics



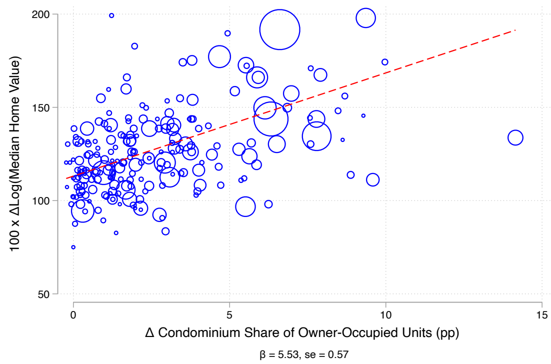
Panel B: Housing Units Per Capita



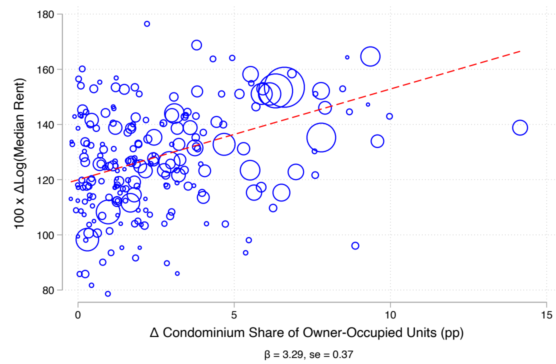
Notes: The unit of analysis is a census tract, and data are from the Neighborhood Change Database. In Panel A, data values are indexed to 100 in 1990, the earliest year consistently available for these outcomes. In Panel B, data values are indexed to 100 in 1970.

Figure 2: Gentrification and the Rise of Condominiums

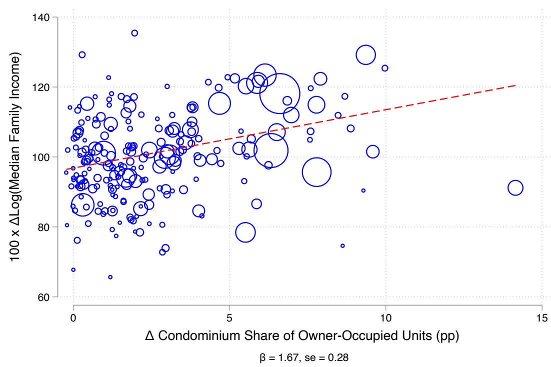
(a) Panel A: Δ Log Home Values (1980-2010)



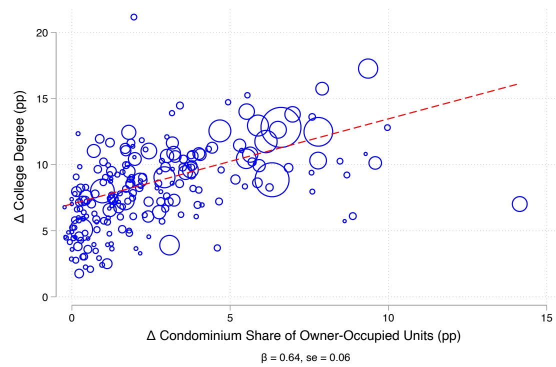
(b) Panel B: Δ Log Rents (1980-2010)



(c) Panel C: Δ Log MFI (1980-2010)

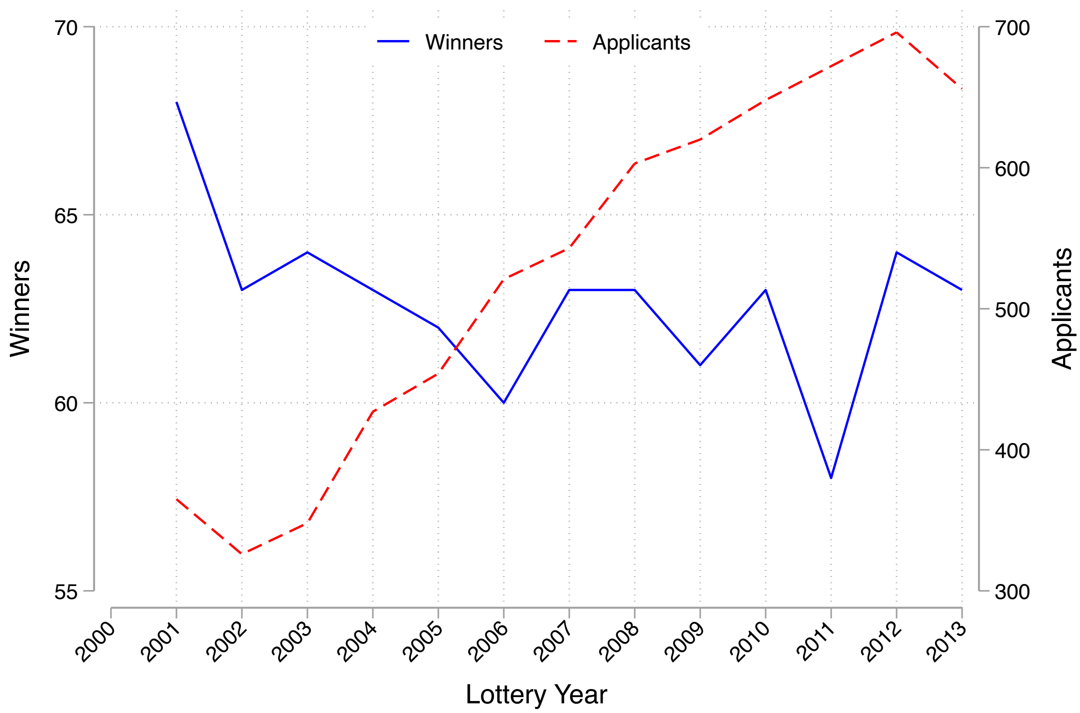


(d) Panel D: Δ College Share (pp, 1980-2010)



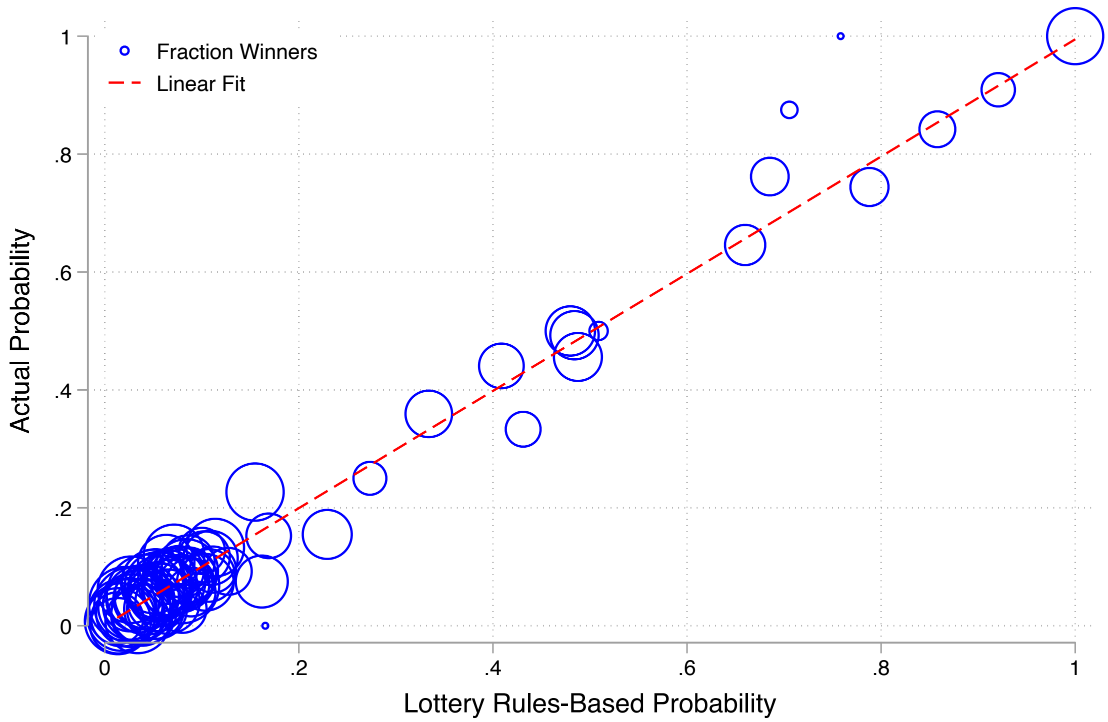
Notes: The unit of analysis is a city, and the sample includes the roughly 220 metropolitan areas with various demographic and owner-occupied units data. Data are from the census. The figures show a scatter plot of the long-run change in city demographics against the long-run change in owner-occupied units that are condominiums. Panel A plots this relationship for the log of city home values, panel B for the log of city rents, panel C for the log of city median family income, and panel D for the percentage of the city's population with a college degree. The size of circles is proportional to the city's population in 2010. A line of best fit is shown in red, with its coefficient and standard error noted below the chart.

FIGURE 3: LOTTERY APPLICANTS AND WINNERS



Notes: The figure plots the number of lottery applicants (right axis) and winners (left axis) for each year of the sample. Data are from the City of San Francisco Assessor's Office.

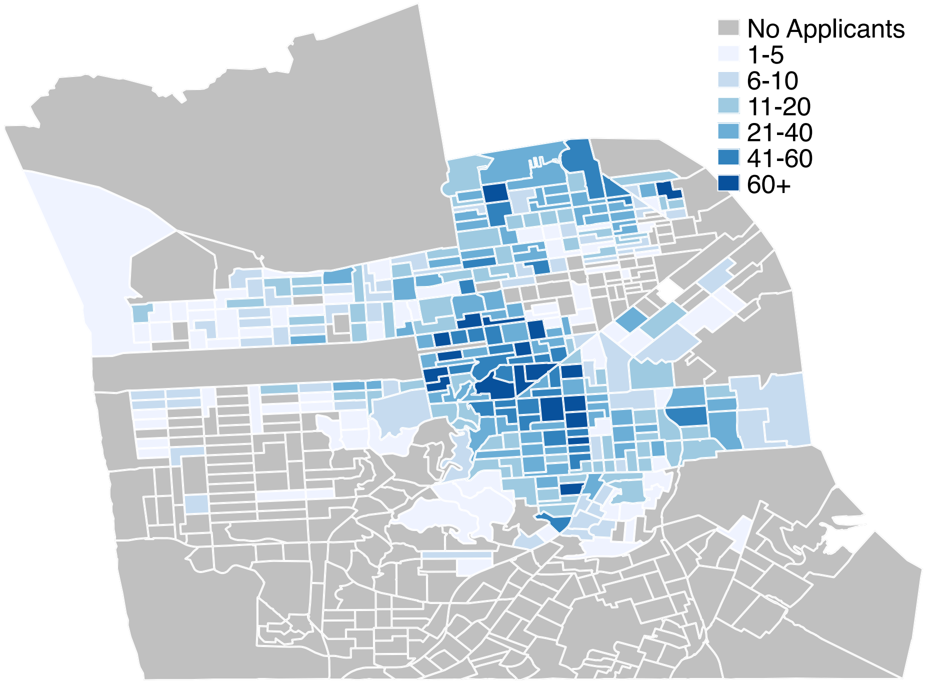
FIGURE 4: LOTTERY PROBABILITY OF WINNING



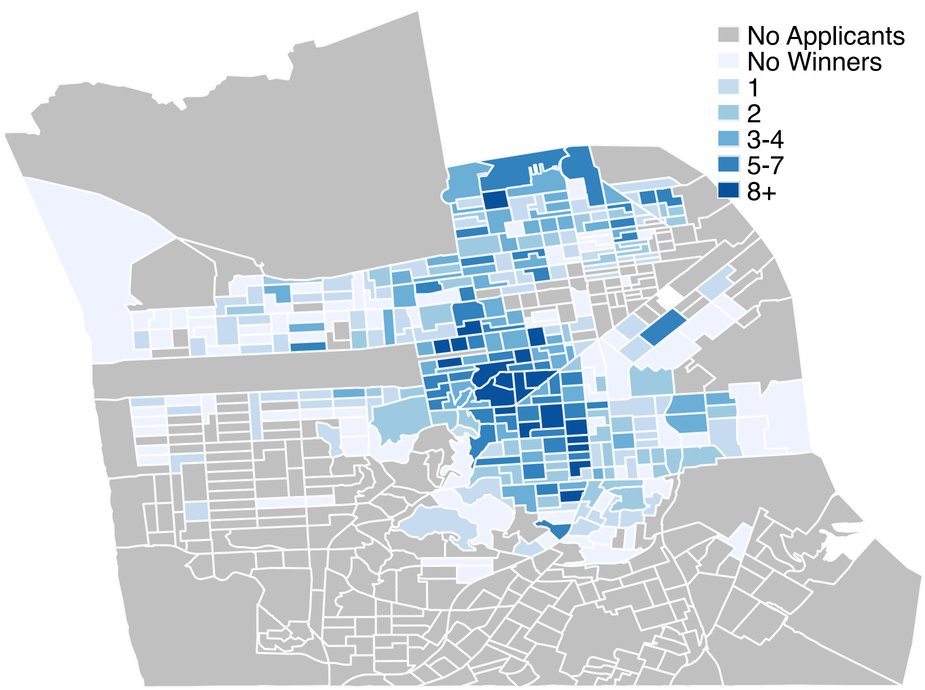
Notes: The unit of analysis is a lottery applicant, and marker sizes are proportional to the number of applicants. Data are from the City of San Francisco Assessor's Office. The x-axis reports each applicant's predicted probability of winning the lottery, based on the lottery rules and regulations described in section 2.3, and the y-axis reports the corresponding share of actual lottery winners. The dashed line shows the linear best-fit, which lies precisely on the 45-degree line.

FIGURE 5: MAP OF LOTTERY APPLICANTS AND WINNERS

PANEL A: APPLICANTS

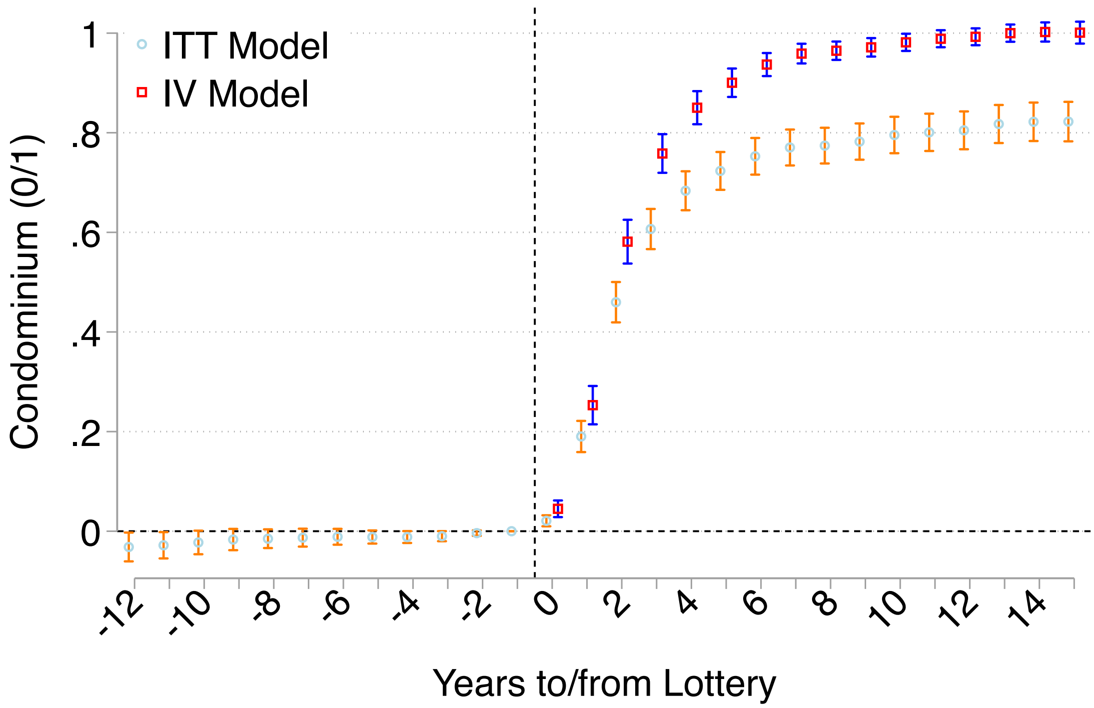


PANEL B: WINNERS



Notes: The figure llustrates geographic variation in the cumulative number of lottery applicants (Panel A) and lottery winners (Panel B) across Census block groups over the sample period.

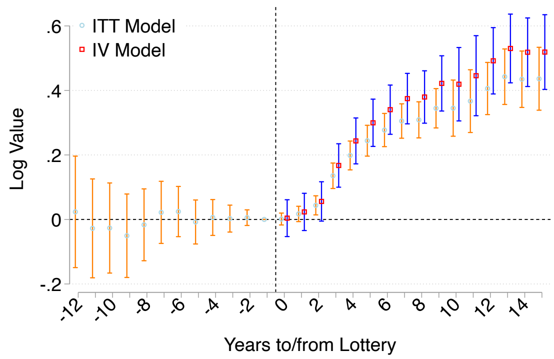
FIGURE 6: FIRST-STAGE: EFFECT OF WINNING LOTTERY ON CONDOMINIUM CONVERSIONS



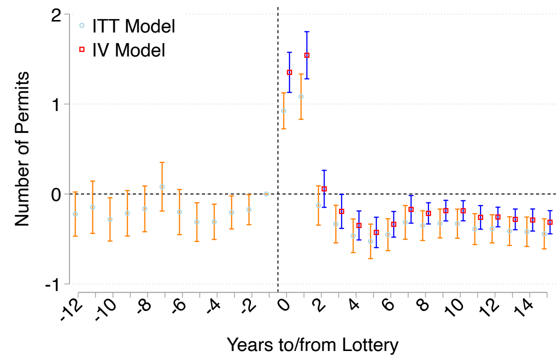
Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery. Data are from the City of San Francisco Assessor's Office. The outcome is an indicator for converting to a condominium. The figure reports the β_k^{ITT} and β_k^{IV} coefficients from Equations 4 and 5, respectively. These specifications compare trends in conversions of lottery winners versus losers. In the IV model, the endogenous variable is a time-invariant indicator for properties that ever convert to a condominium, interacted with years to/from the lottery. Standard errors are clustered by lottery applicant, and error bands show 95% confidence intervals.

Figure 7: Effect of Winning the Lottery on Property Values and Permits

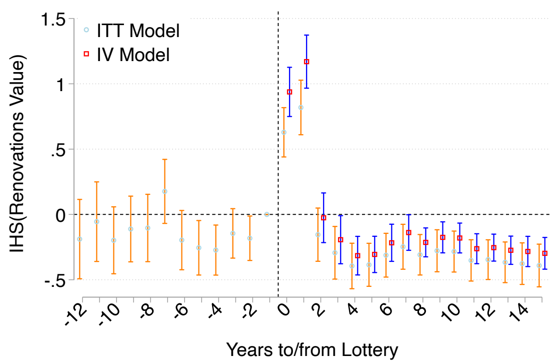
(a) Panel A: Log Property Value



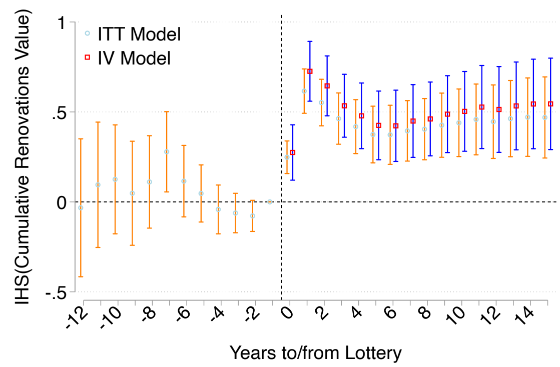
(b) Panel B: Total Building Permits



(c) Panel C: IHS Value of Renovations



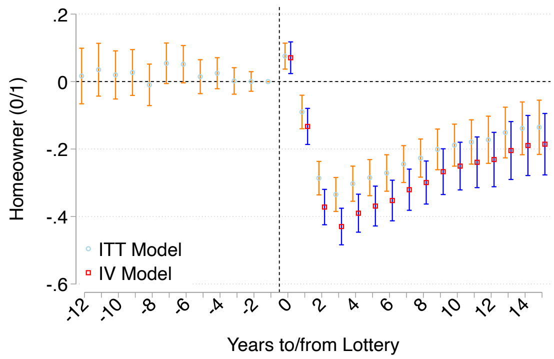
(d) Panel D: IHS Cumulative Value of Renovations



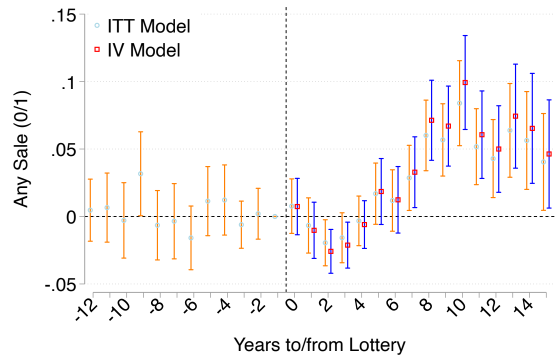
Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery. Data are from the City of San Francisco Assessor's Office. The figure reports the β_k^{ITT} and β_k^{IV} coefficients from Equations 4 and 5, respectively. These specifications compare trends in outcomes of lottery winners versus losers. In the IV model, the endogenous variable is a time-invariant indicator for properties that ever convert to a condominium, interacted with years since the lottery. Standard errors are clustered by lottery applicant, and error bands show 95% confidence intervals.

FIGURE 8: EFFECT OF WINNING THE LOTTERY ON HOMEOWNERSHIP, SALES, AND EVICTIONS

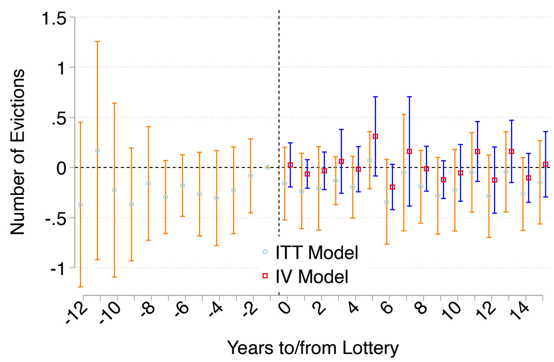
(A) PANEL A: HOMEOWNER-OCCUPIED (0/1)



(B) PANEL B: PROPERTY SALES (0/1)



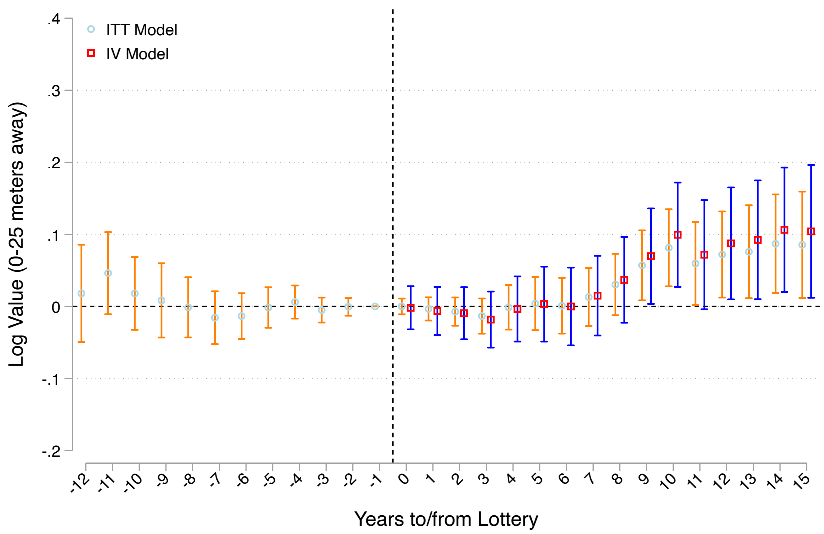
(C) PANEL C: EVICTIONS



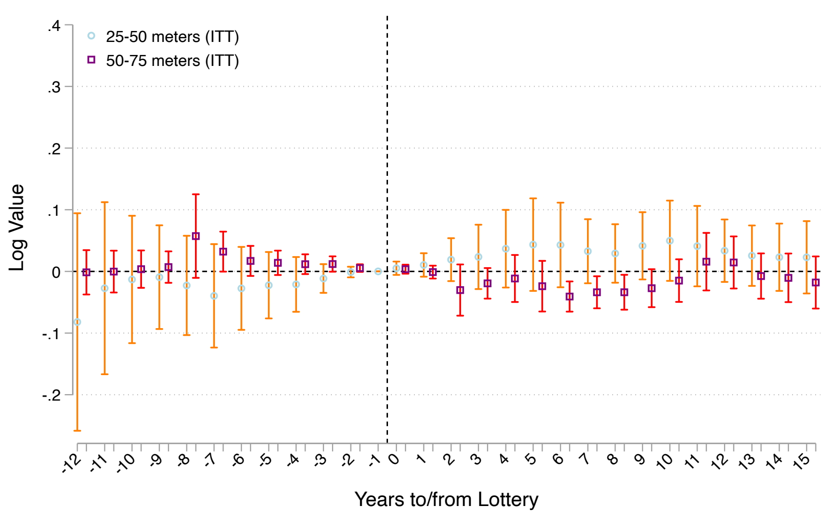
Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery. Data are from the City of San Francisco Assessor's Office. The figure reports the β_k^{ITT} and β_k^{IV} coefficients from Equations 4 and 5, respectively. These specifications compare trends in outcomes of lottery winners versus losers. In the IV model, the endogenous variable is a time-invariant indicator for properties that ever convert to a condominium, interacted with years since the lottery. Standard errors are clustered by lottery applicant, and error bands show 95% confidence intervals.

Figure 9: Spillovers on Nearby Property Values

(a) Panel A: Log Value of Properties Within 25 Meters



(b) Panel B: Log Value of Properties Within 25-50 Meters and 50-75 Meters

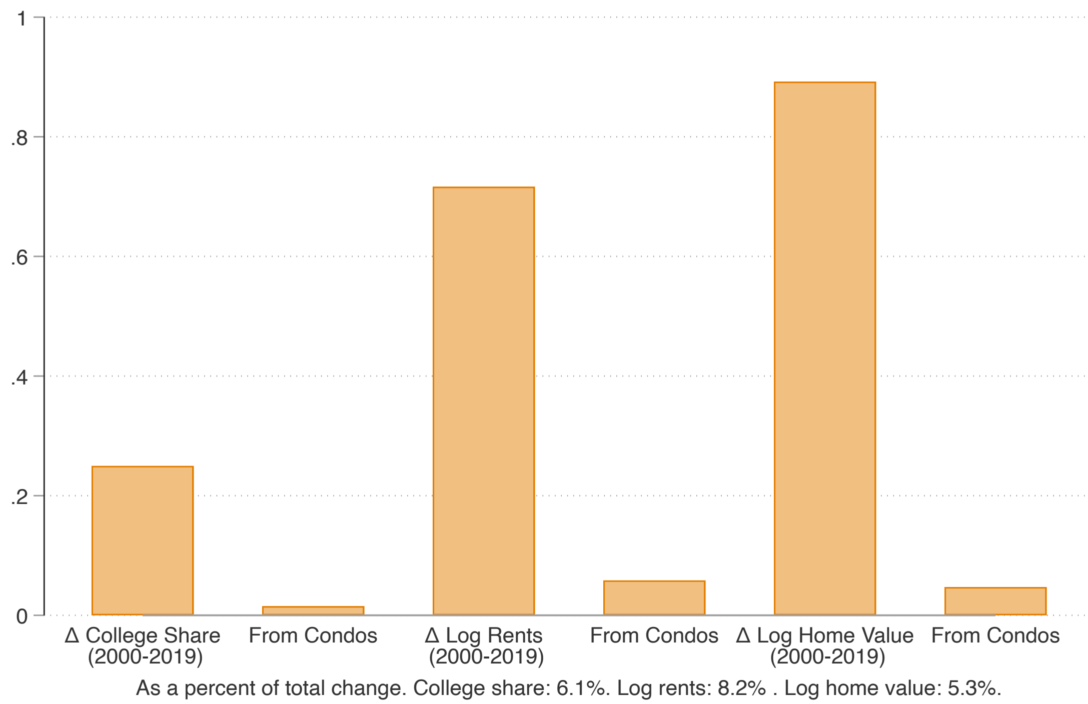


Notes: The unit of analysis is a property-year, and the sample includes "nearby" properties within 75 meters. Data are from the City of San Francisco Assessor's Office. Panel A of the figure reports the β_k^{ITT} and β_k^{IV} coefficients from Equation 7 for distance band 0-25 meters. Panel B reports the β_k^{ITT} coefficients for distance bands 25-50 and 50-75 meters, together. The specifications compare trends in log home prices of properties located near lottery winners versus properties located near lottery losers. The regressions control for predicted probabilities of treatment, as in Borusyak and Hull (2023); see section 4.3 for details. In the IV model, the endogenous variable is a time-invariant indicator for properties that ever convert to a condominium, interacted with years since the lottery. Standard errors are clustered by lottery applicant, and error bands show 95% confidence intervals.

FIGURE 10: NEIGHBORHOOD HETEROGENEITY

Notes: The unit of analysis is a block-group-year, and the sample includes block groups with lottery applicants over the sample period. Data are from the City of San Francisco Assessor's Office and LODES, and the outcome is share of residents earning more than \$40k per year. The figure reports the β_x coefficients from Equation 10. These specifications estimate how the neighborhood effects of lottery winnersvary with a one standard deviation increase in initial neighborhood characteristics. Standard errors are clustered by census block group, and error bands show 90% confidence intervals.

FIGURE 11: NEIGHBORHOOD COUNTERFACTUALS



Notes: The unit of analysis is a census block group. The total change from 2000-2019 in the college share, the log of median rents, and the log of median home values are depicted in Columns 1, 3, and 5, respectively. The data for these figures comes from the ACS. As outlined in Section 4.4, we also calculate a counterfactual change in each of these outcomes, using the estimates from our neighborhood analysis and the total change in the condominium share of the housing stock. These estimates are included in Columns 2, 4, and 6 for each of the college share, log rents, and log median home values, respectively.

Tables

TABLE 1: BALANCE TABLE

	Summary Statistics						
	Winners		Losers		Difference*		
Parcel Characteristic	mean	s.d.	mean	s.d.	diff	s.e.	pval
Value (1000s USD)	999	696	1,231	1,191	21	35	0.55
Year Built	1915	20	1915	20	-0	1	0.60
Homeowner	0.67	0.47	0.58	0.49	0.00	0.02	0.95
Evictions	0.03	0.26	0.02	0.24	0.01	0.01	0.25
Units	3.23	1.09	3.24	1.21	0.02	0.06	0.68
Rooms	14.99	4.52	14.82	4.60	-0.00	0.23	0.98
Sq. Ft. Per Unit	1,321	473	1,284	475	17	25	0.48
Beds	1.21	2.69	1.16	2.72	0.22	0.14	0.13
Baths	3.60	1.35	3.58	1.39	0.07	0.07	0.35
Permits	0.47	1.16	0.63	1.58	-0.06	0.08	0.43
Permit Costs (1000s USD)	5.27	26.53	8.25	45.30	-1.43	2.06	0.49
N	812		6023		6835		

Notes: The table reports the means and standard deviations of building characteristics for winning and losing applicants two years prior to the lottery. The difference in means reported in Column (5) controls for the probability of winning the lottery and year fixed effects. Sample includes lotteries from 2001 to 2013.

TABLE 2: ROBUSTNESS OF MAIN EFFECTS TO GEOGRAPHIC TRENDS

	(1)	(2)	(3)	(4)
	$\Delta_{t=-1}^{15}$Log Value	$\Delta_{t=-1}^{15}$Log Value	$\Delta_{t=-1}^{15}$Log Value	$\Delta_{t=-1}^{15}$Log Value
Condo Conversion	0.519***	0.525***	0.490***	0.506***
	(0.0591)	(0.0597)	(0.0650)	(0.0666)
Observations	122,055	119,101	121,871	121,430
Model	IV	IV	IV	IV
Geography x Year FE	None	Nbhd	Tract	Block Group

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery. Data are from the City of San Francisco Assessor's Office, and the outcome is log property value. The table reports the $\beta_{k=15}$ coefficient from Equation 5, comparing the values of properties that win the lottery versus those that lose. Column 1 reports the benchmark specification. Columns 2-4 include controls for local trends by neighborhood (Column 2), Census tract (Column 3), and Census block group (Column 4). Standard errors are clustered by lottery applicant.

Table 3: Effects of Lottery Winners on Neighborhood Demographics

	Panel A: Population and Income			
	$100 \times \log$ Pop.	Poverty (pp)	College Deg. (pp)	$100 \times \log$ MHI
Lottery Winners	0.28	-0.30	0.87^{*}	2.47^{*}
	(2.68)	(0.31)	(0.49)	(1.46)
	Panel B: Demographics			
	White (pp)	Asian (pp)	Black (pp)	Hispanic (pp)
Lottery Winners	1.57^{***}	-1.46^{***}	-0.09	-0.03
	(0.51)	(0.44)	(0.25)	(0.31)
	Panel C: Home Values			
	$100 \times \log$(Home Val. Q25)	$100 \times \log$(Home Val. Q50)	$100 \times \log$(Home Val. Q75)	
Lottery Winners	2.34^{*}	2.22^{**}	2.19^{***}	
	(1.33)	(1.01)	(0.81)	
	Panel D: Rent			
	$100 \times \log$(Rent Q25)	$100 \times \log$(Rent Q50)	$100 \times \log$(Rent Q75)	
Lottery Winners	0.70	2.57^{*}	2.18^{**}	
	(1.60)	(1.44)	(0.92)	
N	2200	2200	2200	2200
Year FE	✓	✓	✓	✓
Block Group Pairs	✓	✓	✓	✓
Tract Value in 2000	✓	✓	✓	✓

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a census block group, and the sample includes all block groups with lottery applicants over the sample period. Data are from the City of San Francisco Assessor's Office and from the 2000 and 2019 American Community Surveys. The table reports the β coefficients from Equation 9. The specifications estimate the effect of an additional lottery winner on the long-run change in neighborhood demographics. See section 6 for details.

TABLE 4: EFFECTS OF LOTTERY WINNERS ON RESIDENT AND WORKFORCE COMPOSITION

	Panel A: Share of Jobs by Age (Residents)			
	$100 \times$ Job Share, Age < 30	$100 \times$ Job Share, $29 <$ Age < 55	$100 \times$ Job Share, Age > 54	
Lottery Winners	0.34^{**}	0.29^{***}	-0.63^{***}	
	(0.17)	(0.11)	(0.14)	
	Panel B: Share of Jobs by Age (Workers)			
	$100 \times$ Job Share, Age < 30	$100 \times$ Job Share, $29 <$ Age < 55	$100 \times$ Job Share, Age > 54	
Lottery Winners	1.14^{***}	0.24	-1.37^{***}	
	(0.33)	(0.23)	(0.30)	
	Panel C: Share of Jobs by Earnings (Residents)			
	$100 \times$ Job Share, Earn $< \$15k$	$100 \times$ Job Share, $\$15k <$ Earn $< \$40k$	$100 \times$ Job Share, Earn $> \$40k$	
Lottery Winners	-0.46^{***}	-0.46^{***}	0.92^{***}	
	(0.10)	(0.11)	(0.19)	
	Panel D: Share of Jobs by Earnings (Workers)			
	$100 \times$ Job Share, Earn $< \$15k$	$100 \times$ Job Share, $\$15k <$ Earn $< \$40k$	$100 \times$ Job Share, Earn $> \$40k$	
Lottery Winners	-1.22^{***}	0.13	1.09^{*}	
	(0.46)	(0.39)	(0.65)	
N	2200	2200	2200	2200
Year FE	✓	✓	✓	✓
Gen. P-score	✓	✓	✓	✓
Block Value in 2002	✓	✓	✓	✓

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a census block group, and the sample includes all block groups with lottery applicants over the sample period. Data are from the City of San Francisco Assessor's Office and from the 2002-2019 waves of the LODES data. The table reports the β coefficients from Equation 9. The specifications estimate the effect of an additional lottery winner on the long-run change in neighborhood resident and workforce composition. See section 6 for details.

TABLE 5: EFFECTS OF LOTTERY WINNERS ON SECTORAL COMPOSITION (RESIDENTS)

	Panel A: Sectors					
	Utilities %	Construction %	Manufacturing %	Wholesale %	Retail %	Transport %
Lottery Winners	-0.01	-0.03	0.04	0.00	-0.11^{***}	-0.06^{***}
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
	Panel B: Sectors					
	Information %	Finance %	Real Estate %	Professional %	Management %	Admin %
Lottery Winners	0.29^{***}	0.07^{*}	-0.02	0.36^{***}	0.01	0.05
	(0.07)	(0.04)	(0.02)	(0.09)	(0.02)	(0.05)
	Panel C: Sectors					
	Education %	Health Care %	Arts %	Food %	Other %	Public %
Lottery Winners	0.04	-0.63^{***}	0.06^{***}	-0.02	-0.00	-0.04
	(0.06)	(0.13)	(0.02)	(0.07)	(0.02)	(0.03)
N	2200	2200	2200	2200	2200	2200
Year FE	✓	✓	✓	✓	✓	✓
Gen. P-score	✓	✓	✓	✓	✓	✓
Block Value in 2002	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a census block group, and the sample includes all block groups with lottery applicants over the sample period. Data are from the City of San Francisco Assessor's Office and from the 2002-2019 waves of the LODES data. The table reports the β coefficients from Equation 9. The specifications estimate the effect of an additional lottery winner on the long-run change in neighborhood resident composition. See section 6 for details.

Table 6: Effects of Lottery Winners on Sectoral Composition (Workforce)

	Panel A: Sectors					
	Utilities %	Construction %	Manufacturing %	Wholesale %	Retail %	Transport %
Lottery Winners	-0.07	0.34	0.38^{*}	0.25	-0.19	-0.31
	(0.06)	(0.52)	(0.23)	(0.20)	(0.45)	(0.19)
	Panel B: Sectors					
	Information %	Finance %	Real Estate %	Professional %	Management %	Admin %
Lottery Winners	0.01	0.23	-0.09	0.23	-0.10	0.08
	(0.23)	(0.22)	(0.16)	(0.61)	(0.15)	(0.27)
	Panel C: Sectors					
	Education %	Health Care %	Arts %	Food %	Other %	Public %
Lottery Winners	0.20	-2.59^{***}	0.61^{**}	0.57	0.96^{*}	-0.53^{**}
	(0.76)	(0.89)	(0.24)	(0.66)	(0.53)	(0.25)
N	2200	2200	2200	2200	2200	2200
Year FE	✓	✓	✓	✓	✓	✓
Gen. P-score	✓	✓	✓	✓	✓	✓
Block Value in 2002	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a census block group, and the sample includes all block groups with lottery applicants over the sample period. Data are from the City of San Francisco Assessor's Office and from the 2002-2019 waves of the LODES data. The table reports the β coefficients from Equation 9. The specifications estimate the effect of an additional lottery winner on the long-run change in neighborhood workforce composition. See section 6 for details.

Table 7: Neighborhood Effects (Business Counts)

	Panel A: Local Sectors (New)			
	$100 \times IHS$(New Food)	$100 \times IHS$(New Retail)	$100 \times IHS$(New Educ.)	$100 \times IHS$(New Arts & Entertainment)
Lottery Winners	-1.75	-1.31	2.96	-0.82
	(2.65)	(1.84)	(1.94)	(1.76)
	Panel B: Local Sectors (Total)			
	$100 \times IHS$(Tot. Food)	$100 \times IHS$(Tot. Retail)	$100 \times IHS$(Tot. Educ.)	$100 \times IHS$(Tot. Arts & Entertainment)
Lottery Winners	-6.41^{*}	-3.24	7.70^{***}	3.40
	(3.59)	(2.74)	(2.98)	(2.98)
	Panel C: Other Sectors (New)			
	$100 \times IHS$(New Prof. Services)	$100 \times IHS$(New Manufacturing)	$100 \times IHS$(New Real Estate)	$100 \times IHS$(New Construction)
Lottery Winners	5.07^{**}	-1.13	2.34	-4.10^{***}
	(2.31)	(1.09)	(1.75)	(1.54)
	Panel D: Other Sectors (Total)			
	$100 \times IHS$(Tot. Prof. Services)	$100 \times IHS$(Tot. Manufacturing)	$100 \times IHS$(Tot. Real Estate)	$100 \times IHS$(Tot. Construction)
Lottery Winners	5.10^{*}	-1.34	2.20^{*}	-9.93^{***}
	(2.65)	(3.02)	(1.25)	(3.30)
N	2200	2200	2200	2200
Year FE	✓	✓	✓	✓
Gen. P-score	✓	✓	✓	✓
Block Value in 2000	✓	✓	✓	✓

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a census block group, and the sample includes all block groups with lottery applicants over the sample period. Data are from the City of San Francisco Assessor's Office and SF Open Data. The table reports the β coefficients from Equation 9. The specifications estimate the effect of an additional lottery winner on new business entry. See section 6 for details.

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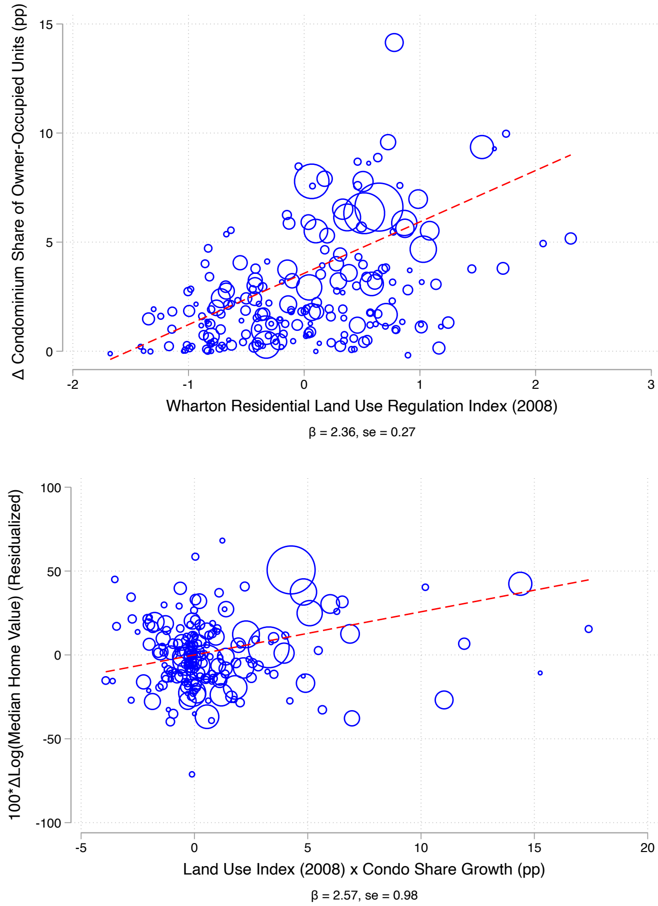
Appendices

A Appendix

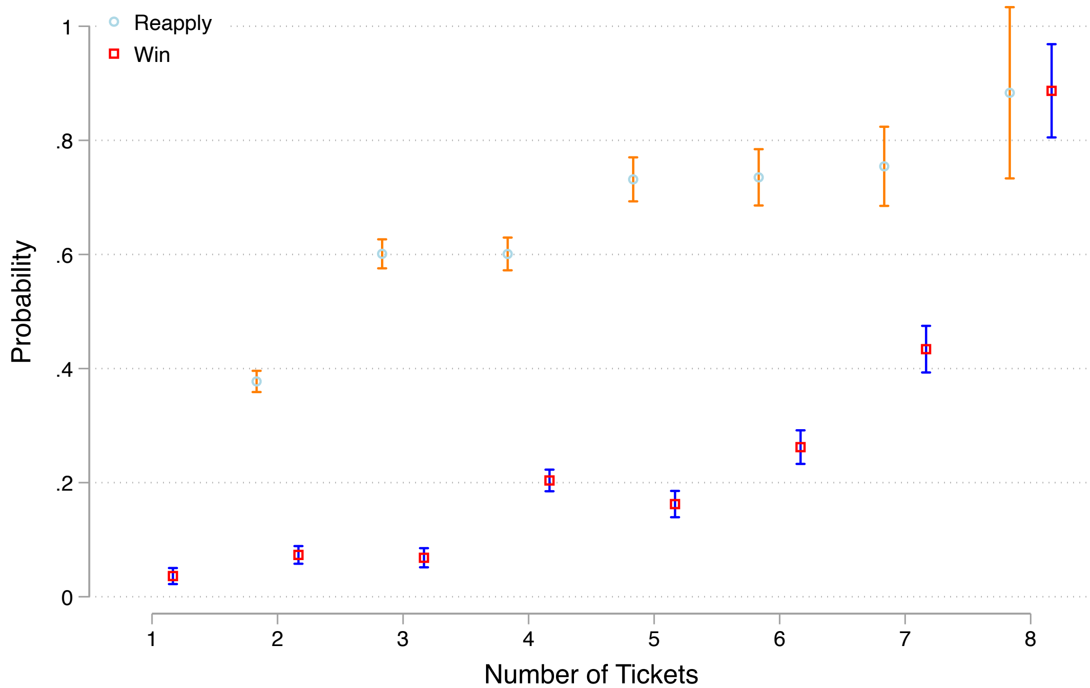
Appendix Figures

FIGURE A.1: CONDOMINIUMS, HOME VALUE GROWTH, AND LAND USE RESTRICTIONS



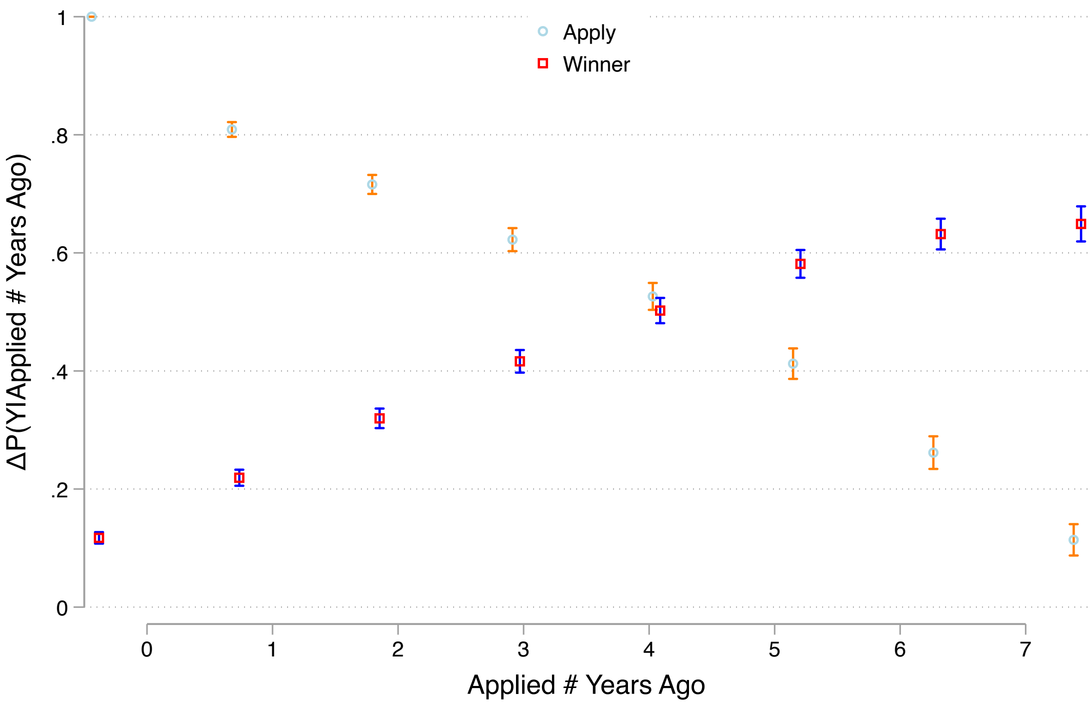
Notes: The unit of analysis is a city, and the sample includes the 199 metropolitan areas with census home values and owner-occupied units, and Wharton Land Use data. The figure in Panel A shows a scatter plot of the long-run change in owner-occupied units that are condominiums against the 2006 Wharton Residential Land Use Regulation Index (WRLURI). In Panel B, we run a regression of the long-run change in home values against the long-run change in condominiums, the WRLURI measure, and their interaction. We then subtract off the non-interacted components from home values, and plot this residualized outcome on the interacted variable. The line of best fit and the reported *beta* capture the interaction coefficient from the full regression. The size of circles is proportional to the city's population in 2010. A line of best fit is shown in red, with its coefficient and standard error noted below both charts.

FIGURE A.2: APPLICATION BEHAVIOR BY NUMBER OF TICKETS



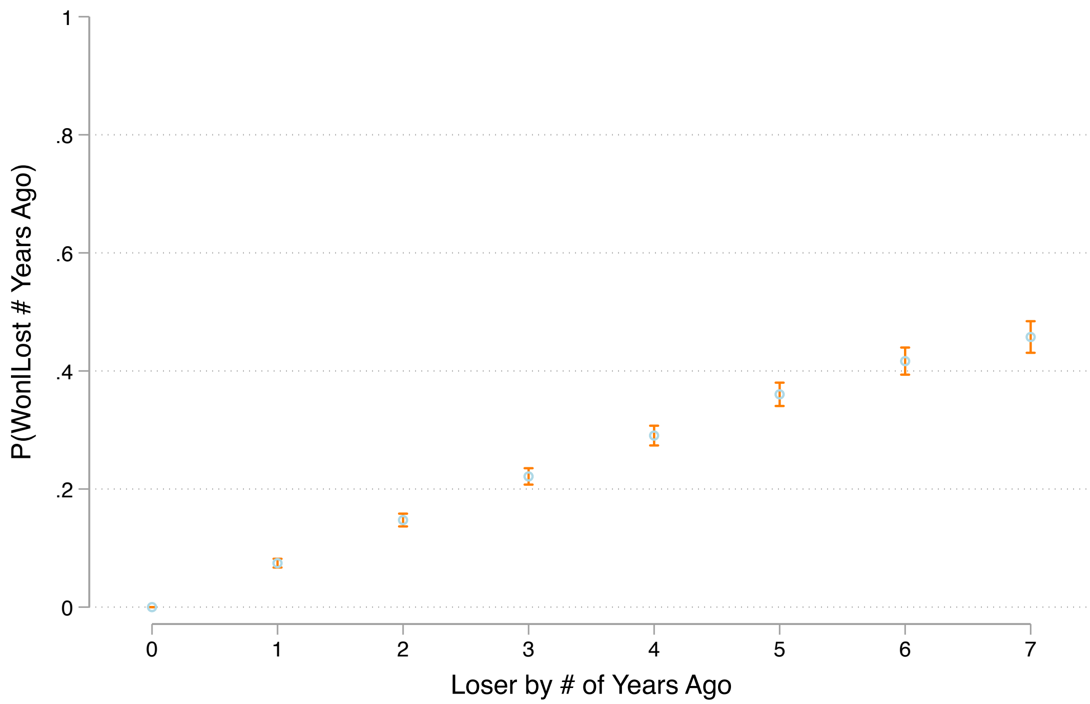
Notes: The unit of analysis is a lottery applicant from 2001-2013, and data from the City of San Francisco Assessor's Office. The square markers indicate how an applicant's probability of winning the lottery varies with their number of tickets. The circle markers indicate how an applicant's probability of re-applying to the lottery varies with the number of tickets. See section 2.3 for details. Errors bands show 95% confidence intervals.

FIGURE A.3: APPLICATION BEHAVIOR BY PREVIOUS APPLICATION



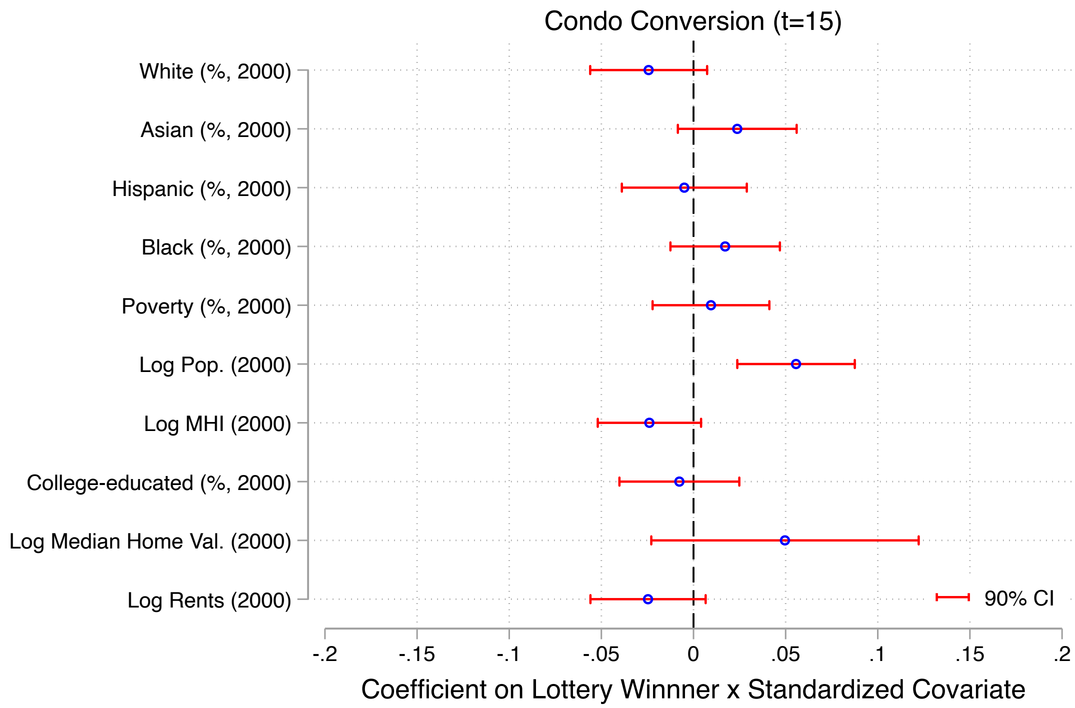
Notes: The unit of analysis is a lottery applicant from 2001-2013, and data from the City of San Francisco Assessor's Office. The square markers indicate how an applicant's probability of winning the lottery varies with the number of times they previously applied. The circle markers indicate how an applicant's probability of re-applying to the lottery varies with the number of times the have previously applied.

FIGURE A.4: FRACTION OF LOSERS WHO WIN BY NUMBER OF YEARS



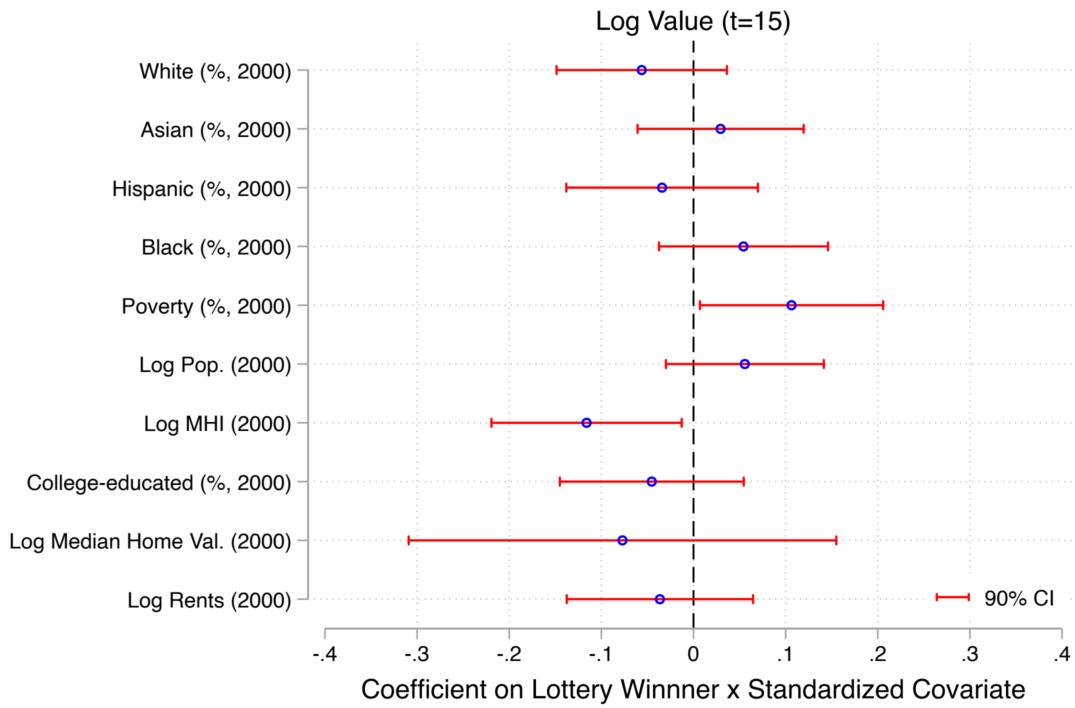
Notes: The unit of analysis is a lottery applicant from 2001-2013, and data from the City of San Francisco Assessor's Office. The figure plots the probability that an applicant who loses the lottery in year t=0 wins the lottery in a later year. Standard errors are clustered by applicant, and error bands show 95% confidence intervals.

FIGURE A.5: NEIGHBORHOOD HETEROGENEITY IN CONDOMINIUM CONVERSIONS



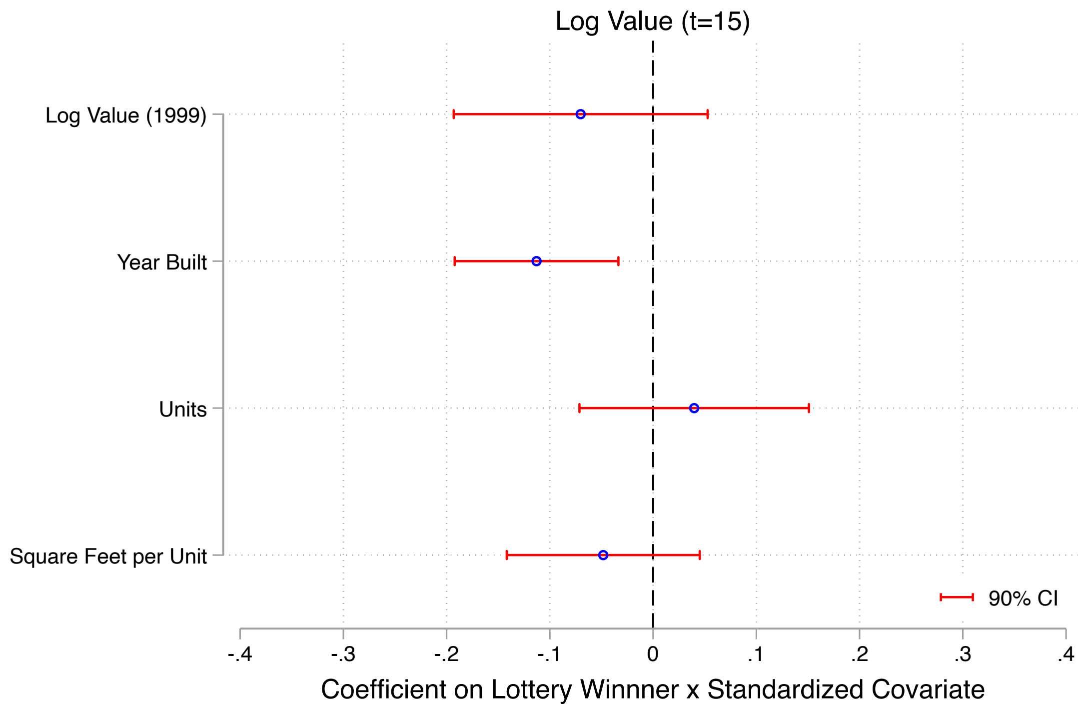
Notes: The unit of analysis is a property whose owners apply to the lottery, and the outcome is an indicator for condominium conversions. The figure reports interaction coefficients from alternate specifications of Equation 5 where the treatment indicators β_k are interacted with initial neighborhood characteristics. Standard errors are clustered by applicant, and error bands show 90% confidence intervals.

FIGURE A.6: NEIGHBORHOOD HETEROGENEITY IN CONDOMINIUM VALUE APPRECIATION



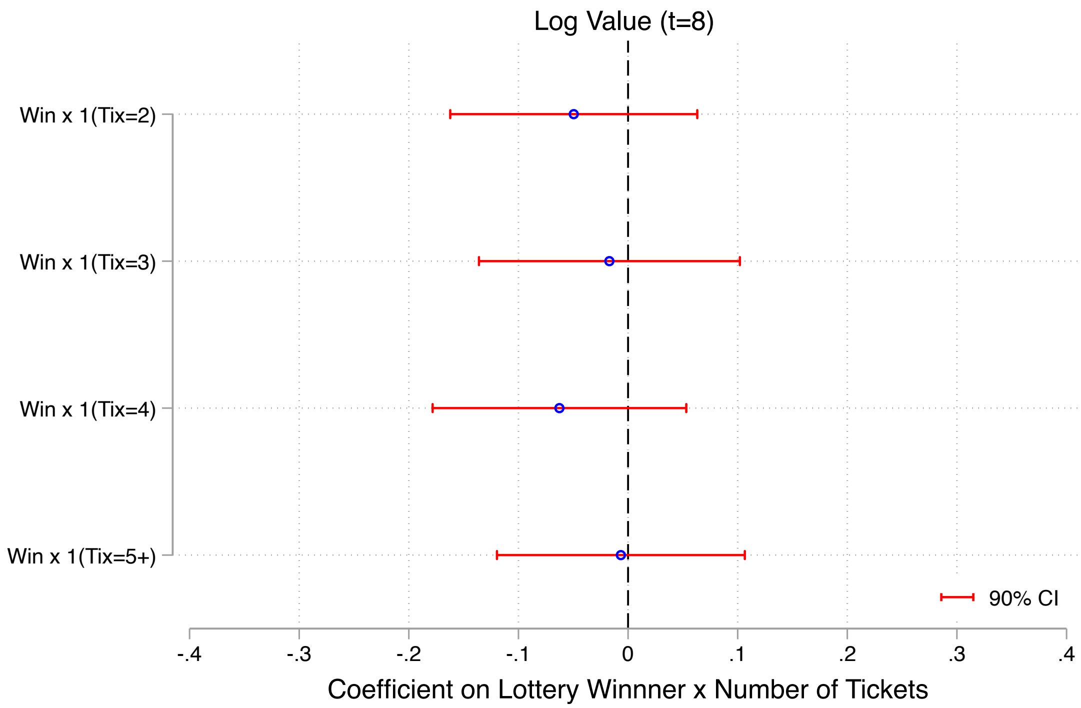
Notes: The unit of analysis is a property- whose owners apply to the lottery, and the outcome is log property value. The figure reports interaction coefficients from alternate specifications of Equation 5 where the treatment indicators β_k are interacted with initial neighborhood characteristics. Standard errors are clustered by applicant, and error bands show 90% confidence intervals.

FIGURE A.7: BUILDING HETEROGENEITY IN CONDOMINIUM VALUE APPRECIATION



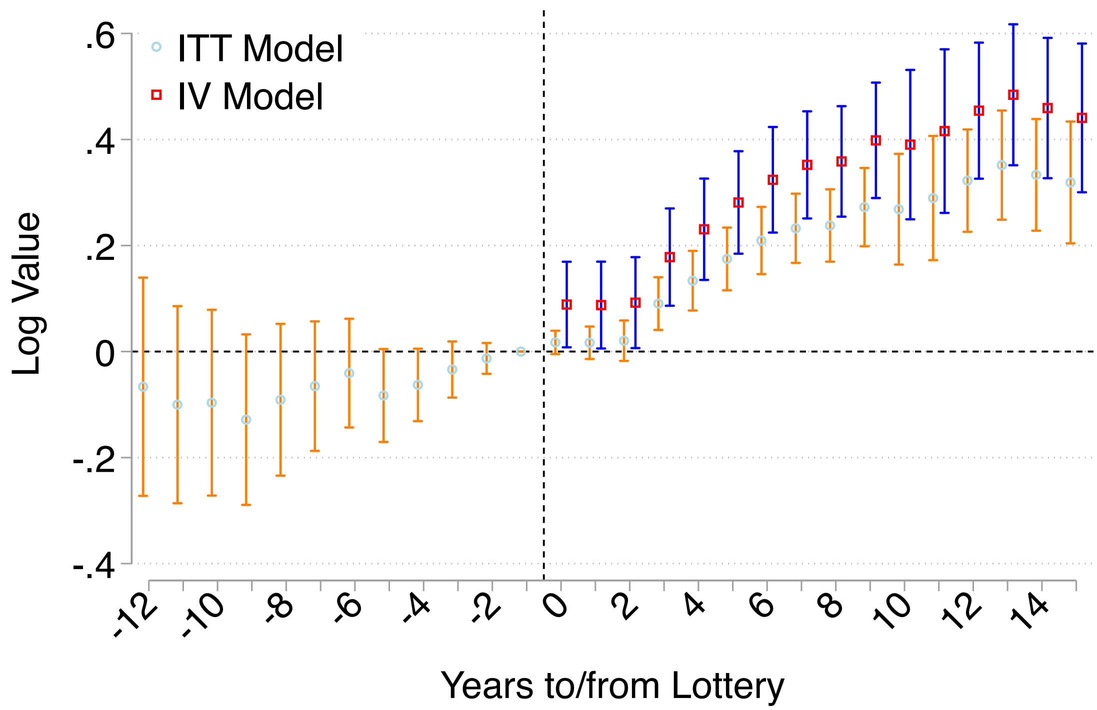
Notes: The unit of analysis is a property whose owners apply to the lottery, and the outcome is log property value. The figure reports interactions coefficients from alternate specifications of Equation 5 where the treatment indicators β_k are interacted with initial property characteristics. Standard errors are clustered by applicant, and error bands show 90% confidence intervals.

FIGURE A.8: CONDOMINIUM VALUE APPRECIATION BY NUMBER OF TICKETS



Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery. Data are from the City of San Francisco Assessor's Office. The figure reports the β_8^{IV} coefficient from a version of Equation 5, where condominium status 8 years since the lottery is interacted with how many lottery tickets were held at the time of application. The coefficients assess whether home value appreciation is significantly different for properties that have applied once, twice, three, and four or more times before, relative to those that won after their first attempt. Standard errors are clustered by lottery applicant, and error bands show 90% confidence intervals.

FIGURE A.9: CONDOMINIUM VALUE APPRECIATION WITH NEVER WINNERS AS CONTROL GROUP



Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery. However, for this analysis, the control group is restricted to properties that never win the lottery. Data are from the City of San Francisco Assessor's Office. The figure reports the β_k^{ITT} and β_k^{IV} coefficients from Equations 4 and 5, respectively. These specifications compare trends in outcomes of lottery winners versus losers. In the IV model, the endogenous variable is a time-invariant indicator for properties that ever convert to a condominium, interacted with years since the lottery. Standard errors are clustered by lottery applicant, and error bands show 95% confidence intervals.

Appendix Tables

TABLE A.1: EFFECT OF WINNING THE LOTTERY ON CONDOMINIUM STATUS

	(1) Condominium (0/1)	(2) Condominium (0/1)	(3) Condominium (0/1)
Winner x 1(t = 0)	0.0155	0.0175	0.0334***
	(0.0139)	(0.0136)	(0.00816)
Winner x 1(t = 1)	0.164***	0.166***	0.183***
	(0.0176)	(0.0172)	(0.0167)
Winner x 1(t = 2)	0.346***	0.347***	0.368***
	(0.0197)	(0.0196)	(0.0210)
Winner x 1(t = 3)	0.402***	0.405***	0.400***
	(0.0185)	(0.0186)	(0.0212)
Winner x 1(t = 4)	0.377***	0.379***	0.364***
	(0.0179)	(0.0181)	(0.0209)
Winner x 1(t = 5)	0.325***	0.326***	0.302***
	(0.0178)	(0.0179)	(0.0208)
Winner x 1(t = 6)	0.274***	0.274***	0.254***
	(0.0178)	(0.0180)	(0.0206)
Winner x 1(t = 7)	0.230***	0.231***	0.220***
	(0.0181)	(0.0182)	(0.0204)
Winner x 1(t = 8)	0.193***	0.193***	0.191***
	(0.0183)	(0.0183)	(0.0202)
Winner x 1(t = 9)	0.174***	0.175***	0.179***
	(0.0187)	(0.0188)	(0.0207)
Winner x 1(t = 10)	0.164***	0.165***	0.177***
	(0.0194)	(0.0194)	(0.0213)
Winner x 1(t = 11)	0.161***	0.161***	0.174***
	(0.0199)	(0.0199)	(0.0221)
Winner x 1(t = 12)	0.161***	0.158***	0.160***
	(0.0214)	(0.0208)	(0.0229)
Winner x 1(t = 13)	0.159***	0.152***	0.153***
	(0.0218)	(0.0213)	(0.0239)
Winner x 1(t = 14)	0.147***	0.140***	0.139***
	(0.0227)	(0.0223)	(0.0249)
Winner x 1(t = 15)	0.138***	0.132***	0.126***
	(0.0238)	(0.0233)	(0.0269)
Observations	90,621	90,621	90,589
P win FE	Yes	Yes	Yes
Event time FE	Yes	Yes	Yes
Year FE	No	Yes	Yes
P win x t FE	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery, for all years after the lottery. Data are from the City of San Francisco Assessor's Office, and the outcome is condominium status. The table reports the β_k coefficients from Equation **??**, comparing the condominium status of lottery winners and losers at a certain event time from the lottery. Columns vary in fixed effect structure. Column 1 reports a sparse specification with fixed effects according to lottery strata. Column 2 includes year fixed effects. Column 3 includes lottery strata by event time fixed effects. Standard errors are clustered by lottery applicant.

TABLE A.2: EFFECT OF WINNING THE LOTTERY ON PROPERTY VALUES

	(1) Log Value	(2) Log Value	(3) Log Value
Condo x 1(t = 0)	-0.815	-0.324	0.386
	(0.873)	(0.842)	(0.860)
Condo x 1(t = 1)	-0.105	-0.0387	0.143
	(0.166)	(0.162)	(0.157)
Condo x 1(t = 2)	0.00963	0.0298	0.108
	(0.0846)	(0.0833)	(0.0805)
Condo x 1(t = 3)	0.175**	0.179**	0.269***
	(0.0749)	(0.0741)	(0.0755)
Condo x 1(t = 4)	0.314***	0.308***	0.348***
	(0.0802)	(0.0801)	(0.0838)
Condo x 1(t = 5)	0.438***	0.420***	0.424***
	(0.0938)	(0.0944)	(0.101)
Condo x 1(t = 6)	0.518***	0.488***	0.460***
	(0.110)	(0.111)	(0.117)
Condo x 1(t = 7)	0.599***	0.555***	0.464***
	(0.128)	(0.129)	(0.133)
Condo x 1(t = 8)	0.598***	0.544***	0.412***
	(0.151)	(0.152)	(0.157)
Condo x 1(t = 9)	0.670***	0.609***	0.474***
	(0.165)	(0.167)	(0.175)
Condo x 1(t = 10)	0.601***	0.569***	0.439**
	(0.188)	(0.188)	(0.217)
Condo x 1(t = 11)	0.654***	0.628***	0.527**
	(0.200)	(0.200)	(0.238)
Condo x 1(t = 12)	0.703***	0.735***	0.637***
	(0.185)	(0.183)	(0.222)
Condo x 1(t = 13)	0.722***	0.766***	0.742***
	(0.190)	(0.190)	(0.248)
Condo x 1(t = 14)	0.650***	0.713***	0.598**
	(0.213)	(0.214)	(0.296)
Condo x 1(t = 15)	0.680***	0.766***	0.614*
	(0.244)	(0.246)	(0.367)
Observations	90,618	90,618	90,586
P win FE	Yes	Yes	Yes
Event time FE	Yes	Yes	Yes
Year FE	No	Yes	Yes
P win x t FE	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery, for all years after the lottery. Data are from the City of San Francisco Assessor's Office, and the outcome is log property value. The table reports the β_k coefficients from Equation 5, comparing the values of properties that are condominiums with those that are not condominiums at a certain event time from the lottery, instrumenting condominium status with whether the property won the lottery. The first-stage for these regressions are included in the appendix. Columns vary in fixed effect structure. Column 1 reports a sparse specification with fixed effects according to lottery strata. Column 2 includes year fixed effects. Column 3 includes lottery strata by event time fixed effects. Standard errors are clustered by lottery applicant.

TABLE A.3: DYNAMIC EFFECT OF CONVERTING ON LOG HOME VALUES

Dynamic IV (Cellini et al. 2010) Results								
Win Lottery or ECP			Log Value			Log Value (Dynamic)		
	coef	s.e.		coef	s.e.		coef	s.e.
π_0	0.98***	(0.00)	β_0	0.03	(0.03)	θ_0	0.03	(0.03)
π_1	-0.28***	(0.01)	β_1	0.04	(0.03)	θ_1	0.04	(0.03)
π_2	-0.17***	(0.01)	β_2	0.06*	(0.03)	θ_2	0.07*	(0.04)
π_3	-0.10***	(0.01)	β_3	0.14***	(0.04)	θ_3	0.17***	(0.05)
π_4	-0.08***	(0.01)	β_4	0.17***	(0.04)	θ_4	0.23***	(0.06)
π_5	-0.05***	(0.00)	β_5	0.17***	(0.04)	θ_5	0.27***	(0.07)
π_6	-0.03***	(0.00)	β_6	0.15***	(0.04)	θ_6	0.29***	(0.07)
π_7	-0.02***	(0.00)	β_7	0.13***	(0.04)	θ_7	0.30***	(0.08)
π_8	-0.01***	(0.00)	β_8	0.10***	(0.04)	θ_8	0.29***	(0.08)
π_9	-0.01***	(0.00)	β_9	0.12***	(0.04)	θ_9	0.32***	(0.09)
π_{10}	-0.01***	(0.00)	β_{10}	0.10**	(0.05)	θ_{10}	0.31***	(0.10)
π_{11}	-0.02***	(0.00)	β_{11}	0.12**	(0.05)	θ_{11}	0.34***	(0.11)
π_{12}	-0.01***	(0.00)	β_{12}	0.13***	(0.05)	θ_{12}	0.36***	(0.11)
π_{13}	-0.02***	(0.00)	β_{13}	0.13***	(0.05)	θ_{13}	0.38***	(0.12)
π_{14}	0.00	(0.00)	β_{14}	0.10*	(0.05)	θ_{14}	0.36***	(0.13)
π_{15}	0.00	(0.00)	β_{15}	0.10*	(0.06)	θ_{15}	0.37***	(0.13)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a property-year, and the sample includes properties whose owners apply to the lottery, for all years after the lottery. Data are from the City of San Francisco Assessor's Office. The table reports the π_τ, β_τ, and θ_τ coefficients in Columns 1, 2, and 3 respectively, from Equation 11 and as described in the text. In words, Column 1 captures the probability of a winning property to win in a future lottery; because winning properties can no longer win after $\tau = 0$, this indicates the fraction of losers that apply again and win. Column 2 captures the log home value difference between properties that have converted and losing properties. Column 3 can be interpretted as the log home value difference between properties that convert and those that do not. Standard errors are clustered by lottery applicant, and are calculated by the delta method in Column 3.

TABLE A.4: SPILLOVER EFFECTS OF CONDOMINIUM CONVERSIONS ON NEARBY PROPERTIES

	(1)	(2)	(3)	(4)
	$\Delta_{t=-1}^{15}$Log Value	$\Delta_{t=-1}^{15}$Log Value	$\Delta_{t=-1}^{15}$Log Value	$\Delta_{t=-1}^{15}$Log Value
Condo Conversion (0-25m)	0.111**	0.0853*	0.0828*	0.0873*
	(0.0477)	(0.0463)	(0.0471)	(0.0461)
Observations	3,706,112	3,706,112	3,706,112	3,706,103
Model	IV	IV	IV	IV
Geography x Year FE	None	Nbhd	Tract	Block Group

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is a property-year, and the sample includes "nearby" properties within 25 meters of a lottery winner. Data are from the City of San Francisco Assessor's Office. The figure reports the $\beta_{k=15}^{IV}$ coefficients from Equation 7. The specifications compare trends in log home prices of properties located near lottery winners versus properties located near lottery losers. The regressions control for predicted probabilities of treatment, as in Borusyak and Hull (2023); see section 4.3 for details. Column 1 shows the benchmark specification. Columns 2-4 respectively add controls for local time trends by neighborhood, census tract, and census block group. Standard errors are clustered by lottery applicant.

Appendix

Robustness: Instrument for Current Condominium Status

In a third exercise, we implement an alternative specification to account for treatment non-compliance generated by including as control units lottery losers who reapply and eventually win a future lottery. To do so, we use the entire sample of applicants and their outcome histories for every period after the lottery, and instrument for condominium status with whether the applicant won the lottery (and where both the instrument and the endogenous regressor are interacted with event time indicators). An advantage of this approach is that while losing properties may eventually convert, the estimates rely solely on exogenous variation in conversions stemming from the lottery design. A disadvantage is that the approach cannot account for how outcomes are likely to vary relative to the timing of the condominium conversion, and losing applicants are likely to convert later than winning ones.

Table A.1 shows the first-stage results from these IV regressions. All specifications include lottery strata fixed effects, and Columns 1 through 3 add year, event time, and strata-by-event-time fixed effects, respectively. The main specification in Column 3 peaks three years after the lottery, with lottery winners being 40 percentage points more likely to be condominiums than lottery losers. As losing applicants win future lotteries, or convert through the ECP process after 2013, the first-stage coefficient declines to 13 percentage points 15 years out, but remains highly significant. The second-stage results on the log of assessed home values for each of the fixed effects specifications are shown in Table A.2. The main specification shown in Column 3 indicates that condominium conversion causes 64 percentage points of home value appreciation 12 years after the lottery. These estimates are quantitatively similar to our main set of results.

Robustness: Dynamic Effect of Conversions on Home Values, Cellini et al. (2010)

As a final robustness test, we implement the dynamic approach of Cellini et al. (2010).[1] The innovation in Cellini et al. is to explicitly purge the estimated treatment effects of the effects of a current lottery on future lottery and conversion outcomes. Following their nomenclature, let π_τ

[1] This approach has been applied in other dynamic lottery settings, for example see Gelber et al. (2016) and Pecenco et al. (2020).

be the effect of winning the lottery τ years later, and let β_τ be the "static" effect of condominium conversions on our main outcome, log home values.[2] The static effect is generated by classifying a property as "treated" if it wins the lottery and later converts. To purge this reduced-form effect of downstream effects from losers winning future lotteries, Cellini et al. (2010) estimate the "dynamic" effect θ_τ which is defined recursively as follows.

$$\theta_\tau = \beta_\tau - \sum_{m=1}^{\tau} \pi_m \theta_{\tau-m} \tag{11}$$

The coefficients π_τ can be estimated by a regression of whether a property wins a future lottery on whether they won the current lottery (interacted with event time). The β_τ can be estimated by an IV regression of log home values on whether a property won and converted using whether they won the current lottery as an instrument (both conversions and winning the lottery are also interacted with event time). The two regressionscan then combined according to the relationship in Equation 11. We include year, event time, and lottery-strata-by-event-time fixed effects. We also include neighborhood by year fixed effects to increase the precision of our estimates. Standard errors are calculated using the delta method. The method relies on several strong assumptions, including that treatment effects are not heterogeneous across lottery waves or for properties that win after a few applications versus those that win after many applications.

Table A.3 reports the results. Column 1 shows the estimates of the effect of winning the lottery on winning in the future, π_τ. Column 2 shows estimates of the effectof conversions on log home values, β_τ . Column 3 shows the combined dynamic effects, θ_τ. The results in Column 1 indicate that many lottery losers win in future years: 28%, 17%, and 10% win in the first, second, and third years, respectively, following an initial lottery. Column 2 shows that, despite the fact that losing applicants sometimes win future lotteries and convert, there is still a 17% difference in home values between winning and losing applicants five years after the lottery. This difference attenuates somewhat but nevertheless remains large 15 years after the lottery. These effects grow larger as we account for lottery losers that later convert, as shown in Column 3. The results imply that home values are 37% higher for converters relative to losers 15 years after the lottery. Taken

[2]To account for applicants that lost the lottery but converted through the ECP process, which occurred after the lotteries were discontinued, we code those losing properties as having "won" in 2014. Doing so ensures that we continue to adjust our effects for lottery losers still being able to convert. The results are also robust to exlcuding those properties from the sample.

together, the magnitude and precision of these estimates are consistent with the main set of results