How Ridesharing Changed the Demographics of Cities

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Abstract

We study the staggered entry of ridesharing services across U.S. metropolitan areas and estimate its effects on residential sorting and household outcomes.By lowering transportation costs, ridesharing services encourage the residential sorting of higher-income individuals from suburbs into urban cores, raising urban rents and housing prices by about 6 and 9 percent, respectively. The effect on incumbent urban residents is conditional on ex ante homeownership. For homeowners, displacement is negligible and delinquency rates decline. For renters, displacement and delinquency rates increase by 11 percent and 42 percent, respectively. Our study shows that the provision of high-end transportation technologies can accelerate gentrification and exacerbate inequality.

JEL codes: O33, J23

Keywords: Consumer Finance, Gentrification, Household Finance, Mortgages, Residential real estate, Ridesharing services.

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1 Introduction

Transportation infrastructure, including roads, highways, and public transit, shapes economic activity by facilitating connectivity, reducing transportation costs, and promoting local economic development and financial access (Asher and Novosad, 2020; Aggarwal, 2018). While the overall economic impact of such infrastructure is largely positive, it often results in geographic segregation of high- and low-income individuals. This spatial sorting exacerbates wealth inequality, reduces intergenerational mobility, and affects long-term life outcomes such as education, access to credit, and income.[1]

One of the most prominent innovations in transportation in recent times has been the rapid global proliferation of ridesharing services. Since their inception in 2010, ridesharing companies such as Uber and Lyft have dramatically reshaped commuting patterns, quickly becoming integral components of urban mobility. Independent traffic audits show that, as of 2019, Uber and Lyft already accounted for 7–13 percent of all vehicle miles traveled in the urban cores of San Francisco, Boston, and Washington, D.C. (Fehr & Peers, 2019).[2] This unprecedented expansion is anticipated to accelerate further with the advent of autonomous taxis, which could significantly reduce transportation costs over the next decade (Goldman Sachs Research, 2025). Yet, despite this sweeping transformation of everyday mobility, we know remarkably little about how a private, for-profit, on-demand transport technology reshapes residential location choices and real estate markets; existing urban economics work remains focused on publicly financed transit, highways, or broad amenity shifts (Baum-Snow, 2007; Glaeser et al., 2008).[3]

Our study fills that gap by providing the first rigorous analysis of how the entry and expansion of ridesharing services across U.S. metropolitan statistical areas (MSAs)

[1]For instance, see Boustan et al. (2010); Boustan (2010); Baum-Snow et al. (2019); Chyn and Katz (2021); Couture et al. (2024); Kulkarni and Malmendier (2022); Cook et al. (2024).

[2]The share of American adults who have ever used a ride-hailing service jumped from 15 percent in 2015 to 36 percent by 2018, with adoption heavily skewed toward young, high-income city dwellers.

[3]See Boustan et al. (2013) and Couture and Handbury (2023) for a survey. Relative to public sector infrastructure, ride-hailing is characterized by its convenience and flexibility—it is market-priced, app-mediated, and supply-elastic, making its general equilibrium effects theoretically ambiguous.

affect urban gentrification, household spatial sorting, and residential real estate markets. Leveraging the staggered introduction of Uber and Lyft across different cities as a natural experiment, we demonstrate significant spatial redistribution effects that attract higher-income, younger individuals to urban areas, in turn increasing urban rent and housing prices. Specifically, we uncover three stylized findings. First, ride-hailing entry induces the in-migration of high-income, young, child-free households into urban cores, and the displacement of low-income residents into the suburbs. Second, the resulting demand shock raises house and rental prices in urban areas. Contemporaneously, mortgage originations increase, particularly in urban areas with higher poverty rates and lower housing prices, two classic signatures of gentrification. Third, we highlight critical distributional consequences conditional on homeownership status. After ridesharing services enter, homeowners in urban areas generally don't relocate and their financial health improves substantially. Meanwhile, renters are substantially more likely to move out and to experience future delinquencies. We reconcile these three findings through a parsimonious stylized model in which ride-hailing (and potentially robotaxis) reduces car ownership costs in dense urban cores.

To examine the impact of ridesharing services on urban gentrification, we use the staggered entry of two ridesharing services—Uber and Lyft—into MSAs throughout the United States, and use the difference-in-differences (DID) estimator proposed by Borusyak et al. (2021). Specifically, we compare ZIP codes in treated MSAs—i.e., with access to ridesharing services—against not-yet-treated ZIP codes.This DID specification is enhanced with a rich set of controls, including location-time fixed effects, and is robust to alternative specifications and robustness checks.

To reconcile our empirical findings and discipline our tests, we create a simple framework in which individuals trade off consumption with travel time. Concretely, they can choose between cheaper public transportation, or faster private transportation, and between expensive urban housing or remote suburban housing—far from city amenities.

In equilibrium, and matching empirical regularities, the highest-income individuals choose urban areas with private transportation, high-income individuals live in suburban areas with private transportation, and low- and medium-income individuals use public transportation and can live in both areas. The entry of ridesharing services reduces the cost of private transportation, especially in urban areas where car-ownership costs are higher (e.g., parking), thereby increasing the relative attractiveness of these areas. This leads to an inflow of high-income individuals from suburban areas, increasing urban housing prices and forcing the out-migration of lower-income individuals into the suburbs. These effects are stronger in cities with higher car-ownership costs and are consistent with recent gentrification patterns observed in urban areas (Baum-Snow et al., 2019).

We start our empirical analysis by uncovering the impact of rideshare entry on the composition of households across urban and suburban ZIP codes. In particular, we examine the effects of ridesharing services on the number of high- and low-income households in treated MSAs. Consistent with gentrification, we find a gradual annual increase averaging 3.5 percent in the number of high-income households in urban ZIP codes in the five years following the entry of ridesharing services. In contrast, we find a slight reduction in the number of low-income households of around 0.8 percent in urban ZIP codes. We do not observe these patterns in our control group of suburban ZIP codes.

To shed further light on changes in the demographic composition of treated MSAs and since younger people are more likely to use ridesharing services (Hall et al., 2018), we examine the age composition of individuals in a ZIP code. As expected, we find a decrease in the average age of individuals of around 0.8 percent in treated urban ZIP codes, with no impact on suburban areas. Finally, we analyze the fraction of households claiming a child tax credit, a proxy for being a household with children, and find that rideshare entry is associated with a decline of roughly 6 percent in the fraction of households claiming a child tax credit, with no effect on suburban areas. Overall, these aggregate results

present no distinct pre-trends and are consistent with an in-migration of high-income and younger individuals into urban ZIP codes at the expense of a small out-migration of lower-income households.

Since such in-migration tends to increase the price of amenities (Berkes and Gaetani, 2023; Couture et al., 2024), we next analyze the effects that this wave of urban gentrification has on incumbent residents—more concretely, on their location and on their financial health. Given that the entry of rideshare services led to a sharp increase in housing prices, we split our analysis into existing homeowners and non-homeowners (renters). The underlying idea is that rideshare-led gentrification is likely to cause financial stress for low-income renters in urban areas due to increased housing prices, whereas homeowners are more likely to benefit from house price appreciation, notwithstanding the increase in property taxes. Overall, we find a significant increase in the likelihood of individuals moving out of urban ZIP codes in treated MSAs, with a gradual increase averaging 11 percent of the number of people moving out of urban ZIP codes in treated MSAs. However, we find that the subsample of renters drives these effects. Insofar as homeownership and income are correlated, these results support the hypothesis that rideshare entry is associated with urban gentrification and the displacement of lower-income borrowers.

How does such a change in urban demographics affect housing markets? Given that a significant proportion of residential home purchases are financed through mortgages (Garriga and Hedlund, 2020), we focus on the number and characteristics of mortgage originations. We find a significant increase in the number of mortgage originations in treated MSAs, with originations in urban areas increasing 8.1 percent after the entry of ridesharing services. In contrast, in suburban ZIP codes, we do not find any effect.[4] Consistent with the in-migration of high-income individuals into urban ZIP codes, we find that the average income of mortgage applicants increases by 6.5 percent in the

[4]Similarly, and related to the increase in demand for housing, we also find a decline in the number of vacant homes in urban ZIP codes, with vacancy rates dropping 11 percent in the years after treatment. Again, there is no effect in suburban areas.

years after the entry of ridesharing services. Relatedly, we also find a sharp reduction of roughly 30 percent in the share of (subsidized) mortgages insured by the Federal Housing Administration (FHA). This is consistent with the reduction in the opportunities for lower-income groups to live in a gentrified area (Couture and Handbury, 2023) and suggests a decline in the inflow of low-income individuals into urban MSAs, further intensifying spatial economic segregation. Again, we detect no distinct pre-trends and no effect on suburban ZIP codes for all outcomes of interest.

These newly originated mortgages cluster in more affordable areas within urban ZIP codes, in line with the mechanism proposed by Guerrieri et al. (2013). Indeed, we find that within urban areas, there is a larger increase in mortgages originated in ZIP codes with lower ex-ante house prices and higher ex-ante poverty rates, suggesting that an improvement in amenities—as the one potentiated by the entry of ride-hailing services—can engender an in-migration of higher-income individuals into lower-priced neighborhoods adjacent to richer areas.

This increased demand for housing, combined with the low elasticity of housing supply in the short run, leads to higher prices. The entry of ridesharing services leads to an average 9 percent increase in house prices in urban areas in the four years after treatment. Similarly, we find that rental prices increase on average by 6 percent in the years following the entry of ridesharing services. As an important robustness check of our identification strategy, we use the temporary exit of ridesharing services from Austin in May 2016 to examine whether it led to a reversal in housing demand in urban areas. Focusing on rental prices, which tend to be more sensitive in the short term to fluctuations in demand, we find an economically and statistically significant impact on rental prices in urban areas of around 2 percent, which reversed once ridesharing services reentered in mid-2017.[5]

[5]Despite the absence of any pre-trends, to ensure our results are not driven by a spurious relation between the rideshare entry and changes in preferences for urban areas, we further verify the validity of our identification strategy. In particular, we instrument for the entry of rideshare services in an MSA with their entry in the state, as it is a strong predictor of entry in the state's MSAs. Furthermore, we limit our

We conclude our paper by analyzing the effects that this wave of urban gentrification has on the financial health of incumbent residents. We find a gradual increase in the likelihood of late repayments of incumbent residents in treated urban ZIP codes, averaging 11 percent, with this increase driven by renters, which more than offsets the decline in late repayments of homeowners. More concretely, renters increased their late repayments by 42 percent, likely due to rising housing costs, whereas homeowners had a decline in their late repayments of around 36 percent, likely due to higher property values and net worth. These differential impacts highlight the role of ridesharing-induced gentrification in exacerbating urban inequality

Overall, ours is the first study to emphasize the impact that the provision of high-end personal transportation through ride-hailing services has on the spatial reorganization of households and on the residential mortgage and real estate markets. Specifically, ride-hailing services increased the relative desirability of poorer ZIP codes in treated urban MSAs, thus encouraging higher-income individuals to move into such areas. An important implication is that ride-hailing services may facilitate the gentrification of low-income neighborhoods by increasing access to convenient transportation. These findings are consistent with the theory and empirical evidence presented in Guerrieri et al. (2013), showing that, in the presence of neighborhood externalities, housing-demand shocks induce migration of higher-income individuals into poorer neighborhoods with lower housing values that are adjacent to wealthier neighborhoods. The resultant increase in demand for housing in these areas causes home prices to increase and the displacement of low-income renters, further exacerbating inequality.

Our research contributes to multiple strands of the literature. First, we add to the literature on urbanization and the spatial sorting of households. Previous work identifies public transportation technology, natural amenities, and income distribution as significant

sample to MSAs with fewer than 1 million individuals and with income per capita and density in the three middle quintiles, as entry decisions into these MSAs are likelier to be a by-product of their decision to enter a state, and gentrification trends are also more likely to be similar in these MSAs. All results remain similar to our benchmark findings.

determinants in location decisions (Glaeser et al., 2008; Couture et al., 2024; Lee and Lin, 2018; Severen, 2023; Su, 2022). This research has predominantly examined the effect of subsidized public transportation and commute time on the residential location of individuals, with mixed findings: highways contributed to suburbanization (Baum-Snow, 2007), while public transit effects range from attracting low-income residents to urban cores (Glaeser et al., 2008) to having negligible effects on relocation (Severen, 2023). In contrast, ours is the first study to document that the proliferation of *private* transportation services brought about by ridesharing technology increased urban gentrification.

Second, our work speaks to the literature on the welfare and distributional consequences of urban gentrification. This literature documents that rising income inequality, improved amenities, and urban transit infrastructure have contributed to the gentrification of urban cores, leading to higher housing prices and the displacement of poorer residents (Appel and Nickerson, 2016; Guerrieri et al., 2013; Berkes and Gaetani, 2023; Baum-Snow et al., 2019; Boustan et al., 2019; Couture et al., 2024; Chyn and Katz, 2021; Asquith et al., 2021; Lee and Tan, 2024). We expand this literature by documenting asymmetric welfare consequences for homeowners versus renters, and by showing that rideshare entry exacerbated economic segregation by both displacing low-income residents and curbing their inflow into urban MSAs.

Third, our work contributes to extant work on mortgage markets and house price dynamics (Cellini et al., 2010; Hurst et al., 2016; Badarinza and Ramadorai, 2018; Favilukis and Van Nieuwerburgh, 2021; Duca et al., 2021; Korevaar, 2023). A consistent theme in this literature is that public infrastructure and local amenities significantly affect housing prices—for example, the Second Avenue subway extension in New York increased property prices by 8 percent (Gupta et al., 2022), while school facility investments are associated with a 6 percent rise (Cellini et al., 2010). Most directly related to our work, Gorback (2020) documents that UberX entry is associated with higher housing prices in previously inaccessible areas. We extend this literature by showing that rideshare-induced

price effects are of comparable magnitude and are concentrated in lower-value, poorer urban neighborhoods, consistent with gentrification dynamics.

Finally, we contribute to the emerging literature on autonomous vehicles and urban spatial organization (Zakharenko, 2016; Larson and Zhao, 2020; Gelauff et al., 2019). This literature highlights two opposing effects: privately owned autonomous vehicles may encourage suburbanization by reducing the disutility of long commutes, while shared autonomous vehicles (SAVs) may increase the attractiveness of urban centers by making transit more convenient. Our findings speak to the latter channel and suggest that SAVs are likely to exacerbate urban gentrification, worsening housing affordability and economic segregation. This has important policy implications: the welfare benefits and distributional consequences of vehicle automation will depend significantly on whether autonomous vehicles are privately owned or deployed through ridesharing platforms.

The remainder of the paper proceeds as follows. Section 2 describes our data sources. Section 3 presents the empirical strategy and discusses identification assumptions. Section 4 documents gentrification effects on household composition and relocation. Section 5 analyzes housing market outcomes. Section 6 examines the financial health of incumbent residents. Section 7 presents robustness tests, and Section 8 concludes.

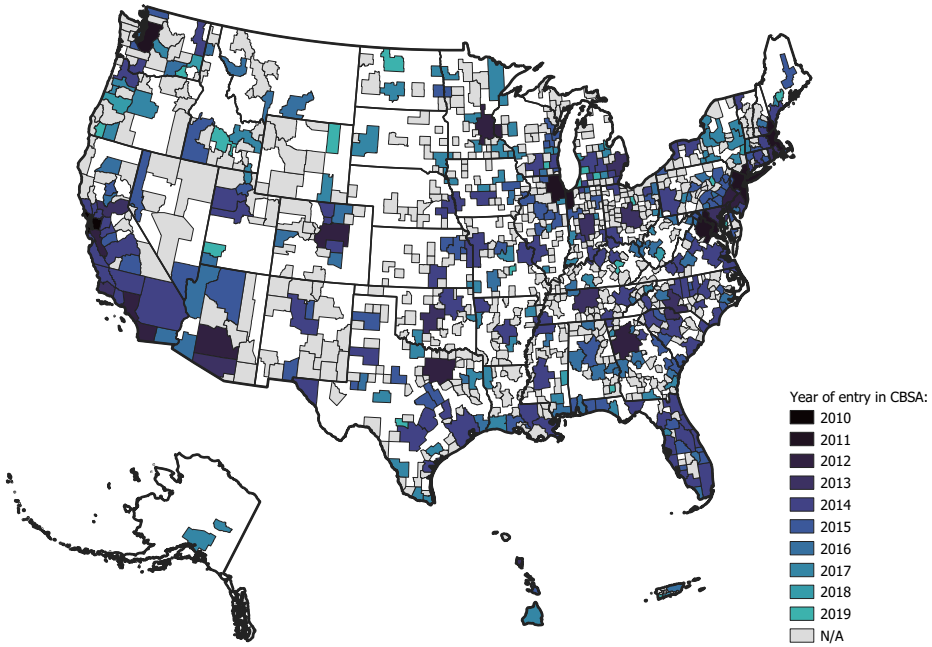
2 Data and Summary Statistics

We construct a ZIP-year panel of U.S. MSAs from 2009 to 2019 that links neighborhood characteristics, housing outcomes, income, household credit, and the use of ridesharing services. We augment this panel with MSA-level rollout dates of ridesharing services. We begin in 2009 in order to test for pre-trends, but not earlier, to limit outliers related to the Global Financial Crisis. Similarly, we end in 2019 to avoid COVID-19-related disruptions. Thus, unless noted otherwise, all data sets listed below cover 2009–2019.

Information on the entry of ridesharing companies for each MSA was provided directly

by Uber and Lyft. These data list the entry date of ridesharing apps (Uber and Lyft) for 312 MSAs between 2010 and 2019, as seen in Figure 1, which displays its geographical and temporal distribution. As we discuss in more detail in Section 3.1, the entry was staggered over time, with ridesharing companies prioritizing entry into larger MSAs.

Figure 1: ***Entry of ridesharing services across time and geography***



This figure replicates Figure 4 of Hall et al. (2018) with our updated MSA sample. It displays the entry of ridesharing services across time for all core-based statistical areas (CBSAs). CBSAs include both metropolitan statistical areas (MSAs) and micropolitan statistical areas. Each CBSA is colored according to the year the first ridesharing service appeared in the area (either Uber or Lyft).

The number of Uber trips within an MSA was compiled from regulatory data available for five locations: Massachusetts, Chicago, New York, Los Angeles, and San Francisco. The frequency of internet searches on the terms *Uber*, *Lyft*, or *Rideshare app* in a Zip code in the month before the entry of ridesharing services in the MSA was collected from Google Trends. Summary statistics on both measures are displayed in the third panel of Table 1.

The perceived level of urbanization of Zip codes, "urbanness", is obtained from the Urbanization Perceptions Small Area Index (UPSAI) compiled in 2017 by the U.S.

Table 1: *Summary Statistics*

	Num. Obs.	Mean	p10	Median	p90	Std. Dev.
Urban Perception Index						
Urban_z	10,777	0.52	0.03	0.19	0.7	0.26
Rideshare Entry and Drivers						
$\text{Entry}_{m,y}$	8,614	0.05	0.00	0.00	0.00	0.21
$\text{Number of drivers}_{m,y}$	5,072	4.37	2.08	4.06	7.18	2.03
$\text{Revenue drivers}_{m,y}$	5,072	7.14	4.74	6.84	9.95	2.11
$\text{Share of number drivers}_{m,y}$	5,072	0.004	0.001	0.003	0.009	0.004
$\text{Share of revenue drivers}_{m,y}$	5,072	0.011	0.002	0.007	0.028	0.011
Zip code Statistics at Time of Rideshare Services Entry						
Trips capita_z	711	8.4	4.6	10.4	14.1	3.7
Google searches_z	2,288	81.2	48.1	88.1	100	20.8
IRS Statistics						
$\text{Number of households}_{z,y}$	52,198	9.0	7.9	9.2	9.9	0.8
$\text{Number of households - High income}_{z,y}$	52,198	8.0	6.8	8.2	9.1	0.9
$\text{Number of households - Low income}_{z,y}$	52,198	8.5	7.3	8.6	9.5	0.9
$\text{Child credit}_{z,y}$	43,769	0.15	0.08	0.13	0.27	0.08
Mortgage Statistics						
$\text{\#Mortgage originations}_{z,y}$	32,921	5.0	3.6	5.2	6.4	1.2
$\text{Applicant income}_{i,y}$	7,804,222	4.5	3.7	4.5	5.4	0.7
$\text{FHA-insured}_{i,y}$	7,804,222	0.19	0.00	0.00	1.00	0.39
$\text{Mortgage value}_{i,y}$	7,804,222	5.4	4.5	5.4	6.2	0.7
Housing Statistics						
$\text{House price index}_{z,y}$	31,210	5.1	4.7	5.1	5.4	0.3
$\text{Rental prices}_{z,y}$	33,254	7.4	6.9	7.3	7.9	0.4
$\text{Vacancy rate}_{z,y}$	30,813	2.9	0.1	1.9	7.2	3.1
$\text{Number of vacancies}_{z,y}$	30,813	8.9	7.8	9.1	9.9	0.9
Equifax Statistics						
$\text{Age}_{z,y}$	36,384	4.3	4.0	4.3	4.5	0.2
$\text{Move out of Zip code}_{i,y}$	2,473,268	0.09	0.05	0.08	0.05	0.31
Late repayment	2,473,268	0.03	0.00	0.00	0.00	0.16
Other Statistics						
$\text{Average house price in Zip code}_{i,y}$	7,804,222	12.4	11.7	12.4	13.1	0.6
$\text{Average poverty rate in Zip code}_{i,y}$	7,804,222	0.09	0.03	0.09	0.27	0.09
$\text{Average minority share in Zip code}_{i,y}$	7,804,222	0.27	0.06	0.19	0.59	0.20

This table displays summary statistics for the main variables discussed in the paper. See Table B.1 in the Appendix for detailed definitions of each of these variables.

Department of Housing and Urban Development (HUD). This measure avoids taking a narrow stance on what constitutes urbanness, and instead defines it based on resident perceptions of whether an area is urban, suburban, or rural, as reported in the 2017 American Housing Survey conducted by the HUD. To extrapolate this variable from a survey to the universe of census tracts, the HUD used a random forest to regress the urbanness survey responses against a battery of 23 variables including density and land use. The predicted values of this regression are used to construct the share of each census tract that falls in each of these three categories (**?**). We then aggregate these variables to the Zip code level, using the census tract population as weights, and restrict predominantly rural Zip codes—i.e. those with a rural share above 50 percent. The top panel of Table 1 reports the summary statistics of this index. We further split the index into quartiles of urbanness and classify Zip codes as urban if they are in the top quartile and as suburban if they are in the bottom one. On average, suburban areas are primarily residential and have lower population density, limited public services such as public transportation and healthcare facilities, higher car dependency, and more green space and recreational facilities.[6] Also, as discussed in more detail in Section 3.2 and Appendix A, both the demand and the supply of ridesharing services are higher in urban Zip codes than in suburban ones.

Data on housing prices are obtained from CoreLogic. It consists of annual Zip code-level housing price indices, computed under a weighted repeat-sales methodology. Data on rental prices are obtained from Zillow using a smoothed yearly measure of the typical observed market rate rent in a Zip code. It is a repeat-rent index that is weighted to the rental housing stock to ensure representativeness across the entire Zip code, not just the homes listed for rent. The index is calculated as the mean of the listed rents in the 40th to

[6] Table B.2 in Appendix B contrasts the main characteristics of urban and suburban Zip codes. On average, urban Zip codes have a population density nine times higher, their households have a 17 percentage point lower share of car ownership, a 20 percent lower commute time, 45 percent higher parking costs, significantly higher amenities and transportation scores, and represent 63.6 percent of the population across MSAs.

60th percentile range for all homes and apartments in a given region.

We obtain data on vacant houses from the HUD Authority. Using information from the United States Postal Service (USPS), the HUD compiles data on addresses identified as having been "vacant" in a given census tract. Vacant addresses include addresses that delivery staff have identified as vacant for 90 days or more. This is only available from 2012 onwards, and at the census-tract level, which we aggregate to the Zip code level, weighing census tracts by their relative population in a Zip code. The summary statistics of these housing statistics are displayed in the *Housing Statistics* panel of Table 1.

Information on the number of households per income group and Zip code is obtained from the Internal Revenue Service's (IRS) Statistics of Income, a yearly data set collected at the Zip code*income-group level based on individual income tax returns. Data include items such as the number of returns (which approximates the number of households), adjusted gross income and salaries, mortgage interest deductions, and child tax credits. The summary statistics of the main variables of interest from this data set are displayed in the *IRS Statistics* panel of Table 1.

Mortgage information is obtained from the confidential Home Mortgage Disclosure Act data set, which contains regulatory information reported by depository institutions and certain for-profit non-depository institutions. Data are compiled yearly by the Federal Financial Institutions Examination Council and include records on loan originations and loan applications that did not result in originations. Mortgage information includes property location, borrower demographics (e.g., applicant income, information on co-applicants, and race), whether the loan is government-guaranteed (e.g., FHA), and the loan amount. Further mortgage information, including the home value and the applicant's credit score, is obtained from McDash. Summary statistics of the main variables of interest are shown in the *Mortgage Statistics* panel of Table 1.

Information on consumer credit usage and performance is obtained from the Equifax Consumer Credit Panel (CCP) of the Federal Reserve Bank of New York. This database

contains credit report data for a nationally representative 5-percent sample of all adults with a Social Security number and a credit report. The data set is a quarterly panel, with snapshots of consumers' credit profiles captured at the end of each quarter. It includes variables on certain demographics of individuals (e.g., age, current Zip code of their address, and FICO scores), along with debt information on housing, credit cards, and auto, as well as on loan performance. We use its fourth-quarter data from 2009 to 2019. The summary statistics of the main variables of interest are displayed in the *Equifax Statistics* panel of Table 1.

Zip code information on the level of poverty and racial composition is obtained from the Census Bureau's Current Population Survey (CPS). The CPS includes comprehensive yearly statistics on the percentage of individuals living below the poverty line and the demographic breakdown of minority populations within each Zip code. Summary statistics of the main variables of interest are displayed in the *Other Statistics* panel of Table 1.

Walkscore and Transitscore data sets are obtained from Redfin. Walkscore provides information on the walkability of locations. It measures how easily residents can access amenities like restaurants, shops, parks, and schools within walking distance. It is a numerical score from 0 to 100, where higher scores indicate better walkability. TransitScore measures how well a location is served by public transit on a scale from 0 ("Minimal Transit") to 100 ("Rider's Paradise"). It calculates a score for a specific point by summing the relative "usefulness" of nearby routes, depending on the distance to the nearest stop on the route, the frequency of the route, and the type of route. We use the available waves collected in 2015 and 2017.

3 Empirical Strategy

We estimate the effects of ridesharing entry on MSAs using the imputation difference-in-differences (DID) estimator of Borusyak et al. (2021). This estimator circumvents a recently documented limitation of two-way fixed effects (TWFE) models under heterogeneous treatment effects and staggered adoption. When MSAs are treated at different points in time, the canonical TWFE model uses as controls not only the never-treated and not-yet-treated MSAs, but also MSAs treated in earlier rounds. In the presence of dynamic treatment effects, such comparisons can lead to bias and erroneous conclusions about the impact of an intervention; see Roth et al. (2023) for a survey, and Deb et al. (2024) for an equivalent estimator that uses an alternative approach. This is particularly relevant for our context, since the number of ridesharing drivers in each MSA increases only gradually after entry (Figure 5), and thus the impact of ridesharing could be increasing over time.

Our specification is thus:

$$y_{z,t} = \alpha_z + \gamma_{s(z),t} + \sum_{j=-2}^{4} \beta_j \, \mathbf{1}_{t-j=T_{m(z)}} + \epsilon_{z,t} \tag{1}$$

where $s(z)$ and $m(z)$ are the state and MSA that correspond to Zip code z,[7] $y_{z,t}$ is a Zip code-level outcome, α_z are Zip code fixed effects, $\gamma_{s(z),t}$ are state-year fixed effects, $T_{m(z)}$ is the year when ridesharing entered the MSA m, and $\mathbf{1}$ is an indicator variable equal to one if this entry took place at time $t - j$. The sequence of coefficients $\{\beta_j\}$ thus captures the dynamic effects of ridesharing entry, and $\beta_{j<0}$ coefficients allow testing for pre-trends. Notice that the inclusion of state-year fixed effects implies that the dynamic effects of entry will be computed within-state, i.e., relative to MSAs in the same state where ridesharing has not entered yet. This allows us to control for time-varying shocks at the state level,

[7] On rare occasions, a Zip code could correspond to multiple MSAs or even states, as defined by the HUD crosswalk. In these cases, we select the pair with the higher weights, but results are unaffected by this choice.

but could potentially reduce the number of control-group MSAs, particularly at the end of our sample as well as for smaller states. Thus, for robustness, our main specifications show results both with and without state-year fixed effects.

To motivate and discipline our empirical analysis, Appendix C presents a simple static model where individuals trade off consumption against the transportation time required for that consumption. For brevity, in this paragraph we summarize its main assumptions and predictions. Individuals have heterogeneous income, and can decide both their location within an MSA (urban or suburban) and mode of transportation (private or public). Urban areas endogenously have higher house prices but benefit from more efficient transportation.[8] In equilibrium, this model generates well-documented regularities of urban areas such as higher income inequality than suburban areas, as well as lower car ownership and higher use of public transit. The entry of ridesharing services, modeled as a decrease in the cost of private transportation, leads to an inflow of higher-income individuals to urban areas, which in turn increases housing prices and forces lower-income individuals to relocate to the suburbs. These effects are larger in regions with larger ex ante car-ownership costs.

Because our model predicts very different effects of ridesharing entry for urban and suburban areas, and because ridesharing services are overwhelmingly used in urban areas rather than in suburban areas (as shown below in Section 3.2), all our empirical results will be split by the degree of urbanicity of Zip codes within an MSA. In particular, we use $Urban_z$, the UPSAI measure of perceived urbanicity, to classify Zip codes into quartiles of urbanicity within an MSA. We denote *urban* Zip codes as those in the top quartile of urbanicity and *suburban* Zip codes as those in the bottom quartile. Thus, Sections 4-6 estimate Equation (1) separately for urban and suburban samples, and contrast their effects.

[8] As noted in Table B.3, walk scores and transit scores are significantly higher in urban Zip codes, suggesting that both amenities and public transit options are more readily available in these areas.

3.1 Entry Assumptions

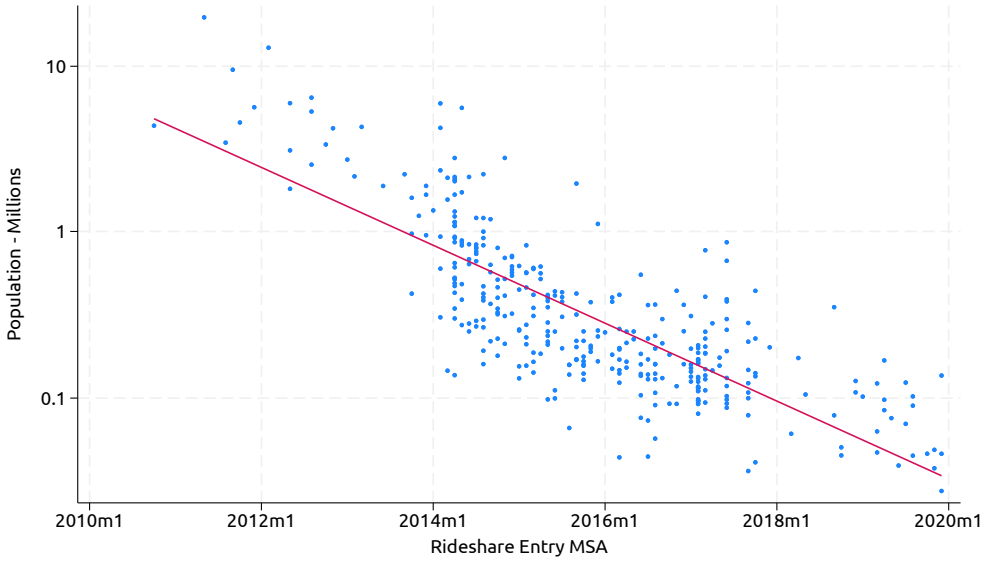
Our empirical setup maintains the two key identifying assumptions of the canonical DID model: no anticipation and parallel trends. *No anticipation* implies that ridesharing services have no causal effect before their actual entry. It would fail if e.g., households decide to relocate or otherwise change their decisions before entry in order to preempt some of its consequences, such as an increase in house prices. As shown in Section 4, the pre-treatment coefficients of Equation (1) are for the most part statistically indistinguishable from zero, which provides evidence against any anticipation effects. *Parallel trends* assumes that trends in the outcome variables are the same in the pre-treatment period as in the counterfactual post-treatment period where no treatment actually took place. This assumption would be violated if the entry decision of ridesharing services was correlated with shocks to local economic conditions such as economic or population growth.

To search for any evidence that parallel trends could be violated, we briefly study the main drivers for the entry of ridesharing services. First, we observe that the main driver is the population *level* of an MSA, which has a strong negative correlation with the entry year (Figure 2). This finding has also been noted by previous literature relying on the same identification strategy, such as Hall et al. (2018), Barrios et al. (2022), Fos et al. (2023), and Buchak (2024). Moreover, these studies show that dynamic factors such as economic or population growth appear uncorrelated with the timing of entry.[9]

To corroborate this, we apply a Cox proportional hazards model to assess the relationship between entry of ridesharing services and several economic and demographic variables of interest including MSA population levels and growth, local unemployment rates, and house price growth. The results of this exercise are shown in Table B.4. We find that the entry of ridesharing services is most strongly associated with the population of the MSA and, to a lesser extent, with whether ridesharing services were already operating

[9]While some research (Hall et al. (2018)) suggests that education levels may correlate with entry timing, our hazard model in Table B.4 controls for income per household, which is highly correlated with education, and finds no significant relationship.

Figure 2: *MSA population and the entry of ridesharing services*



This figure replicates Figure 5 of Hall et al. (2018) with our updated MSA sample. It displays the population size of an MSA along with the month in which ridesharing services first entered an MSA.

in the state.[10] In summary, we find no evidence that the timing of ridesharing services was systematically driven by the economic conditions of the MSA, such as average income or unemployment. This suggests that the not-yet-treated MSAs should be a valid counterfactual for the treated ones.

3.2 Heterogeneous Effects of Ridesharing Entry within MSAs

Previous research has shown that the use of ridesharing services is particularly high in the more urban areas of an MSA (Gorback, 2020; Li et al., 2022). There are several reasons for this phenomenon. Shorter urban distances lead to lower prices per trip compared to suburban areas, resulting in higher demand for rides (Cramer and Krueger, 2016). This higher demand, combined with higher density, allows for a more efficient

[10]This last result is consistent with the findings that companies expand locally, benefiting from familiar regulations and infrastructure, before entering new regions (Holmes, 1998; Duranton and Puga, 2001). Anil and Fisher-Ellison (2022) also find that Uber is more likely to enter MSAs with higher regulatory barriers for entry of conventional cab services. Insofar as ex ante regulations governing the entry of taxi operators are orthogonal to local economic conditions, this finding adds another layer of exogenous variation in the entry decision of ridesharing services.

passenger–driver matching, thus increasing passenger turnover and ultimately reducing operational costs (Cohen et al., 2016). Ridesharing also helps avoid costs associated with car ownership, such as parking, which are larger in urban areas (Glaeser et al., 2008).[11] Finally, ridesharing services can provide last-mile connectivity for public transit, which predominantly serves urban areas (Hall et al., 2018). For all these reasons, we expect the effect of the entry of ridesharing services to be relatively stronger in urban areas.

We provide some evidence of this by studying the usage of ridesharing services in Zip codes within four jurisdictions: Massachusetts, Chicago, San Francisco, and New York City.[12] In particular, we regress the number of ridesharing trips per capita against the HUD's UPSAI index of perceived urbanicity. To control for additional drivers of demand, we include other Zip code level variables such as annual household income. Furthermore, to control for local characteristics (e.g., urban sprawl), we also include MSA fixed effects.

The results of this exercise are shown in Table 2. The baseline result of column 1 shows that a one standard deviation increase in the perceived urbanicity of a Zip code is associated with a 30 percent increase in the number of trips per capita. Results are robust to including Zip code level controls (column 2) and MSA fixed effects (column 3). In both specifications, the results remain qualitatively similar, showing a robust correlation between Zip code urbanization and ridesharing usage. Lastly, column 4 divides the sample of Zip codes into four quartiles of $Urban_z$ and compares ridesharing usage for MSAs in the top three quartiles with those in the bottom quartile. Ridesharing usage is monotonically increasing in urbanness, with the number of trips per capita in the top urban quartile more than double that of the bottom quartile.

Since data on trips per capita is only available for a small subset of MSAs, for robustness, in columns 5 to 8 of Table 2, we use Google queries for the terms *Uber*, *Lyft*, or *Rideshare app* in a Zip code as a proxy for rideshare demand. Specifically, $GoogleSearches_z$

[11] In Figure B.5 of Appendix B, we display the positive relation between our measure of perceived urbanicity of Zip codes in New York City and its monthly parking costs.

[12] This information is available due to local regulations, and so we cannot extend it to all of the MSAs studied in the main section.

Table 2: ***Urbanicity of Zip code and Rideshare Usage***

	Trips Capita$_z$				Google Searches$_z$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Urban$_z$	9.62***	12.98***	9.80***		8.45***	11.70***	8.31***	
	(1.54)	(4.27)	(3.31)		(1.34)	(2.60)	(1.57)	
Urban$_{z,Q2}$				1.51				2.16***
				(1.36)				(0.79)
Urban$_{z,Q3}$				5.06**				2.64***
				(2.21)				(0.96)
Urban$_{z,Q4}$				7.65***				5.79***
				(2.35)				(1.18)
Observations	711	579	579	579	2,288	2,197	2,197	2,197
R-squared	0.07	0.18	0.53	0.53	0.01	0.18	0.76	0.76
Zip-code Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
MSA FE	No	No	Yes	Yes	No	No	Yes	Yes
Average(dependent variable)	8.4	8.4	8.4	8.4	81.2	81.2	81.2	81.2

This table shows the results of regressions of the number of ridesharing trips and Google searches for ridesharing services against perceived Zip code urbanicity. The sample is restricted to metropolitan statistical areas (MSAs) in which ridesharing services operate. *Trips Capita*$_z$ is the number of trips per capita using ridesharing services in Zip code z. Information is only available for Zip codes in four jurisdictions: Massachusetts, Chicago, San Francisco, and New York City. *Google Searches*$_z$ is an index of the relative number of searches on Google querying for the terms *Uber*, *Lyft*, or *Ridesharing services* in Zip code z, in the month following the entry of the ridesharing services in an MSA. *Urban*$_z$ is a measure of the urbanicity of Zip code z compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *Urban*$_{z,Qn}$ is an indicator of whether the urban measure of Zip code z is in quartile n. *Zip code controls* include income per household, home value, share of individuals commuting using personal car, commute time, walkscore, and transit score. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 for detailed variable definitions.

indicates the relative number of Google queries for the terms *Uber*, *Lyft*, or *Rideshare app* in Zip code z in the month following the entry of ridesharing services in the MSA. Consistent with the results reported in columns 1 to 4, ridesharing-related Google searches are significantly more prevalent in urban Zip codes.

Overall, these results suggest that ridesharing adoption is significantly larger in the most urban areas of cities.

4 Ridesharing and Gentrification

As discussed earlier, ridesharing works better and has a wider adoption in urban areas than in the suburbs, and this technology has also been shown to be skewed toward higher-income and younger individuals (Hall et al., 2018). Thus, in this section, we test if the introduction of ridesharing might have led to spatial sorting within MSAs—that is, whether the individuals who benefit more from ridesharing choose to relocate into the areas where ridesharing works best.

We find that this is indeed the case. As documented in Table 3, after entry, urban areas shifted their composition towards a higher-income, younger population, while suburbs tilted towards poorer, older households. Moreover, Table 4 shows that households in urban areas become more likely to relocate into different Zip codes, and that this is driven by renters and not by homeowners.

For our first set of results, we consider *high-income households* as those with annual income above 50,000 dollars, as reported by the IRS Statistics of Income.[13] Columns 1 and 2 of Table 3 show that, consistent with gentrification, the number of high-income households in urban Zip codes gradually increases after entry, becoming about five percent higher three years after entry than otherwise would have been. We do not observe any significant change in our control group of high-income households in suburban Zip

[13]High-income households account for 41 percent of total households in our study.

codes. In contrast, columns 3 and 4 show that the number of low-income households declined in urban Zip codes—by about one percent over the first three years—and increased in suburban Zip codes—by around one to two percent, although not always with strong statistical significance. Reassuringly, we do not find any differential pre-trends in any of these four specifications. Overall, these results support the hypothesis that the entry of ridesharing services is associated with the relocation of high-income individuals into urban Zip codes and of lower-income individuals into suburban areas. As we will see in section 5, this is likely partly due to the increase in house and rental prices that followed ridesharing entry.

To shed further light on how the demographic composition of treated MSAs changed, we examine next the average age of individuals living in a Zip code, as well as the fraction of households claiming a child tax credit, which acts as a proxy for households with children.[14] Column 5 shows that, following entry, the average age in urban areas declined by up to 1.5 percent in the years after entry, equivalent to half a year for someone at the U.S. median age (39 years old as of 2024). Meanwhile, column 6 shows no effect on suburban areas. These findings are consistent with previous literature documenting a large increase in the number of younger, high-income individuals in urban areas over the past two decades (Couture and Handbury, 2023). Lastly, columns 7 and 8 show the effects on the fraction of households claiming child tax credit in urban and suburban areas, respectively. This fraction falls by up to 1.2 percent in urban areas, and remains unchanged in suburban areas. A possible channel for these results is that the entry of ridesharing and the subsequent urban gentrification might be increasing the price of local services (Gorback, 2020), reducing the affordability of urban areas for families with children.

As discussed in section 3, our results might be invalid if ridesharing entry was driven by shocks to local economic conditions. To allay concerns about this, as a robustness test

[14]The average age of individuals in a Zip code comes from the Equifax CCP, and children's tax deductions comes from the IRS Statistics of Income.

Table 3: ***Entry of Ridesharing Services and Income Composition of Households***

	Number of Households - High Income$_{z,y}$		Number of Households - Low Income$_{z,y}$		Age$_{z,y}$		Child Credit$_{z,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PreEntry 2-Years	0.003	0.003	-0.002	0.008	-0.002	0.000	0.001	-0.000
	(0.004)	(0.004)	(0.003)	(0.005)	(0.002)	(0.001)	(0.001)	(0.000)
PreEntry 1-Years	0.008	0.003	-0.002	0.011	-0.003	0.001	0.000	-0.001
	(0.005)	(0.005)	(0.004)	(0.008)	(0.002)	(0.002)	(0.001)	(0.001)
PostEntry 0-Years	0.009***	-0.002	-0.010**	0.009	-0.002***	0.000	-0.001	-0.000
	(0.003)	(0.002)	(0.005)	(0.008)	(0.001)	(0.000)	(0.001)	(0.000)
PostEntry 1-Years	0.023***	-0.003	-0.015***	0.015	-0.004***	-0.001	-0.003***	0.000
	(0.004)	(0.003)	(0.006)	(0.013)	(0.001)	(0.001)	(0.001)	(0.000)
PostEntry 2-Years	0.036***	-0.002	-0.014**	0.020*	-0.008***	-0.001	-0.005***	0.001
	(0.005)	(0.004)	(0.006)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
PostEntry 3-Years	0.049***	-0.007	-0.010	0.026***	-0.011***	-0.002	-0.007***	0.002
	(0.007)	(0.006)	(0.007)	(0.006)	(0.002)	(0.002)	(0.002)	(0.001)
PostEntry 4-Years	0.067***	-0.008	0.011	0.014*	-0.015***	-0.003	-0.012***	0.001
	(0.010)	(0.008)	(0.011)	(0.008)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	23,356	21,559	23,356	21,559	12,940	10,424	20,148	18,989
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample of Zip codes	Urban	Suburban	Urban	Suburban	Urban	Suburban	Urban	Suburban
Avg. Dep. Variable	8.2	7.8	8.6	8.3	4.3	4.5	0.13	0.17

This table displays the relation between the entry of ridesharing services and the number of high- and low-income households in a Zip code*year in urban and suburban Zip codes. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *Number of Households - High Income$_{z,y}$ (- Low Income$_{z,y}$)* is the number of individual tax returns (in logs) in Zip code z in year y with a household income equal or above (below) USD 50,000. *Age$_{z,y}$* is the average age (in logs) of individuals with a credit report in Zip code z in year y, compiled from the Equifax CCP. *Child Credit$_{z,y}$* is the share of tax returns on income that claim a child credit in Zip code z in year y, obtained from the Internal Revenue Service. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 in the appendix for detailed variable definitions.

we do a triple difference-in-differences exercise, where we pool all Zip codes in an MSA (urban and suburban) and estimate a variant of Equation (1) where we replace state-year fixed effects by MSA-year fixed effects, and modify the pre/post indicators so they apply only to the urban Zip codes:

$$y_{z,t} = \alpha_z + \gamma_{m(z),t} + \sum_{j=-2}^{4} \beta_j \, \text{Urban}_z \, \mathbf{1}_{t-j=T_{m(z)}} + \epsilon_{z,t} \tag{2}$$

Results of this specification are displayed in Table B.5. All results are quantitatively similar to the previous specification, comparing urban and suburban Zip codes separately. In particular, after ridesharing entry, the number of high-income households increases by up to 7.8 percent after entry in urban Zip codes relative to suburban Zip codes. Similarly, the average age declines by up to 1.1 percent in urban Zip codes, whereas the fraction of households reporting a child tax credit declines by up to 0.8 percentage points (5.3 percent).

While these results are overall suggestive of relocation of low-income households with children out of urban Zip codes, it is not conclusive as they could reflect changes in the characteristics of existing residents rather than out-migration of poorer residents and in-migration of richer residents. For instance, existing residents might become poorer or decide to have fewer kids. To address this, we use the Equifax CCP to create an indicator variable on whether an individual moves out of his existing Zip code from one year to the next, and use it as the outcome variable on Equation (1). Table 4 displays the results. Column 1 shows that, in urban Zip codes, there is a significant increase in the likelihood of individuals moving out following the entry of ridesharing. This increase averaged about 1.2 percentage points, or 11 percent, in the years after ridesharing entry. In contrast, as shown in column 2, there are no meaningful changes in suburban Zip codes. Interestingly, the change in urban Zip codes seems to be almost exclusively driven by renters (column 3) and not by homeowners (column 4). [15]

[15] Table B.11 repeats the robustness checks of the previous results, estimating equation (2). All results

Table 4: ***Entry of Ridesharing Services and Relocation Away from Zip code***

	Moving Out of Zip-Code$_{i,y}$			
	(1)	(2)	(3)	(4)
PreEntry 2-Years	-0.004	-0.005	0.001	0.002
	(0.005)	(0.005)	(0.007)	(0.004)
PreEntry 1-Years	0.000	0.001	0.005	0.001
	(0.004)	(0.007)	(0.008)	(0.006)
PostEntry 0-Years	0.004	0.005	-0.003	-0.003
	(0.005)	(0.007)	(0.007)	(0.003)
PostEntry 1-Years	0.004	0.003	0.000	-0.004
	(0.004)	(0.005)	(0.006)	(0.007)
PostEntry 2-Years	0.022***	0.027***	0.006	0.002
	(0.007)	(0.004)	(0.012)	(0.006)
PostEntry 3-Years	0.012*	0.014**	0.006	0.001
	(0.007)	(0.007)	(0.015)	(0.008)
PostEntry 4-Years	0.028***	0.031***	0.021*	0.005
	(0.006)	(0.006)	(0.007)	(0.011)
Observations	668,649	513,131	155,506	537,769
Controls	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Zip codes	Urban	Urban	Urban	Suburban
Sample	All	Renter	Homeowner	All
Avg. Dep. Variable	0.11	0.12	0.07	0.08

This table displays the results of a regression relating the entry of ridesharing services to the moving of individuals away from their current Zip code of residence. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *Moving Out of Zip code*$_{i,y}$ is an indicator of whether individual *i* has a different residential Zip code in year *y+1* relative to year *y*. *Homeowner (renter)* are individuals who have (not) had a mortgage or home equity loan in their current Zip code. *Controls* are a series of individual controls, including age (in logs), FICO score, and an indicator of late repayment. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 in the appendix for detailed variable definitions.

5 Ridesharing and the Housing Market

In the previous section, we observed that the entry of ridesharing mostly led to the relocation of existing renters and not of homeowners. To understand if housing costs play a role in these results, this section studies the housing and rental markets in more detail.

5.1 Mortgage Originations

As high-income households move into urban areas, we expect the demand for owner-occupied housing to increase relative to rental housing (Sinai and Souleles, 2005). This could prompt landlords and developers to either convert rental units to condominiums, or to build high-end housing to meet the increase in demand (Boustan et al., 2023). Because housing purchases are financed mainly through mortgages (Garriga and Hedlund, 2020), we thus expect to see increasing mortgage originations in urban areas, particularly from higher-income individuals.

We study this by looking at the universe of mortgage loans reported through the Home Mortgage Disclosure Act (HMDA) confidential dataset, aggregating individual loans into the Zip code-year level. Table 5 shows this exercise. We find an economically and statistically significant increase in the number of mortgages originated in urban Zip codes of treated MSAs after the entry of ridesharing services (column 1). Originations increase gradually over time, averaging around 8.1 percent over the five years following their entry, and with no evidence of preexisting trends for treated MSAs. In contrast, the effect on suburban Zip codes is muted (column 2). These results are consistent with the relative increase in the demand for housing in urban areas following the introduction of ridesharing services.[16]

remain qualitatively similar and estimates have similar magnitudes.

[16]Using mortgage originations as a measure for housing demand has two limitations. First, wealthy individuals might purchase homes without going through a mortgage. To verify our results are not affected by this channel, we compute a separate set of regressions using home vacancy rates as outcome variables: home vacancies decrease when housing demand increases, and are not affected by the cash purchase-versus-mortgage decision. The results of these regressions are shown in Table B.7, and show that

We also verify that after the entry of ridesharing, mortgages in urban areas are increasingly taken by high-income households. Column 3 shows an immediate increase in the income of loan applicants in urban areas, which does not occur in suburban ones (column 4). The same pattern is present if we use an alternative outcome, the share of mortgages insured by the Federal Housing Administration (FHA). FHA-insured loans have lower FICO and downpayment requirements, and are widely interpreted to be correlated to low-income or low-wealth borrowers. In the five years following the introduction of ridesharing services, the share of FHA-insured loans decreased by an average of 6.4 percentage points or about 30 percent in urban Zip codes (column 5). In contrast, we do not see any effect in the suburban areas of the treated MSAs (column 6).

As before, as a robustness test, we pool urban and suburban Zip codes using MSA*year fixed effects using urban Zip codes as a control group. The results of this specification are shown in Table B.6. All results are qualitatively similar to the specifications, comparing urban and suburban Zip codes separately. The number of mortgage originations increases 8.6 percent in urban Zip codes compared to suburban ones. The average income of mortgage applicants rises 2.2 percent, while the fraction of FHA-insured loans decreases 1.9 percentage points (10.2 percent).

5.2 Where are mortgages originated?

The last subsection showed that mortgage originations in urban areas increase substantially following the entry of ridesharing services, driven by high-income individuals. However, urban areas are quite heterogeneous.

This subsection studies where exactly within urban areas these high-income indi-

vacancy rates decrease sharply immediately after ridesharing entry, validating our earlier results. Further, Table B.8 shows an alternative specification pooling urban and suburban Zip codes using MSA*year fixed effects, which again shows quantitatively similar results. Second, originations depend not only on the volume of mortgage applications but on their approval rates, driven partly by credit supply. To verify that our results are not driven by e.g. a change in lender risk appetite correlated to ridesharing entry, we conducted a similar regression (not shown) using approval rates as outcome, and found no meaningful differences.

Table 5: ***Entry of Ridesharing Services, Mortgage Originations, and Characteristics of Applicants***

	#Mortgage Originations$_{z,y}$		Applicant Income$_{i,y}$		FHA-Insured$_{i,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)
PreEntry 2-Years	-0.003	-0.001	0.005	0.005	-0.002	-0.009
	(0.025)	(0.023)	(0.004)	(0.005)	(0.009)	(0.015)
PreEntry 1-Years	0.023	-0.011	0.001	0.016**	-0.008	-0.025**
	(0.033)	(0.021)	(0.005)	(0.005)	(0.012)	(0.012)
PostEntry 0-Years	0.017	0.012	0.020***	0.010**	-0.020***	-0.016
	(0.024)	(0.014)	(0.004)	(0.004)	(0.007)	(0.015)
PostEntry 1-Years	0.014	0.006	0.041***	0.009	-0.034***	-0.012
	(0.022)	(0.012)	(0.006)	(0.006)	(0.007)	(0.016)
PostEntry 2-Years	0.117***	0.033	0.069***	0.012	-0.075***	-0.024
	(0.020)	(0.034)	(0.009)	(0.008)	(0.016)	(0.018)
PostEntry 3-Years	0.248***	0.010	0.094***	0.014	-0.108***	-0.029
	(0.039)	(0.031)	(0.012)	(0.011)	(0.013)	(0.019)
PostEntry 4-Years	0.056*	0.031	0.114***	0.007	-0.085***	-0.031
	(0.030)	(0.032)	(0.014)	(0.013)	(0.016)	(0.027)
Observations	9,335	11,410	2,295,577	3,534,990	2,295,577	3,534,990
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip codes	Urban	Suburban	Urban	Suburban	Urban	Suburban
Avg. Dep. Variable	4.7	5.3	4.6	4.5	0.21	0.18

This table displays the relation between the entry of ridesharing services with the number of mortgage originations and with characteristics of mortgage applicants in urban and suburban Zip codes. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *#Mortgage Originations*$_{z,y}$ is the number of mortgage originations (in logs) in Zip code z in year y. *Applicant Income*$_{i,y}$ is the gross annual income (in logs) of applicant i in year y. *FHA Insured*$_{i,y}$ is an indicator that mortgage i originated in year y and is insured by the Federal Housing Administration. Dependent variables were obtained from Home Mortgage Disclosure Act confidential dataset. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 in the appendix for detailed variable definitions.

viduals purchase homes, and finds this takes place in the Zip codes with lower house values, higher poverty rates, and larger shares of minorities. These characteristics are consistent with the patterns of gentrification previously outlined in this paper, as well as with the endogenous gentrification mechanism proposed by Guerrieri et al. (2013) where high-income individuals cluster their home purchases in more affordable areas.

For this specification, we still split the sample into urban and suburban Zip codes and use state*year fixed effects, but replace Zip code fixed effects with MSA fixed effects. This is because our outcome variables are at the Zip code level and are relatively constant across time. Our object of study is precisely the area where mortgages are being originated, rather than the individuals obtaining them. Therefore, all our results effectively study variation within urban (suburban) Zip codes in an MSA.

The results relating mortgage originations to the median value of homes in the Zip code are shown in Table 6 and Figure 3. In columns 1 and 2, we display the results for median house prices in urban and suburban Zip codes. They show that within urban areas in an MSA, mortgages are originated in Zip codes with 2.2 percent lower median house prices in the five years following the entry of ridesharing services. Furthermore, this effect is gradual, with the demand for lower-priced Zip codes increasing over time. By the fifth year after entry, mortgage originations in urban areas are for Zip codes with 5 percent lower home values. The results of the average poverty rate are displayed in columns 3 and 4. After the introduction of ridesharing services within urban areas, more mortgages tend to originate in Zip codes with higher poverty. The average poverty rate of these Zip codes is 0.3 percentage points (1.5 percent) higher. Again, the effect is gradual, and we find no effect on suburban Zip codes. Finally, in columns 5 and 6, we analyze the composition of minorities. In urban Zip codes, new mortgages originated in Zip codes with a 0.7 percentage point (1.5 percent) higher fraction of minorities. Again, effects on suburban areas are significantly lower and exhibit pre-trends. The results of the pooled specification are displayed in Table B.9. They show that the urban Zip codes of mortgage

originations have 1.1 percent lower house prices, 1.8 percent higher poverty rates, and a 2.7 percent higher share of minorities.

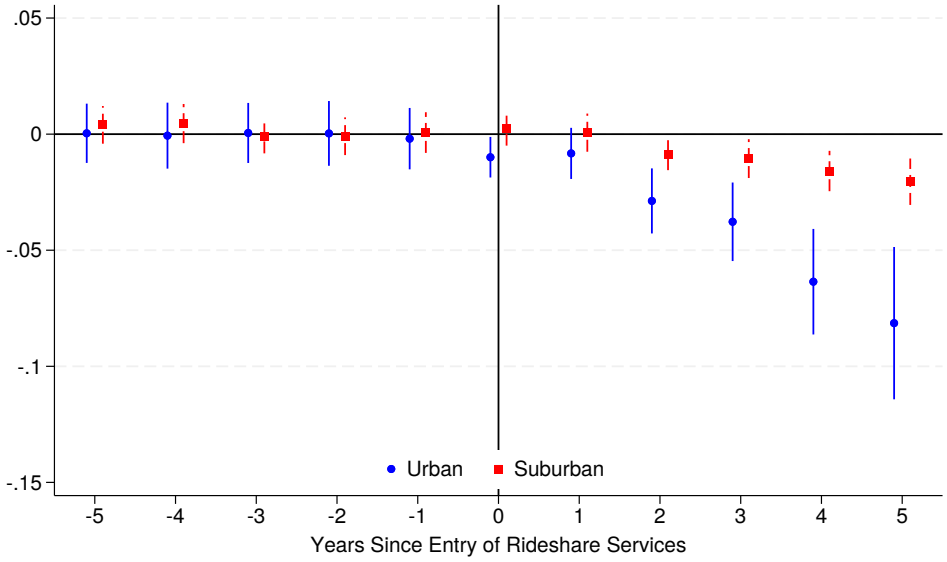
Table 6: ***Entry of Ridesharing Services and Characteristics of Zip codes of Mortgage Originations***

	Median House Price in Zip-code$_{i,y}$		Average Poverty Rate in Zip-code$_{i,y}$		Average Minority Share in Zip-code$_{i,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)
PreEntry 2-Years	0.001	-0.003	-0.001	0.001	0.001	-0.003**
	(0.003)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
PostEntry 1-Years	0.004	-0.001	-0.002	0.000	0.000	-0.004***
	(0.003)	(0.006)	(0.002)	(0.001)	(0.001)	(0.002)
PostEntry 0-Years	-0.004	-0.003	0.000	-0.000	0.000	0.002
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
PostEntry 1-Years	-0.009**	-0.006	0.000	-0.000	0.003**	0.000
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)
PostEntry 2-Years	-0.020***	-0.016***	0.003*	0.000	0.006***	0.002
	(0.005)	(0.005)	(0.002)	(0.001)	(0.002)	(0.002)
PostEntry 3-Years	-0.032***	-0.011***	0.004**	0.001	0.010***	0.003**
	(0.006)	(0.004)	(0.002)	(0.000)	(0.002)	(0.001)
PostEntry 4-Years	-0.050***	-0.019***	0.006***	0.001*	0.015***	0.004**
	(0.008)	(0.006)	(0.002)	(0.001)	(0.003)	(0.002)
Observations	2,295,577	3,534,990	2,295,577	3,534,990	2,295,577	3,534,990
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip codes	Urban	Suburban	Urban	Suburban	Urban	Suburban
Avg. Dep. Variable	12.3	12.4	0.20	0.06	0.43	0.18

This table displays the results of a regression relating the entry of ridesharing services with the characteristics of Zip codes of the properties for which the mortgages were issued in urban and suburban Zip codes. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *Median House Price in Zip code*$_{i,y}$ is the median house price (in logs) in the Zip code of the property financed by mortgage i originated in year y. *Average Poverty Rate in Zip code*$_{i,y}$ is the average poverty rate of the Zip code of the property financed by mortgage i originated in year y. *Average Minority Share in Zip code*$_{i,y}$ is the average share of minority individuals of the Zip code of the property financed by mortgage i originated in year y. Mortgage information was obtained from the Home Mortgage Disclosure Act, while information on the dependent variables was obtained from Zillow and the Census Bureau. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 in the appendix for detailed variable definitions.

In summary, our results suggest that ride-hailing services, by improving access to easy and convenient transportation, increased the relative attractiveness of poorer neighborhoods in treated MSAs. Therefore, an important consequence of the entry of ride-hailing services is that they are conducive to the gentrification of poorer urban neighborhoods. Next, we analyze whether the resulting increase in demand for housing in urban areas leads to an increase in home prices, especially in more affordable urban neighborhoods.

Figure 3: ***Entry of Ridesharing Services and Ex Ante Median Home Values of Zip codes of Mortgage Originations***



This figure displays the evolution of yearly coefficients of a regression relating the entry of ridesharing services with the median home values (in logs) of the Zip codes of the mortgage originations in urban and suburban Zip codes, in the left and right panels, respectively. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. Regressions include metropolitan statistical area and state*year fixed effects. Standard errors are clustered at the Zip code level. The blue vertical bars represent confidence intervals of the coefficients at the 95 percent significance level. See Table B.1 in the appendix for detailed variable definitions.

5.3 Housing and Rental Prices

So far, our results are suggestive of an increase in the demand for housing in urban areas. In this section, we analyze whether this higher demand leads to higher home and rental prices given the low elasticity of housing supply in the short run (Glaeser and Gyourko, 2018). The results of our benchmark specification for house prices and rental prices are shown in Table 7 and in Figure 4. Columns 1 and 2 report the results on house prices for the subsamples of urban and suburban Zip codes, respectively. The coefficients in column 1 indicate a gradual increase in house prices of around 9 percent in the five years after treatment, consistent with higher demand for ridesharing in urban areas. Conversely, coefficients in column 2 indicate that the effect on suburban prices is muted. The rental prices results are shown in columns 3 and 4. In line with the results on house prices, we find an overall differential increase in rental prices in treated MSAs. Following the introduction of ridesharing services, rental prices in urban Zip codes increase 6 percent on average. We also find a small but statistically significant effect on suburban Zip codes averaging 1.8 percent.[17] Results of the specification that group urban and suburban Zip codes are displayed in Table B.10. Qualitatively, the results are similar to those that split urban and suburban Zip codes. We find that housing prices and rental prices rise 2.5 percent and 1.9 percent, respectively, in the treated urban Zip codes compared to suburban Zip codes.

In summary, the results in this section indicate that the entry of ridesharing services contributed to the sharp increase in housing prices by raising the demand for housing from higher-income individuals in a context of limited supply.

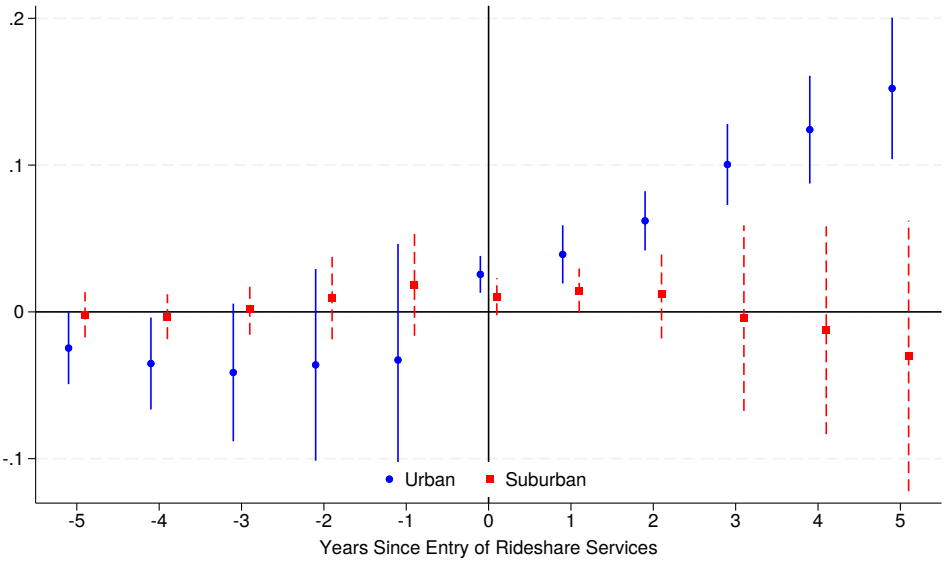
[17]This positive effect on suburban areas could be driven by the displacement of low-income people from urban to suburban areas. Insofar as such individuals are likely to be liquidity constrained, they may be unable to bid up house prices, resulting in a muted effect on house prices in suburban areas. Instead, they are likely to move to rental housing, increasing rental demand and cost in suburban areas.

Table 7: ***Entry of Ridesharing Services and House and Rental Prices***

	House Price Index$_{z,y}$		Rental Prices$_{z,y}$	
	(1)	(2)	(3)	(4)
PreEntry 2-Years	-0.004	0.005	0.015	-0.010
	(0.016)	(0.012)	(0.034)	(0.029)
PreEntry 1-Years	0.005	0.013	0.033	-0.005
	(0.021)	(0.016)	(0.042)	(0.036)
PostEntry 0-Years	0.033***	0.014	0.025***	0.015***
	(0.008)	(0.009)	(0.005)	(0.004)
PostEntry 1-Years	0.057***	0.019	0.042***	0.023***
	(0.011)	(0.013)	(0.007)	(0.006)
PostEntry 2-Years	0.082***	0.017	0.061***	0.029***
	(0.016)	(0.020)	(0.012)	(0.008)
PostEntry 3-Years	0.125***	0.042**	0.078***	0.024***
	(0.018)	(0.022)	(0.018)	(0.009)
PostEntry 4-Years	0.147***	0.022	0.084**	0.013
	(0.029)	(0.023)	(0.035)	(0.015)
Observations	13,431	12,397	17,592	16,162
Zip code FE	Yes	Yes	Yes	Yes
State-Year FE	No	Yes	No	Yes
Sample of Zip codes	Urban	Suburban	Urban	Suburban
Avg. Dep. Variable	5.2	5.0	7.3	7.5

This table displays the results of regressions relating the entry of ridesharing services with housing and rental prices at the Zip code*year level, in urban and suburban Zip codes. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *House Price Index*$_{z,y}$ is an index of house prices (in logs) at the Zip code z in year y, obtained from CoreLogic. *Rental Prices*$_{z,y}$ is the average monthly market rent (in logs) of Zip code z in year y, obtained from Zillow. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 in the appendix for detailed variable definitions.

Figure 4: ***Entry of Ridesharing Services and House Prices***



This figure displays the evolution of yearly coefficients of a regression relating the entry of ridesharing services with housing prices in urban and suburban Zip codes, in the left and right panels, respectively. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. Regressions include Zip code and state*year fixed effects. Standard errors are clustered at the Zip code level. The blue vertical bars represent confidence intervals of the coefficients at the 95 percent significance level. See Table B.1 in the appendix for detailed variable definitions.

6 Ridesharing and the Financial Health of Existing Residents

Taken together, results so far indicate that the entry of ridesharing services led to urban gentrification: after entry, high-income individuals relocated from the suburbs into urban cores, urban house and rental prices increase, and in turn, lower-income residents relocated into the suburbs. In this section, we use granular Equifax CCP data to analyze how these changes affected the financial health of existing urban residents, who either faced higher housing or rental costs, or had to relocate to the suburbs. We measure financial health directly through ex-post outcomes, namely delinquency over the next two years. We create an indicator, $Late\ Repayment_{i,t+2}$, equal to 1 if individual i is late on his or her payments in year t+2.

Given that the appreciation in urban house prices shown earlier in Figure 4 is likely to affect renters and homeowners differently (Autor et al., 2014), and that on Table 4 we observed different relocation patterns across homeowners and renters, we also include regressions on urban areas split by home ownership status. We define homeowners as those individuals that obtained a mortgage or home equity loan in their current Zip code at some point between 1999—the first year with available data—and when ridesharing was introduced in their MSA.[18] The main characteristics of homeowners and non-homeowners are displayed in Table B.14. Consistent with Wolff (2000), we find that homeowners tend to be older, have higher credit scores, move less frequently, and live in wealthier Zip codes.

Results of this exercise are displayed in Table 8. Columns 1 and 2 show the results of ridesharing entry on delinquency rates of individuals living in urban and suburban Zip codes, respectively. In urban areas, delinquencies increase three years after ridesharing

[18]This definition risks misclassifying older individuals as non-homeowners, for two reasons: they might have paid for their home with cash, or their house might have been bought before 1999. To alleviate these concerns, we restrict our analysis to individuals under the age of 55, as roughly 85 percent of home acquisitions by individuals under age 55 are financed through mortgages (of Realtors, 2024).

entry, from a baseline of 2.3 percent to about 3 percent on post-entry years 3 and 4, although the results have weak statistical significance. Meanwhile, there is no meaningful change in delinquency rates in suburban areas, reinforcing the view that ridesharing disproportionally affected urban areas. As expected, the results from column 1 hide a large heterogeneity between homeowners and renters. Column 3 shows that two years after ridesharing entry, delinquency rate of renters is already 0.8 percent higher, compared to a 2.3 percent baseline. This peaks three years after entry, where delinquencies are at a much higher 4.2 percent, double the baseline levels. In contrast, column 4 shows that delinquency rates fall drastically for homeowners after the second year, almost vanishing three and four years after entry. This is likely due to an increase in their property value and net worth, which could relax any preexisting credit constraints.

As before, the results of the specification pooling urban and suburban Zip codes together are displayed in Table B.12. Qualitatively, results are similar to the ones splitting urban and suburban Zip codes. We find that following the entry of ridesharing services, the delinquency rates have increased by 0.4 percentage point (15 percent). Again, we observe that this increase is driven by renters.

Overall, these results suggest that ridesharing entry has uneven effects across urban residents. While homeowners benefit from improved asset returns in the form of housing price appreciation, non-homeowners suffer from an increase in housing prices, which raises the likelihood that they have to move away from their current locations and increases the probability that they will suffer financial stress in the near future in the form of late credit repayments.

Table 8: ***Entry of Ridesharing Services and Change in Credit Quality***

	Late Repayment$_{i,y+2}$			
	(1)	(2)	(3)	(4)
PreEntry 2-Years	-0.001	0.001	-0.007	-0.000
	(0.002)	(0.002)	(0.006)	(0.002)
PostEntry 1-Years	-0.000	0.002	-0.010	-0.002
	(0.003)	(0.003)	(0.008)	(0.003)
PostEntry 0-Years	-0.000	-0.001	0.002	-0.002
	(0.002)	(0.002)	(0.007)	(0.002)
PostEntry 1-Years	-0.003	-0.004	0.001	0.000
	(0.002)	(0.003)	(0.007)	(0.002)
PostEntry 2-Years	0.001	0.008**	-0.010	-0.004
	(0.003)	(0.003)	(0.007)	(0.003)
PostEntry 3-Years	0.006*	0.021***	-0.037***	-0.007
	(0.003)	(0.005)	(0.008)	(0.004)
PostEntry 4-Years	0.007*	0.015***	-0.023***	0.001
	(0.004)	(0.004)	(0.009)	(0.006)
Observations	646,080	494,808	151,261	521,852
Controls	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Zip codes	Urban	Urban	Urban	Suburban
Sample	All	Non-Homeowner	Homeowner	All
Avg. Dep. Variable	0.023	0.021	0.034	0.024

This table displays the results of a regression relating the entry of ridesharing services with changes in the financial health of incumbent residents, proxied by an indicator of credit delinquency. *Urban (Suburban)* Zip codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *Late Repayment*$_{i,y+2}$ is an indicator of whether individual i is late on his or her credit payments in year y+2. *Controls* are a series of individual controls, including age (in logs), FICO score, and an indicator of current late repayment. *Homeowner(Renter)* are individuals who have (not) had a mortgage in their current Zip code. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 in the appendix for detailed variable definitions.

7 Robustness analysis

The results shown throughout this paper hinge on the entry of ridesharing services being uncorrelated with other drivers of gentrification. We argued in section 3 why the entry is exogenous, and this section provides two additional pieces of evidence on this.

First, all the events we have studied correspond to *entries* of ridesharing services, which might be correlated to other entries such as high-end supermarket chains (Whole Foods), homestay rentals (Airbnb), etc. To alleviate concerns on this, we study a high-profile *exit* case driven by a city council decision: the 2016–2017 exit of Uber and Lyft from Austin, Texas. This exit, driven by political factors, was not related to the entry or exit of any other markets or industries, and can thus be used as an alternative event study.

Second, we apply an instrumental variable specification that exploits the fact that ridesharing services often entered multiple cities in a given state at about the same time. For instance, the entry of Lyft in all Alabama MSAs in our sample took place within a span of two months (first, Birmingham in February 2017, followed by five other cities). Similarly, Uber entered North Carolina through Charlotte in September 2013, followed over the next year by seven other MSAs in the state. Thus, we use entry at the state level as instrument for entry at the MSA level.

Exit of Ridesharing Services: The Case of Austin, Texas. There are only a few cases of ridesharing services leaving an MSA, with the longest and highest-profile case taking place in Austin, where ridesharing services—who had entered the MSA in 2014—decided in April 2016 to leave the region due to regulatory concerns. More concretely, in December 2015, the Austin City Council passed an ordinance requiring drivers of rideshare companies to receive fingerprint-based background checks. After this ordinance, a *Ridesharing Works* campaign was organized—with financial support from both Uber and Lyft—creating a citizen-initiative ballot to repeal the ordinance. The vote took place in May 2016, and the ordinance was not repealed (i.e., Uber and Lyft lost). Immediately after

the announcement of the results, Uber and Lyft suspended their operations in Austin. Their subsequent reentry only occurred in mid-2017, after the Texas state legislature passed a bill (House Bill 100) which overrode local regulations and implemented a statewide framework for ridesharing companies. Therefore, we use the exit and posterior reentry of ridesharing services to examine whether it led to a relative decline, and later recovery, in housing demand in urban areas focusing on a short window around the exit and reentry events. In particular, we focus on the effect on housing and rental prices in urban areas using monthly rental price data controlling for ZIP code and state-month fixed effects. Therefore, our analysis focuses on the impact of exit/reentry of ridesharing services on quarterly housing/rental prices within the state of Texas. The results of this test are shown in Figure B.4. Consistent with our baseline results, the exit of rideshare services exit led to a 2 percent fall in housing prices and a 4 percent fall in rental prices in urban areas. Upon re-entry of rideshare services the decline in prices was reversed and resumed their growth. Therefore, these two exogenous shocks support our results that the entry of rideshare services has a relative positive effect on housing in urban areas within an MSA.[19] Importantly, in suburban areas, the effect was indistinguishable from zero (not shown).

Instrumenting Rideshare Entry. As a final robustness check, we ensure that our results are not driven by a spurious relation between the entry of rideshare services with unobserved changes in relative demand for urban areas. For example, the observed gentrification could be driven by a change in the preferences of younger individuals to live in urban areas. Furthermore, if this change in preferences is correlated with the size of the MSA (i.e., if the change in preferences for urban areas is stronger in large MSAs), it may be that the entry of rideshare services coincides with this increased attraction for denser areas. While all of our findings show the absence of any pre-trends, which is inconsistent

[19]The higher sensitivity of rental prices to these demand shocks is consistent with (Anenberg and Ringo, 2022). They find that since rental agreements are relatively short-term and involve smaller transaction costs, rental prices tend to respond more immediately to demand shocks such as interest rate changes or labor market shifts.

with a gradual change in preferences, in this section we provide we instrument for the entry of rideshare services in an MSA with their entry in the state. We do this following our findings in Subsection 3.1 showing that the presence of rideshare services in a state is a strong predictor of entry in the state's MSAs (i.e., rideshare services tend to expand locally once already in a region). Furthermore, we limit our sample to MSAs with fewer than 1 million individuals and with income per capita and density in the three middle quintiles. We do this for two reasons, first, the entry decisions into smaller MSAs is likely to be a by-product of their decision to enter in a state. Second, gentrification trends are more likely to be similar in these subgroups of similar MSAs.[20,21]. The results of this refinement are displayed in Table B.13. In columns 1 and 3, we limit our sample to MSAs with a population under 1 million and income per capita and density in the three middle quintiles. The results for this subsample remain strong and similar to our benchmark findings. In columns 2 and 4, we continue with the same sample of MSAs, but instrument for the entry of rideshare services using the entry in the state. Again, the results remain similar.

8 Conclusion

This study is the first to provide a comprehensive analysis of the effect of ridesharing services on the spatial reorganization of high- and low-income households and, consequently, mortgage and housing markets. Our analysis reveals that the introduction of ridesharing services significantly accelerates urban gentrification by attracting higher-income individuals to previously lower-value urban neighborhoods. This influx drives

[20]ZIP codes in these smaller MSAs represent 33 percent of total ZIP codes in all MSAs.

[21]This relation can be seen graphically in both panels of Figure B.7. In the left panel, we relate the entry of rideshare services in an MSA with its population, restricting the sample to MSAs with fewer than 1 million individuals in states in which rideshare services entered 2010 (circles) and states in which they entered after 2014 (crosses). For MSAs in which rideshare services entered in 2010 in the states, rideshare services entered the smaller MSAs in September of 2014, on average, and in June 2016 for the remaining sample. In the right panel, we improve the comparability of MSAs, restricting to MSAs with income per capita and density in the three-middle quintiles

up housing prices, resulting in the displacement of lower-income residents, particularly non-homeowners, who face increased financial stress and higher rates of out-migration. There is also a decline in the in-migration of poorer individuals into urban MSAs. The findings underscore the role of transportation innovations—specifically, private ridesharing services—in reshaping urban demographics and housing markets, leading to more pronounced economic segregation.

Further, the study highlights the differential effects on homeowners versus renters. While homeowners benefit from rising property values and improved financial health, non-homeowners experience increased vulnerability to displacement and credit delinquency. This dynamic contributes to a widening gap in economic and financial inequality between these two groups as gentrification and economic segregation intensify in areas served by ridesharing services.

These findings have important policy implications, as the use of autonomous vehicles by ridesharing firms is likely to amplify these trends. Policymakers must consider interventions that balance the benefits of improved transportation access with the need to protect vulnerable populations from the negative consequences of gentrification, ensuring that the advantages of autonomous vehicles do not disproportionately benefit higher-income individuals at the expense of others.

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Online Appendix for

"How Ridesharing Changed the Demographics of Cities"

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- Appendix B: Supplementary Figures and Tables
- Appendix C: Model of Ridesharing and Gentrification

A Rideshare Entry and the Supply of Ridesharing Services across MSAs

In this subsection, we examine the effect of ridesharing services' entry on the overall supply and revenue of cab drivers. The idea is to use the total cab drivers' supply in an MSA as a proxy for the supply of ride-hailing services.[22] The evolution of Figure 5 plots the entire paths of the average share of drivers and revenues within the MSA in the years surrounding the entry of ridesharing services. Lines around point estimates depict the corresponding 95 percent confidence intervals. We start by noting that the number and revenues of cab drivers only increase after the entry of ridesharing services (Figure 5 and Table 9), suggesting that the entry of these services into an MSA had an important effect on the provision of transportation services. However, after the introduction of ridesharing services in the MSA, there was a substantial increase in the volume and share of the number and revenue of the sector *Taxi and Limousine Service* of single-worker businesses. From both panels, we can see that before the entry of ridesharing services, the sector represented roughly 0.4 percent of the number and 0.3 percent of the revenue,

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[22] As mentioned in the Section 2, we use somewhat more aggregated data from the Census Bureau at the year and MSA levels in the four-digit NAICS sector *Taxi and Limousine Service*, including both ridesharing drivers and taxi and limousine drivers.

respectively, of businesses with no paid employees in an MSA. However, five years after the entry of ridesharing services, the share of businesses and revenue of the "Taxi and Limousine Service" sector more than tripled to 3.1 percent and 1.1 percent, respectively. Similarly, the results in Table 9 report the point estimates for impulse responses using the specification in 1, with similar qualitative results. These results suggest that the entry of ridesharing services had a very large effect on the use of taxi services within an MSA. Furthermore, they do not display any discernible trend before the entry of ridesharing services into an MSA.

The number and revenue of ridesharing services across time and MSAs come from the Census Bureau's Nonemployer Statistics (NES). The NES provides data for businesses with no paid employees (e.g., sole proprietorships, partnerships, and other forms of small businesses) and that are subject to federal income tax. It is available annually, at the MSA level, and covers the North American Industry Classification System (NAICS) sectors at the four-digit level. For our purposes, we focus on sector 4853 *Taxi and Limousine Service*, which includes both rideshare-service drivers as well as taxi and limousine drivers. Summary statistics on the number and revenue of drivers are reported in the *Rideshare Entry and Drivers* panel of Table 1. As we discuss in Appendix A, the entry of ridesharing services into an MSA led to a significant increase in the number and revenue of businesses in NAICS sector 4853 (which includes ridesharing drivers) operating in the MSA.

Figure 5: ***Entry of Rideshare Services and Evolution of the Share of Drivers and Revenues of "Taxi and Limousine Services"***

This figure displays the relation between the entry of rideshare services and the share of drivers (left panel) and the share of revenues (right panel) of the sector *Taxi and Limousine Service* in an MSA. The lines represent the sample average conditional on the year to/from entry of rideshare services in the MSA. Blue vertical bars represent 95 percent confidence intervals.

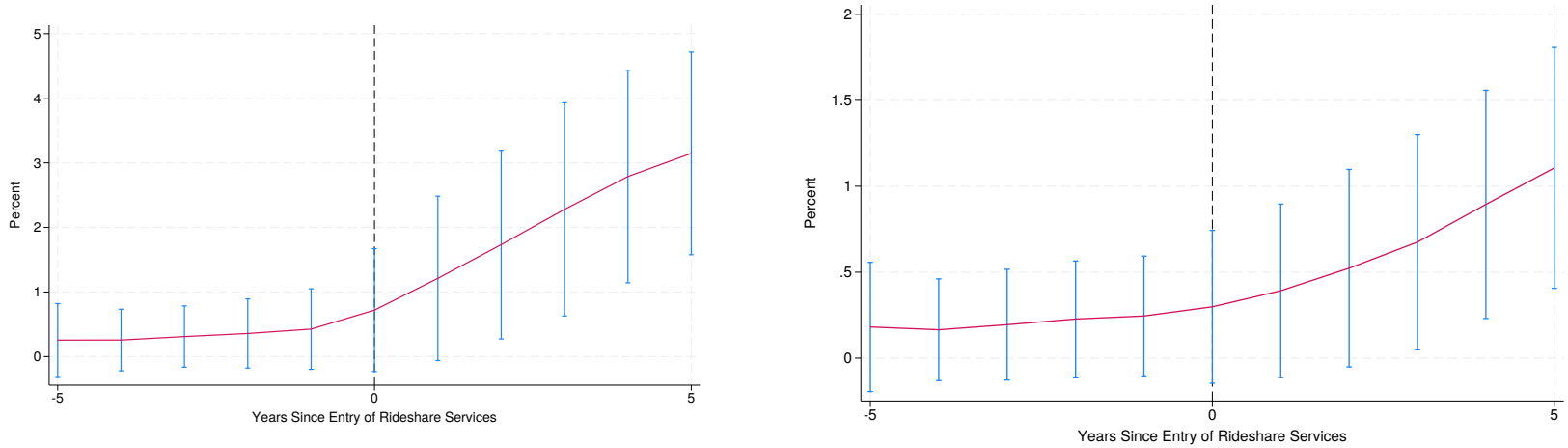


Table 9: ***Impact of Rideshare Services on Supply of Drivers***

This table displays the impact of entry of rideshare services on the supply and revenue of drivers at the MSA level. *Number Drivers*$_{m,y}$, is the number of the drivers (in logs) in MSA m in year y. *Revenue Drivers*$_{m,y}$ is the value of total revenue (in logs) obtained from cab services in MSA m in year y. *Share Number Drivers*$_{m,y}$ is the share of drivers over total workers in MSA m and year y. *Share Revenue Drivers*$_{m,y}$ is the share of revenue received by drivers over revenue of total workers in MSA m and year y. Data on all dependent variables from the *Non-Employer Statistics* compiled by the *Census Bureau*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	Number Drivers$_{m,y}$ (1)	Revenue Drivers$_{m,y}$ (2)	Share Number Drivers$_{m,y}$ (3)	Share Revenue Drivers$_{m,y}$ (4)
PreEntry 2-Years	-0.015	0.029	-0.000	0.000
	(0.061)	(0.086)	(0.000)	(0.000)
PreEntry 1-Years	0.040	0.103	0.000	0.000
	(0.069)	(0.096)	(0.000)	(0.000)
PostEntry 0-Years	0.339***	0.172***	0.002***	0.000***
	(0.029)	(0.038)	(0.000)	(0.000)
PostEntry 1-Years	0.634***	0.401***	0.005***	0.001***
	(0.038)	(0.043)	(0.000)	(0.000)
PostEntry 2-Years	0.747***	0.530***	0.008***	0.002***
	(0.042)	(0.047)	(0.001)	(0.000)
PostEntry 3-Years	0.754***	0.554***	0.011***	0.002***
	(0.044)	(0.054)	(0.001)	(0.000)
PostEntry 4-Years	0.782***	0.656***	0.014***	0.004***
	(0.049)	(0.057)	(0.001)	(0.000)
Observations	5,072	5,072	5,072	5,072
MSA FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Avg. Dep. Variable	4.4	7.1	0.004	0.011

B Supplementary Figures and Tables

Table B.1: ***Variable Definitions***

Variable	Definition
Urban_z	Measure of perceived urbanicity of zip-code z compiled by the *Census' Urbanization Perceptions Small Area Index*.
MSA_m	Geographical region m, defined by the U.S. Office of Management and Budget, that represents a core urban area with a population of at least 50,000, along with adjacent communities that have a high degree of social and economic integration with the core, typically measure by commuting patterns.
$\text{Entry}_{m,y}$	Indicator of whether rideshare services start operations in an MSA m in year y. Data provided by rideshare companies *Uber* and *Lyft*.
$\text{Number of Drivers}_{m,y}$	Number of cab drivers (NAICS 4853) in MSA m in year y as reported by the *Non-Employer Statistics* (NES) from the *Census Bureau* (in logs). Dataset pools drivers of rideshare services with traditional "yellow-cab" drivers.
$\text{Revenue Drivers}_{m,y}$	Value of revenue obtained by cabdrivers in MSA m in year y, as reported by the *NES* (in logs).
$\text{Share of Number of Drivers}_{m,y}$	Fraction of cabdrivers in MSA m over total workers in year y as reported by the *NES*.
$\text{Share of Revenue of Drivers}_{m,y}$	Fraction of revenue in MSA m of cab-driver workers in year y as reported by the *NES*.
Trips Capita_z	Number of rideshare services trips per capita in zip-code z (in logs). Data—for Chicago, New York City, Massachusetts, and San Francisco—obtained from mandatory public reporting.
Google Searches_z	Frequency of per-capita searches of the terms "Uber", "Lyft" or "Rideshare services" in zip-code z relative to total searches in the MSA. Data obtained from *Google Trends* in the month following the entry of a rideshare services in the MSA.
$\text{Number of Households}_{z,y}$	Number of individual income tax returns (in logs) in zip-code z and year y. Data obtained from the *SOI Tax Stats* from the *IRS*.
$\text{Child Credit}_{z,y}$	Share of individual income tax returns that claim a child credit in zip-code z and year y. Data obtained from the *SOI Tax Stats* from the *IRS*.
$\text{Vacancy Rate}_{z,y}$	Percentage of addresses vacant over total addresses in zip-code z in year y. Data obtained from *HUD*.
$\text{Number of Vacancies}_{z,y}$	Number of addresses (in logs) in zip-code z in year y that *USPS* delivery staff have identified as vacant for 90 days or longer. Data obtained from *HUD*.
$\text{Age}_{z,y}$	Average age (in logs) of individuals with a credit report and social security residing in zip-code z and year y. Data obtained from the *Equifax Consumer Credit Panel*.
$\text{\#Mortgage Originations}_{z,y}$	Number of mortgage originations (in logs) in zip-code z in year y. Data obtained from confidential *HMDA*.
$\text{Applicant Income}_{i,y}$	Gross annual income (in logs) of applicant of mortgage i in year y. Data obtained from confidential *HMDA*.
$\text{FHA-Insured}_{i,y}$	Indicator of whether the originated loan i in year y was insured by the Federal House Administration. Data obtained from confidential *HMDA*.
$\text{Mortgage Value}_{i,y}$	Value (in logs) of mortgage i originated in year y. Data obtained from confidential *HMDA*.
$\text{House Price Index}_{z,y}$	Home price index of zip-code z in year y (in logs) calculated using weighted repeat sales. Data obtained from *CoreLogic*.
$\text{Rental Prices}_{z,y}$	Average monthly market rent in zip-code z in year y (in logs). Repeat-rent index weighted by the rental housing stock. Data obtained from *Zillow*.
$\text{Moving Out of Zip-code}_{i,y}$	Indicator that individual i will be living in a different zip-code in $y+1$ relative to the one living in y. Data obtained from the *Equifax Consumer Credit Panel*.
$\text{Late Repayment}_{i,y}$	Indicator that individual i is late on a outstanding debt in year y. Data obtained from the *Equifax Consumer Credit Panel*.
$\text{Median House Price in Zip-code}_{i,y}$	Median house prices (in logs) in the zip-code of the property financed by mortgage i originated in year y. Data obtained from *Zillow Home Value Index*.
$\text{Average Poverty Rate in Zip-code}_{i,y}$	Average poverty rate in the zip-code of the property financed by mortgage i originated in year y. Data obtained from *Census Bureau*.
$\text{Average Minority Share in Zip-code}_{i,y}$	Fraction of non-white households in the zip-code of the property financed by mortgage i originated in year y. Data obtained from *Census Bureau*.
$\text{Population}_{l,y}$	Population in location l in year y (in logs). Data from *Census Bureau*.
$\text{Density}_{l,y}$	Ratio of population to land area of location l in year y. Data from *Census Bureau*.

Table B.1: ***Variable Definitions*** *(Continued)*

Variable	Definition
Car Ownership$_z$	Percent of individuals living in zip-code z who own a car. Data obtained from *American Community Survey*.
Commute Time$_z$	Average commute time (in minutes) in zip-code z. Data obtained from *American Community Survey*.
Parking Cost$_z$	Average cost (in dollars) of monthly parking in zip-code z. Data obtained from *Spot Hero*.
Walkscore$_z$	Measure of how walkable a zip-code z is on a scale from 0 (Car-Dependent) to 100 (Walker's Paradise). Data obtained from *Redfin*.
Transitscore$_z$	Measure of how well a location is served by public transit on a scale from 0 ("Minimal Transit") to 100 ("Rider's Paradise"). Data obtained from *Redfin*.
Rideshare In State$_{m,y-1}$	Indicator of whether rideshare services were operating in the state of MSA m in year *y-1*. Data obtained from *Uber* and *Lyft*.
Income per Household$_{l,y}$	Average income of households in location l and year y as declared in IRS return (in logs).
Unemployment$_{m,y-1}$	Average unemployment rate in MSA m in year *y-1*. Data obtained from *IRS*.

Table B.2: ***Comparison of Urban and Suburban ZIP Codes***

This table compares the average characteristics of *urban* and *suburban* ZIP codes. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. Standard errors are in parenthesis. See Table B.1 in the Appendix for detailed variable definitions.

	Urban	**Suburban**
Population_z('000)	26.7	16.3
	(19.0)	(12.2)
Density_z	3,906	427
	(5,940)	(630)
Income_z	73,906	81,246
	(21,172)	(14,118)
Poverty_z	26.1	6.7
	(12.9)	(5.4)
Car Ownership_z	71.9	95.4
	(13.9)	(3.4)
Commute Time_z	24.3	28.0
	(8.1)	(7.3)
Parking Cost_z	180.5	124.4
	(99.6)	(33.1)
Walkscore_z	62.4	18.9
	(22.0)	(15.4)
Transitscore_z	36.6	16.1
	(24.2)	(20.0)
Number of Zip-Codes	1,952	1,833
Share of Population	63.6	36.4

Table B.3: ***Comparison of Urban and Suburban ZIP Codes***

This table compares the average characteristics of *urban* and *suburban* ZIP codes in the New York MSA. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. Standard errors are in parenthesis. See Table B.1 in the Appendix for detailed variable definitions.

	Urban	**Suburban**
Walkscore_z	95.8	72.4
	(3.7)	(11.8)
Transitscore_z	95.9	62.1
	(6.1)	(13.4)
Parking Costs_z	421.2	315.1
	(109.8)	(56.4)
Car Ownership (High Income)	0.58	0.98
	(0.49)	(0.13)
Car Ownership (Low Income)	0.34	0.88
	(0.48)	(0.32)
Monthly Rent_z	1,405	1,284
	(454)	(232)
Income 90 percentile	316.4	201
	(199.5)	(64.9)
Income 10 percentile	17.1	26.8
	(12.8)	(9.3)
Poverty	0.21	0.11
	(0.11)	(0.09)

Table B.4: ***Characteristics of MSA Prior to Entry of Rideshare Services***

This table relates the characteristics of an MSA with the entry year of rideshare services. The dependent variable $Entry_{m,y}$ is a yearly indicator of whether rideshare services entered MSA m in year y. Observations of an MSA are dropped for all years after entry. $Population_{m,y-1}$ is the population (in logs) living in MSA m in year *y-1*. $Density_{m,y-1}$ is measured as population of MSA m in year *y-1* over the area of the MSA. $Rideshare\ In\text{-}State_{m,y-1}$ is an indicator of whether rideshare services have already entered the state of the MSA m by year *y-1*. $Income\ per\ Household_{m,y}$ are the average earnings (in logs) of households living in MSA m in year *y-1*. $Unemployment_{m,y-1}$is the unemployment rate of MSA m in year *y-1*. $Current\ Economic\ Conditions_{s,y-1}$ is an index of current economic conditions of state s in year *y-1*. $Future\ Economic\ Conditions_{s,y-1}$ is an index of expected economic conditions of state s in year *y-1*. $Population\ Growth_{m,y-1}$ is the yearly growth of population of MSA m in year *y-1*. $Growth\ Young\ Population_{m,y-1}$ is the yearly growth of rate of individuals under 45 year-old in MSA m in year *y-1*. $House\ Price\ Growth_{m,y-1}$ is the yearly growth of rate of house prices in MSA m in year *y-1*. $Mortgage\ Growth_{m,y-1}$ is the yearly growth of rate of the number of mortgages in MSA m in year *y-1*. Data on population, income per household, and unemployment obtained from IRS's individual tax returns. Data on density obtained from the *Census Bureau*. Data on economic conditions obtained from the Philadelphia Fed. Data on young population obtained from *Equifax*. Data on housing price growth obtained from *Corelogic*, while data on mortgages obtained from *HMDA*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors clustered at the MSA level. See Table B.1 in the Appendix for detailed variable definitions.

	$Entry_{m,y}$			
	(1)	(2)	(3)	(4)
$Population_{m,y-1}$	0.132**	0.132**	0.099**	0.093**
	(0.055)	(0.054)	(0.037)	(0.035)
$Rideshare\ In\text{-}State_{m,y-1}$		0.105**	0.102**	0.101**
		(0.033)	(0.033)	(0.033)
$Density_{m,y-1}$			0.132	0.135
			(0.083)	(0.084)
$Income\ per\ Household_{m,y-1}$			0.033	0.066
			0.086)	(0.075)
$Unemployment_{m,y-1}$			-0.920	-0.974
			(0.532)	(0.679)
$Current\ Economic\ Conditions_{s,y-1}$			0.703	-0.987
			(0.636)	(0.798)
$Future\ Economic\ Conditions_{s,y-1}$			-0.005	-0.003
			(0.044)	(0.051)
$Population\ Growth_{m,y-1}$				-0.011
				(0.008)
$Growth\ Young\ Population_{m,y-1}$				0.082
				(0.246)
$House\ Price\ Growth_{m,y-1}$				-0.027
				(0.065)
$Mortgage\ Growth_{m,y-1}$				0.292
				(0.261)
Observations	2,185	2,185	2,185	2,185
R-squared	0.291	0.298	0.301	0.301
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table B.5: ***Entry of Rideshare Services and Demographic Characteristics of Households – Pooled ZIP Codes***

This table displays the results of a regression relating the entry of rideshare services with the number of high- and low-income households, average age and number of child-credit deductions in a ZIP code. Regressions pool urban and suburban ZIP codes together. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the *Census' Urbanization Perceptions Small Area Index*. *Urban* ZIP codes are the treatment group for the entry of rideshare services in an MSA. *Number of High-Income (Low-Income) Households*$_{z,y}$ is the number of individual tax returns (in logs) in ZIP code z in year y with a household income equal or above (below) USD 50,000. *Age*$_{z,y}$ is the average age (in logs) of individuals with credit report in ZIP code z in year y, compiled from *Equifax CCP*. *Child Credit*$_{z,y}$ is the percentage of tax returns that claim a child credit in ZIP code z in year y, obtained from the *IRS*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	Number of High-Income Households$_{z,y}$ (1)	Number of Low-Income Households$_{z,y}$ (2)	Age$_{z,y}$ (3)	Child Credit$_{z,y}$ (4)
PreEntry 2-Years	0.012	-0.016	-0.001	0.000
	(0.009)	(0.007)	(0.015)	(0.001)
PreEntry 1-Years	0.010	-0.027	-0.001	0.001
	(0.010)	(0.007)	(0.017)	(0.001)
PostEntry 0-Years	0.023***	-0.041***	-0.006***	0.001
	(0.005)	(0.006)	(0.001)	(0.001)
PostEntry 1-Years	0.033***	-0.056***	-0.007***	-0.002*
	(0.005)	(0.007)	(0.001)	(0.001)
PostEntry 2-Years	0.040***	-0.076***	-0.010***	-0.001
	(0.006)	(0.008)	(0.001)	(0.001)
PostEntry 3-Years	0.060***	-0.094***	-0.011***	-0.004***
	(0.007)	(0.009)	(0.001)	(0.001)
PostEntry 4-Years	0.078***	-0.115***	-0.011***	-0.008***
	(0.008)	(0.011)	(0.001)	(0.002)
Observations	52,198	52,198	36,384	43,769
Zip-code FE	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes
Average Dep. Variable	8	8.5	4.3	0.15

Table B.6: ***Entry of Rideshare Services, Mortgage Originations and Characteristics of Applicants – Pooled ZIP Codes***

This table displays the results of regressions relating the entry of rideshare services with the number and characteristics of mortgage applicants. Regressions pool urban and suburban ZIP codes together. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. *Urban* ZIP codes are the treatment group for the entry of rideshare services in an MSA. #*Mortgage Originations*$_{z,y}$ is the number of mortgage originations (in logs) in ZIP code z in year y. *Applicant Income*$_{i,y}$ is the gross annual income of applicant i in year y (in logs). *FHA-Insured*$_{i,y}$ is an indicator that mortgage i originated in year y is insured by the Federal Housing Administration. Dependent variables obtained from *HMDA confidential*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	#Mortgage Originations$_{z,y}$ (1)	Applicant Income$_{i,y}$ (2)	FHA-Insured$_{i,y}$ (3)
PreEntry 2-Years	-0.047	0.004	0.005
	(0.035)	(0.009)	(0.005)
PreEntry 1-Years	-0.055	-0.001	0.003
	(0.035)	(0.011)	(0.006)
PostEntry 0-Years	0.005	0.002	-0.005
	(0.012)	(0.006)	(0.004)
PostEntry 1-Years	0.034**	0.011*	-0.014***
	(0.016)	(0.006)	(0.005)
PostEntry 2-Years	0.074***	0.022***	-0.018***
	(0.022)	(0.006)	(0.005)
PostEntry 3-Years	0.130***	0.036***	-0.029***
	(0.027)	(0.009)	(0.005)
PostEntry 4-Years	0.190***	0.040***	-0.036***
	(0.032)	(0.013)	(0.005)
Observations	32,921	7,804,222	7,804,222
Zip-code FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Average Dep. Variable	5	4.5	0.19

Table B.7: ***Entry of Rideshare Services and Housing Vacancies***

This table displays the results of a regression relating the entry of rideshare services with housing vacancies, in urban and suburban ZIP codes. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. *Vacancy Rate*$_{z,y}$ is the percentage of vacant addresses of a ZIP code z in year y. *Number of Vacancies*$_{z,y}$ is the number (in logs) of vacant addresses of ZIP code z in year y, compiled by the USPS. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	Vacancy Rate$_{z,y}$		Number of Vacancies$_{z,y}$	
	(1)	(2)	(3)	(4)
PreEntry 2-Years	-0.047	-0.068	-0.002	-0.003
	(0.126)	(0.103)	(0.020)	(0.069)
PreEntry 1-Years	-0.171	-0.084	-0.039	-0.026
	(0.159)	(0.118)	(0.026)	(0.086)
PostEntry 0-Years	-0.180***	0.052	-0.048***	-0.015
	(0.046)	(0.045)	(0.014)	(0.029)
PostEntry 1-Years	-0.422***	-0.068	-0.145***	-0.116***
	(0.085)	(0.073)	(0.025)	(0.041)
PostEntry 2-Years	-0.430***	-0.144*	-0.112***	-0.143***
	(0.123)	(0.080)	(0.027)	(0.054)
PostEntry 3-Years	-0.632***	-0.089	-0.156***	0.002
	(0.142)	(0.101)	(0.028)	(0.057)
PostEntry 4-Years	-0.762***	-0.131	-0.193***	-0.075
	(0.162)	(0.118)	(0.029)	(0.086)
Observations	11,515	10,093	11,515	10,093
Zip-code FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Sample of Zip-codes	Urban	Suburban	Urban	Suburban
Avg(Dependent Variable)	4.3	1.4	9.2	8.7

Table B.8: ***Entry of Rideshare Services and Housing Vacancies – Pooled ZIP Codes***

This table displays the results of a regression relating the entry of rideshare services with housing vacancies, pooling urban and suburban ZIP codes together. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the *Census' Urbanization Perceptions Small Area Index*. *Urban* ZIP codes are the treatment group for the entry of rideshare services in an MSA. *Vacancy Rate*$_{z,y}$ is the percentage of vacant addresses of ZIP code z in year y. *Number of Vacancies*$_{z,y}$ is the number (in logs) of vacant addresses of ZIP code z in year y, compiled by the USPS. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	Vacancy Rate$_{z,y}$ (1)	Number of Vacancies$_{z,y}$ (2)
PreEntry 2-Years	-0.159	0.001
	(0.102)	(0.009)
PreEntry 1-Years	-0.161	-0.003
	(0.113)	(0.009)
PostEntry 0-Years	-0.303***	-0.011**
	(0.057)	(0.005)
PostEntry 1-Years	-0.823***	-0.029***
	(0.073)	(0.005)
PostEntry 2-Years	-0.685***	-0.035***
	(0.083)	(0.007)
PostEntry 3-Years	-0.626***	-0.041***
	(0.108)	(0.008)
PostEntry 4-Years	-0.583***	-0.054***
	(0.142)	(0.009)
Observations	30,813	30,813
Zipcode FE	Yes	Yes
MSA-Year FE	Yes	Yes
Average Dep. Variable	2.9	8.9

Table B.9: ***Entry of Rideshare Services and ZIP codes of Mortgage Originations – Pooled ZIP Codes***

This table displays the results of regressions relating the entry of rideshare services with the characteristics of ZIP codes of the properties for which mortgages were originated. Regressions pool urban and suburban ZIP codes together. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. *Urban* ZIP codes are the treatment group for the entry of rideshare services in an MSA. *Median House Price in ZIP code*$_{i,y}$ is the median house price (in logs) in the ZIP code of the property financed by mortgage i originated in year y. *Average Poverty Rate in ZIP code*$_{i,y}$ is the average poverty rate in the ZIP code of the property financed by mortgage i originated in year y. *Average Minority Share in ZIP code*$_{i,y}$ is the average share of minority individuals of the ZIP code of the property financed by mortgage i originated in year y. Mortgage information obtained from *HMDA confidential*, while information on the dependent variables obtained from the *Census Bureau*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	Median House Price in Zip-code$_{i,y}$	Average Poverty Rate in Zip-code$_{i,y}$	Average Minority Share in Zip-code$_{i,y}$
	(1)	(2)	(3)
PreEntry 2-Years	0.007	-0.001	-0.002
	(0.005)	(0.001)	(0.002)
PostEntry 1-Years	0.001	-0.001	-0.001
	(0.005)	(0.001)	(0.002)
PostEntry 0-Years	-0.007*	-0.001	0.000
	(0.004)	(0.000)	(0.001)
PostEntry 1-Years	-0.002	0.000	0.003**
	(0.006)	(0.001)	(0.001)
PostEntry 2-Years	-0.010	0.002**	0.008***
	(0.008)	(0.001)	(0.002)
PostEntry 3-Years	-0.018**	0.003***	0.011***
	(0.009)	(0.001)	(0.002)
PostEntry 4-Years	-0.032***	0.006***	0.015***
	(0.009)	(0.001)	(0.003)
Observations	7,804,222	7,804,222	7,804,222
MSA-Urban FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Avg. Dep. Variable	12.4	0.09	0.27

Table B.10: ***Entry of Rideshare Services, House Prices and Rental Prices – Pooled ZIP Codes***

This table displays the results of a regression relating the entry of rideshare services with housing prices and rental prices, pooling urban and suburban ZIP codes together. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the *Census' Urbanization Perceptions Small Area Index*. *Urban* ZIP codes are the treatment group for the entry of rideshare services in an MSA. *House Price Index*$_{z,y}$ is an index of house prices (in logs) at the ZIP code z year y, obtained from *Corelogic*. *Rental Prices*$_{z,y}$ is the average market rental prices (in logs) of ZIP code z in year y, obtained from *Zillow*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	House Price Index$_{z,y}$ (1)	Rental Prices$_{z,y}$ (2)
PreEntry 2-Years	-0.020	0.001
	(0.021)	(0.004)
PreEntry 1-Years	-0.014	0.007
	(0.021)	(0.006)
PostEntry 0-Years	0.008***	0.007*
	(0.002)	(0.004)
PostEntry 1-Years	0.013***	0.014***
	(0.003)	(0.004)
PostEntry 2-Years	0.023***	0.022***
	(0.003)	(0.005)
PostEntry 3-Years	0.035***	0.024***
	(0.004)	(0.006)
PostEntry 4-Years	0.045***	0.029***
	(0.004)	(0.007)
Observations	31,210	33,254
Zipcode FE	Yes	Yes
MSA-Year FE	Yes	Yes
Average Dep. Variable	5.0	7.4

Table B.11: ***Entry of Rideshare Services and Relocation Away From ZIP Code – Pooled ZIP Codes***

This table displays the results of regressions relating the entry of rideshare services with the moving of individuals away from their current ZIP code of residence, pooling urban and suburban ZIP codes together. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. *Urban* ZIP codes are the treatment group for the entry of rideshare services in an MSA. *Moving Out ZIP Code*$_{i,y+1}$ is an indicator of whether individual *i* has a different residential ZIP code in year *y+1* relative to year *y*. *Controls* are a series of individual variables, including age (in logs), outstanding debt (in logs), FICO score (in logs), and an indicator of current late repayment. *Homeowner (Non-Homeowner)* are individuals that have (not) had a mortgage or home-equity loan in their current ZIP code. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	Moving Out of Zip-Code$_{i,y+1}$		
	(1)	(2)	(3)
PreEntry 2-Years	-0.004*	-0.004	-0.002
	(0.002)	(0.003)	(0.003)
PostEntry 1-Years	-0.004*	-0.005*	-0.002
	(0.002)	(0.003)	(0.003)
PostEntry 0-Years	0.003**	0.004**	-0.000
	(0.001)	(0.002)	(0.003)
PostEntry 1-Years	0.002	0.003*	0.001
	(0.002)	(0.002)	(0.003)
PostEntry 2-Years	0.002	0.003*	0.001
	(0.002)	(0.002)	(0.003)
PostEntry 3-Years	0.005***	0.007*	0.004
	(0.002)	(0.002)	(0.003)
PostEntry 4-Years	0.007***	0.008**	0.005***
	(0.002)	(0.003)	(0.003)
Observations	2,412,835	1,409,125	1,001,124
Controls	Yes	Yes	Yes
Zip-code FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Sample	All	Non-Homeowner	Homeowner
Avg. Dep. Variable	0.1	0.12	0.06

Table B.12: ***Entry of Rideshare Services and Late Credit – Pooled ZIP Codes***

This table displays the results of regressions relating the entry of rideshare services with the short-term credit quality of individuals, pooling urban and suburban ZIP codes together. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. *Urban* ZIP codes are the treatment group for the entry of rideshare services in an MSA. *Late Repayment*$_{i,y+2}$ is an indicator of whether individual i is late on his/her payments in year y+2. *Controls* are a series of individual variables, including age (in logs), outstanding debt (in logs), FICO score (in logs), and an indicator of current late repayment. *Homeowner (Non-Homeowner)* are individuals that have (not) had a mortgage or home-equity loan in their current ZIP code. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	Late Repayment$_{i,y+2}$		
	(1)	(2)	(3)
PreEntry 2-Years	-0.000	0.001	-0.006**
	(0.001)	(0.002)	(0.003)
PostEntry 1-Years	0.001	0.001	-0.007**
	(0.002)	(0.002)	(0.003)
PostEntry 0-Years	0.002***	0.002*	0.000
	(0.001)	(0.001)	(0.001)
PostEntry 1-Years	0.003***	0.003***	-0.001
	(0.001)	(0.001)	(0.001)
PostEntry 2-Years	0.004***	0.005***	0.001
	(0.001)	(0.001)	(0.001)
PostEntry 3-Years	0.004***	0.004***	0.001
	(0.001)	(0.001)	(0.002)
PostEntry 4-Years	0.005***	0.004***	-0.001
	(0.001)	(0.001)	(0.002)
Observations	2,175,947	1,279,590	896,338
Controls	Yes	Yes	Yes
Zip-code FE	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes
Sample	All	Non-Homeowner	Homeowner
Avg. Dep. Variable	0.023	0.021	0.027

Table B.13: ***Entry of Rideshare Services and House and Rental Prices - Robustness***

This table displays the results of regressions relating the entry of rideshare services, in both the MSA and in the state, with housing and rental prices at the ZIP code*year level, in urban and suburban ZIP codes of MSAs below 500 thousand individuals. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. *House Price Index*$_{z,y}$ is an index of house prices (in logs) at the ZIP code z in year y, obtained from *Corelogic*. *Rental Prices*$_{z,y}$ is the average monthly market rent (in logs) of ZIP code z in year y, obtained from *Zillow*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table B.1 in the Appendix for detailed variable definitions.

	House Price Index$_{z,y}$		Rental Prices$_{z,y}$	
	(1)	(2)	(3)	(4)
PreEntry 2-Years	-0.017	-0.026	0.018	-0.049
	(0.018)	(0.033)	(0.019)	(0.080)
PreEntry 1-Years	0.003	-0.029	0.026	-0.068
	(0.023)	(0.045)	(0.024)	(0.106)
PostEntry 0-Years	0.032***	0.005	0.045***	-0.0090
	(0.012)	(0.009)	(0.0078)	(0.0084)
PostEntry 1-Years	0.062***	-0.007	0.059***	-0.019
	(0.018)	(0.015)	(0.0098)	(0.015)
PostEntry 2-Years	0.077***	0.032	0.079***	-0.0072
	(0.023)	(0.022)	(0.013)	(0.026)
PostEntry 3-Years	0.106***	0.132***	0.106***	0.050***
	(0.029)	(0.027)	(0.016)	(0.017)
PostEntry 4-Years	0.110***	0.228***	0.097***	0.14***
	(0.032)	(0.034)	(0.017)	(0.032)
Observations	3,911	2,339	6,165	2,749
Zip-code FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Rideshare Entry	MSA	State	MSA	State
MSA Population	<1 Million	<1 Million	<1 Million	<1 Million
Sample of Zip-codes	Urban	Urban	Urban	Urban

Figure B.1: ***Entry of Rideshare Services and Number of Mortgage Originations***

This figure displays the evolution of yearly coefficients of a regression relating the entry of rideshare services and the number of mortgage originations in urban and suburban ZIP codes, in the left and right panels respectively. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. Regressions include ZIP code and state*year fixed effects. Standard errors are clustered at the ZIP code level. The blue vertical bars represent confidence intervals of the coefficients at the 95 percent significance level. See Table B.1 in the Appendix for detailed variable definitions.

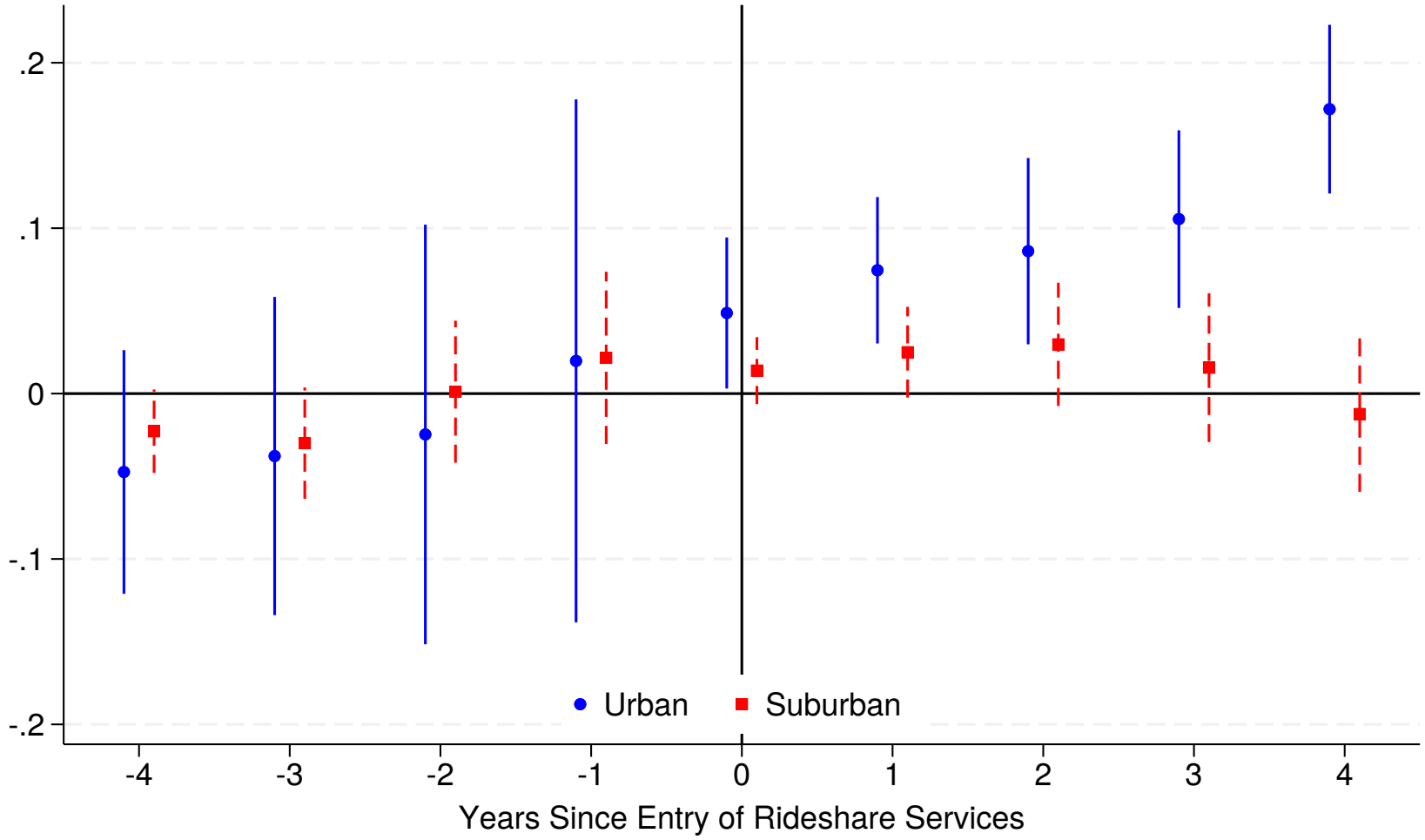
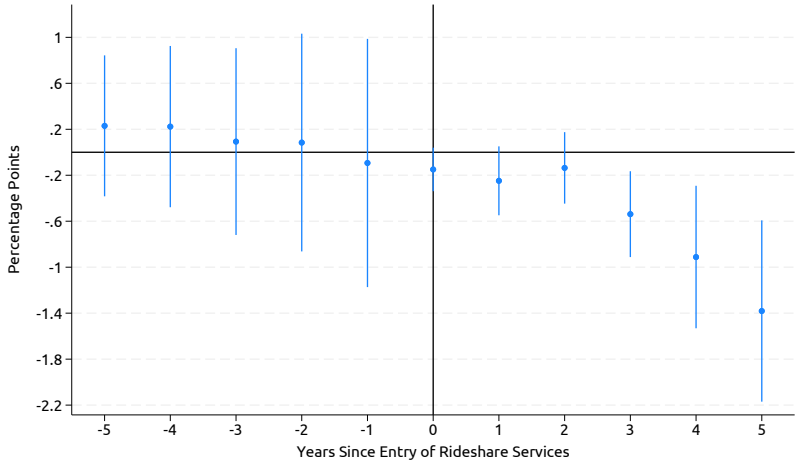


Figure B.2: ***Entry of Rideshare Services and Vacancy Rates***

This figure displays the evolution of yearly coefficients of a regression relating the entry of rideshare services with housing-vacancy rates in urban and suburban ZIP codes, in the left and right panels respectively. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index.* Regressions include ZIP code and state*year fixed effects. Standard errors are clustered at the ZIP code level. The blue vertical bars represent confidence intervals of the coefficients at the 95 percent significance level. See Table B.1 in the Appendix for detailed variable definitions.

(A) Urban ZIP codes



(B) Suburban ZIP codes

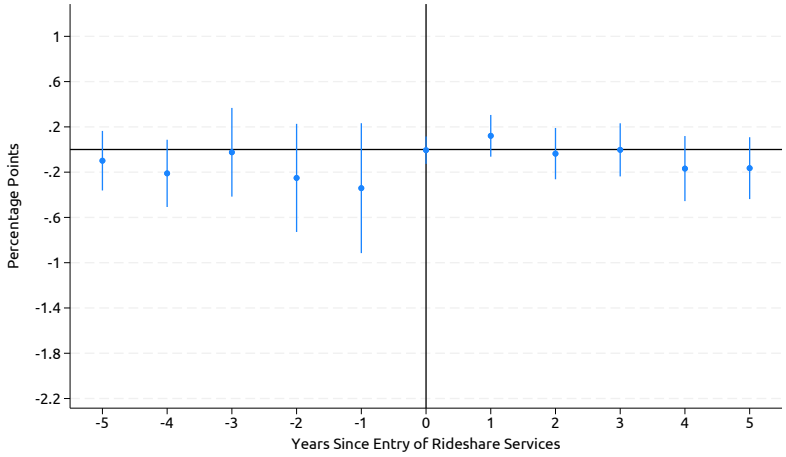
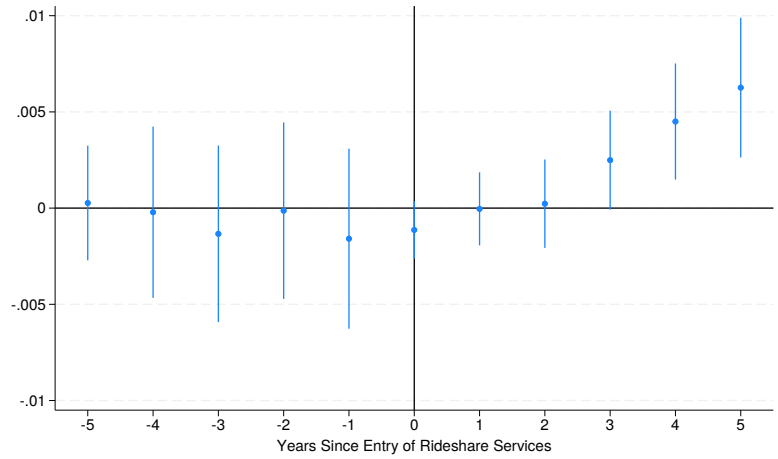


Figure B.3: ***Entry of Rideshare Services and Poverty Rate of ZIP codes of Mortgage Originations***

This figure displays the evolution of yearly coefficients of a regression relating the entry of rideshare services with the poverty rate of the ZIP codes of the mortgage originations in urban and suburban ZIP codes, in the left and right panels respectively. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. Regressions include MSA and state*year fixed effects. Standard errors are clustered at the ZIP code level. The blue vertical bars represent confidence intervals of the coefficients at the 95 percent significance level. See Table B.1 in the Appendix for detailed variable definitions.

(A) Urban ZIP codes



(B) Suburban ZIP codes

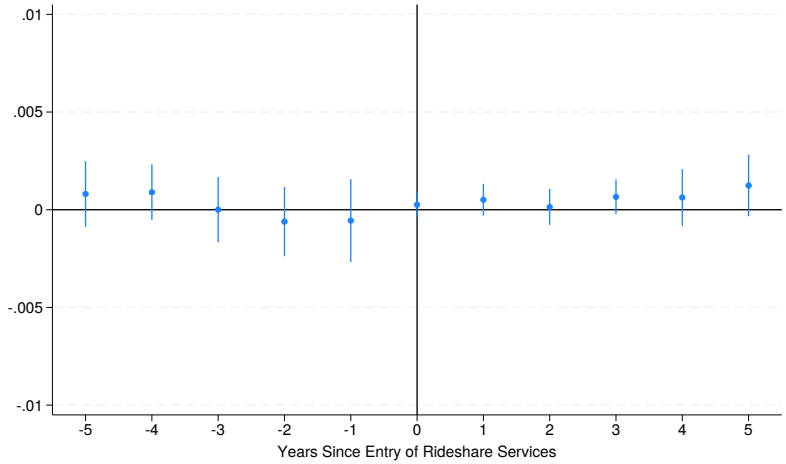
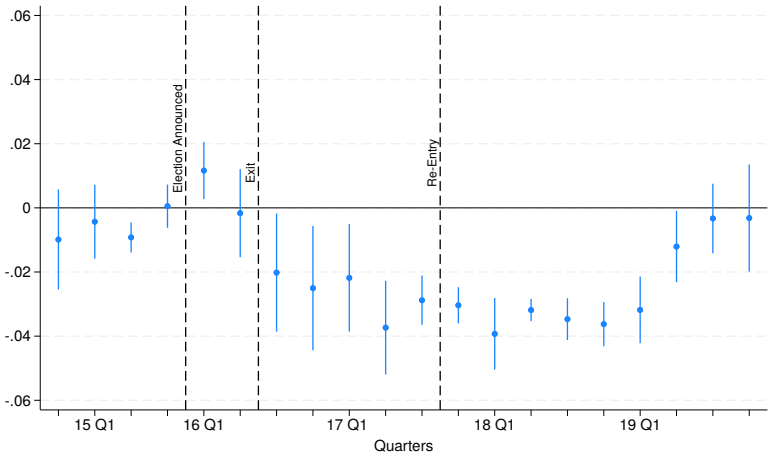


Figure B.4: ***Exit of Rideshare Services and Housing and Rental Prices - The Case of Austin***

This figure displays the evolution of quarterly coefficients of a regression relating the exit of rideshare services from Austin and the average housing and rental prices in urban ZIP codes, in the left and right panels respectively. *Urban* ZIP codes are in the top quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. Regressions include ZIP code and state*quarter fixed effects. Standard errors are clustered at the ZIP code level. The vertical dashed black line to the left represents the quarter in which Austin legislature passed the ordinance regulating rideshare companies. The vertical dashed line in the middle represents the quarter in which *Uber* and *Lyft* stopped operations in Austin. The vertical dashed line in the right represents the quarter in which *Uber* and *Lyft* re-started operations in Austin. The blue vertical bars represent confidence intervals of the coefficients at the 95 percent significance level. See Table B.1 in the Appendix for detailed variable definitions.

(A) Housing Prices



(B) Rental Prices

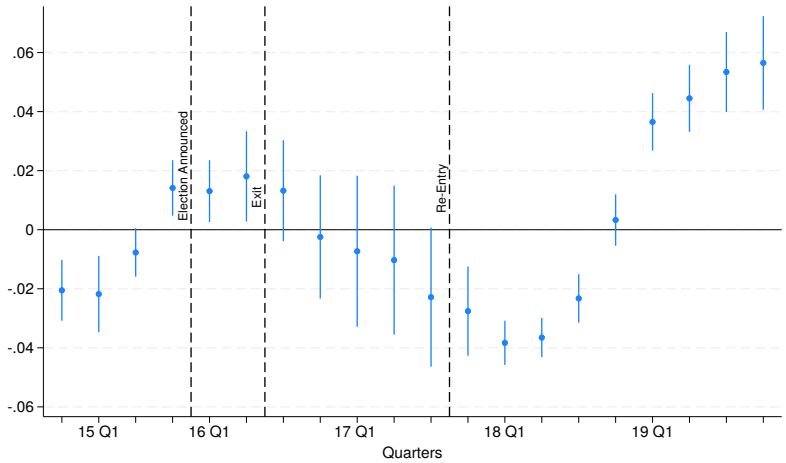


Table B.14: ***Characteristics of Homeowners vs non-Homeowners***

This table compares the average characteristics of homeowners and non-homeowners in our sample. Standard errors are in parenthesis. *Homeowners (Non-Homeowners)*, are those individuals that have had (have not had) either a mortgage or an home-equity loan in current zip-code. See Table B.1 in the Appendix for detailed variable definitions.

	Homeowner	**Non-Homeowner**
Age_i	48.80	42.20
	(9.90)	(11.20)
FICO_i	748	659
	(89)	(161)
Moving Out of Zip-Code_i	0.07	0.12
	(0.26)	(0.33)
Income_z	76,912	56,965
	(21,118)	(20,254)
Poverty_z	0.11	0.19
	(0.09)	(0.10)

Figure B.5: ***Urbanicity and Average Monthly Parking Costs in New York City***

This figure compares the urbanicity of zip-codes in New York City with average monthly parking costs. *urbanicity* is measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*.

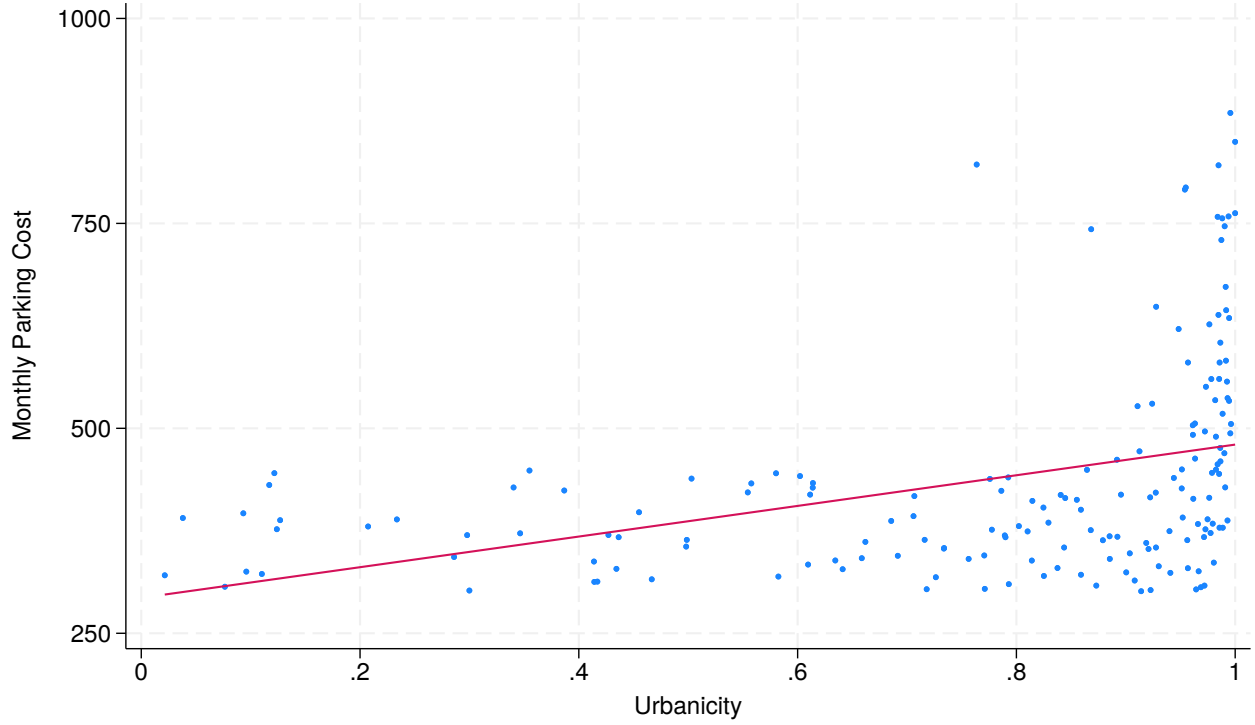
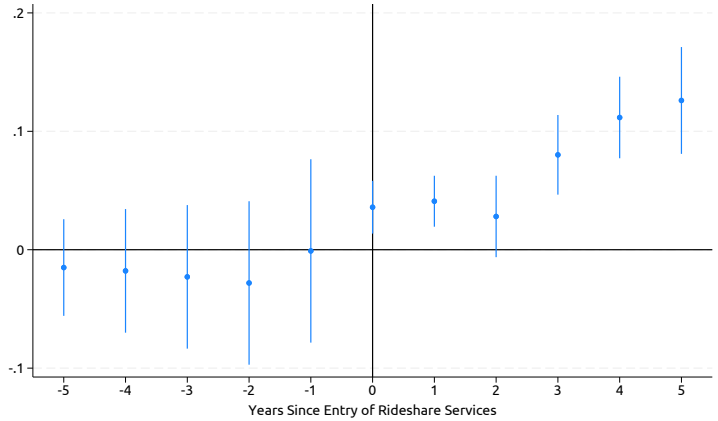


Figure B.6: ***Entry of Rideshare Services and Value of Originated Mortgages***

This figure displays the evolution of yearly coefficients of a regression relating the entry of rideshare services with the average value of originated mortgages (in logs) in urban and suburban zip-codes, in the left and right panels respectively. *Urban (Suburban)* zip-codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census' *Urbanization Perceptions Small Area Index*. Regressions include zip-code and state*year fixed effects. Standard errors are clustered at the zip-code level. The blue vertical bars represent confidence intervals of the coefficients at the 95 percent significance level. See Table B.1 in the Appendix for detailed variable definitions.

(A) Urban Zip-Codes



(B) Suburban Zip-Codes

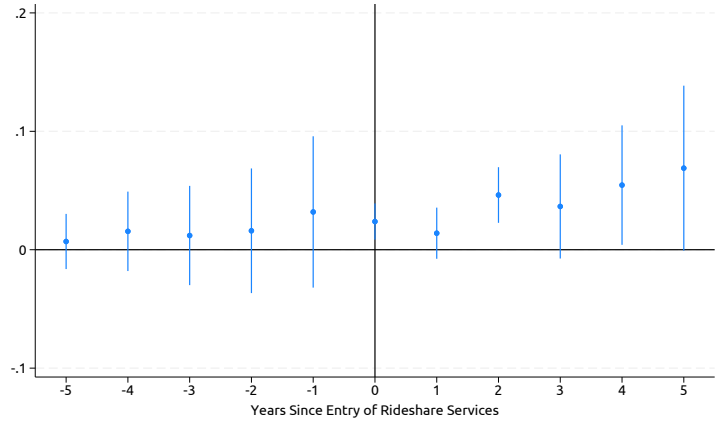
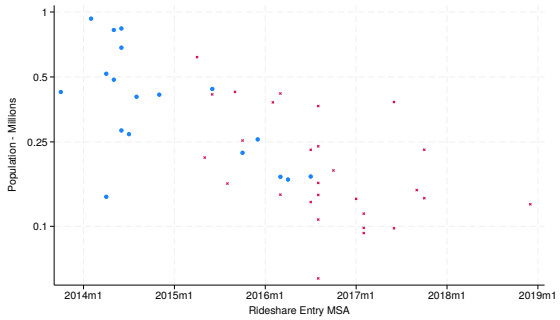


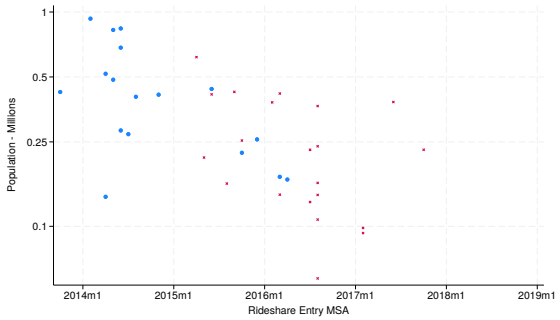
Figure B.7: ***Entry of Rideshare Services in MSAs given Entry in State - MSAs w/ Population <1 Million***

This figure displays the relation between MSA population and entry of rideshare services, in MSAs with rideshare entry in their state in 2010 (circles) after 2014 (crosses). Both panels are limited to all MSAs with a population below 1 million individuals. The panel to the right, is also limited to MSAs with income per capital and density in the three middle-quintiles.

(A) Unconditional



(B) Conditional on MSA Characteristics



C Model of Joint Choice of Housing-Transportation Bundles

In this section, we present a simple model to motivate and illustrate the impact that ridesharing services can have on gentrification. For that we create a simple setup where individuals have to trade-off consumption for transportation time associated with consumption. Importantly, transportation depends on location and mode of transportation (private/public). Urban areas have higher housing prices but more efficient transportation.

C.1 Setup

In the model, individuals differ on income and derive positive utility from consumption and negative utility from the travel time necessary for said consumption. They only decide where to live l∈{u,s} (i.e., urban vs suburban areas) and their mode of transportation v∈{c,p} (i.e., private vs public transportation).

Location. When individuals decide where to live, they must purchase housing services (e.g., rent). There are no operational costs related to running homes, and we assume that the housing market is competitive. Given the relative scarcity of land in denser cores, there is a unit mass of $\mu < 1$ housing available in urban areas and infinite housing available in the suburbs. Therefore, there will be an endogenous price h_l clearing the housing market. This assumption leads mechanically to a potential housing premium of living in urban areas.

Transportation. Travel time to consume amenities depends both on the mode of transportation and individuals' location. Private vehicles reduce travel time, and we assume a lower travel time to consume amenities when living in an urban area.[23] To capture the empirical fact of shorter commute times from suburban areas with personal vehicles compared to urban areas using public transportation, we assume that the travel time from suburban areas using private vehicles is shorter than the travel time in urban areas using public transportation.[24] For simplicity, we assume that the travel time from urban areas using a private vehicle is zero.

Therefore, denoting $\tau^{l,v}$ as the travel time from location l using v we have the following relation:

[23]This assumption is motivated by the higher walk score and transit scores in urban areas.

[24]This assumption also helps capture the hedonic benefits of personal transportation (Baum-Snow, 2007).

$$0 = \tau^{u,c} < \tau^{s,c} < \tau^{u,p} < \tau^{s,p} < \infty \tag{3}$$

For simplicity we assume public transportation is free and that private transportation has two relevant pecuniary costs. The fixed cost of private transportation f along with a a parking cost proportional to the price of housing h^l and equal to λh^l.

Income. There is a mass 1 of individuals with income w_i uniformly distributed in $[0, 1]$. Individual i utility is positively dependent on consumption $g(c_i)$. As standard, we assume that $g(c_i)$ is continuous and $\lim_{c \to 0^+} g(c) = \infty$, $g' > 0$, and $g'' < 0$. Finally, there is a linear disutility related with the travel time to purchase goods $\tau^{l,v} c_i$. As mentioned above, this disutility depends on individuals' location l (urban vs suburban) and on the mode of transportation m (public vs private). Overall, the utility of an individuals is described as:

$$U(c_i; v, l) = g(c_i) - \tau^{l,v} c_i \tag{4}$$

The budget constraint of individuals is such that their income w_i must be greater or equal to the price of housing services plus the financial cost of a vehicle plus the quantity of consumption. More concretely, budget constraint is such that:

$$(1 + \lambda_{l,v}) h_l + f_v + c_i \leq w_i \tag{5}$$

Therefore, the utility from the four different options for individual i are

Table C.15: ***Utility Functions in Urban and Suburban Areas***

	Urban	**Suburban**
Private	$g(w_i - (1+\lambda)h_u - f)$	$g(w_i - f) - \tau^{s,c}(w_i - f)$
Public	$g(w_i - h_u) - \tau^{u,p}(w_i - h_u)$	$g(w_i) - \tau^{s,p} w_i$

Given the decreasing marginal utility on consumption, higher-income individuals have stronger incentives to reduce the linear transportation costs associated with consumption.

C.2 Equilibrium

Given the fixed housing supply in urban areas, we start by establishing that there is a fixed number of individuals living in both urban and suburban areas with a housing price h^l clearing markets such that demand equals supply in urban areas.

Result 1. There is a fixed number of individuals μ living in urban areas and 1 - μ living in suburban areas.

Proof. Given competitive markets, infinite supply of housing and since there are no operational costs of housing services, the price of housing in suburban areas h^s is zero. If the demand for housing in urban areas is below supply μ, then the price of housing in urban areas h_s is zero. In this case, the utility of living in urban areas is always higher than that of suburban areas regardless of the transportation method v, as can be seen directly in Table C.15. Conversely, if demand for housing is above the supply price h_u increases until the market clears.

Result 2. There exists an income level below which all individuals prefer to live in a suburban area using public transportation.

Proof. For a sufficiently low income level, and given the assumptions on functional form of $g(c_i)$ marginal utility of consumption is higher than the disutility of transportation.

Result 3 If an individual i with income w_i prefers to live in an urban location with private transportation, then all individuals with a higher income w_i also prefer to live in urban locations with private transportation.

Proof The marginal utility of increased income is always higher for the pair (urban,private).

For brevity, and given the empirical regularities, in the remainder of this section, we focus on the set of parameters for which there are equilibria in which all four pairs of location/transportation are populated. Let us define three income levels w^*, w_* and w_{**} such that for individuals with w^* we have U(urban,private) = U(suburban,private), for individuals with w_* we have U(suburban,private) = U(urban,public) and for individuals with a w_{**} they have U(urban,public) = U(suburban,public). Therefore, we get the following result.

Result 4. Individuals with incomes w_i such that $w_i > w^*$ choose urban areas with private transportation. Individuals with income w_i such that $w_* < w_i < w^*$ prefer suburban areas with private transportation with $w^* < \mu$. Individuals with income w_i such that $w_{**} < w_i < w_*$ prefer urban areas with public transportation and individuals with income w_i such that $w_i < w_{**}$ prefer suburban areas and use public transportation.

Proof For individuals with income above w^* from result 1, the option (urban, private) dominates. For individuals with income below w_{**} from result 2, the option (suburban, public) dominates. For individuals with income above w_* and below w^* option U(urban,private) = U(suburban,private), with income w_* U(suburban,private) = U(urban,public) and income w_{**} U(urban,public) = U(suburban,public)

A graphical display of these results is presented in the left panel of C.8. Very high-income individuals choose to live in urban areas using private mode of transportation to avoid transportation cost to consume. Individuals with income a touch below w^* prefer to save on housing costs in urban areas (inclding parking) but still use private transportation to reduce transportation costs. Individuals with an income a touch below w_* prefer to pay housing services in urban areas but save on private transportation. Finally, individuals with income below w_{**} prefer to spend all their income on consumption given their relatively high marginal utility of consumption.

Given the above results, we have that housing price h_u is such that housing supply μ is equal to housing demand $1 - w^* + w_* - w_{**}$.

C.3 Entry of Ridesharing Services

We argue that the entry of rideshare services introduces an option of private transportation that reduces associated parking costs λ. Therefore, and in the context of our model, the entry of rideshare services has the direct effect of increasing the value of living in an urban area with private transportation.

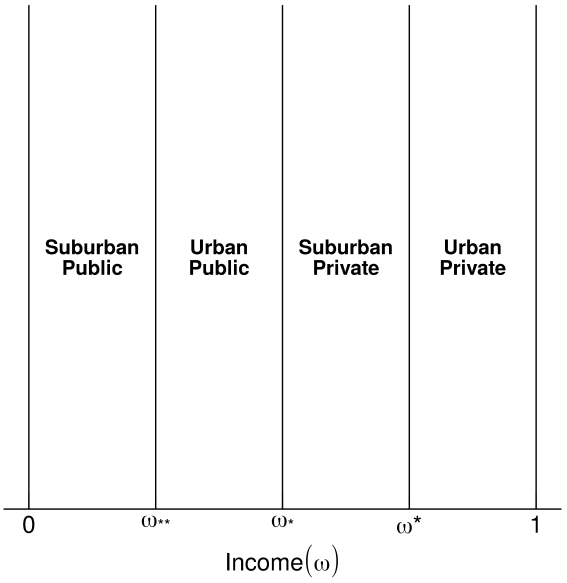
Proposition The entry of rideshare services incentivizes some higher income individuals in suburban areas to move to urban areas using private transportation. This leads to an increase in housing prices, and the out-migration of lower-income individuals in urban areas using public transportation.

Proof A reduction in λ leads to individuals with an income marginally below w^* to prefer living in urban areas using private transportation. This increase in housing demand

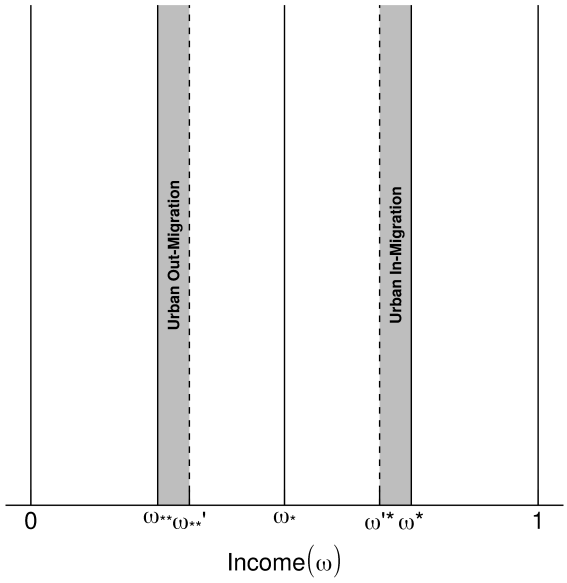
Figure C.8: ***Individuals Location and Mode of Transportation given Income***

Panel (a) displays the different location and transportation decisions given individuals income. Panel (b) displays the change in location and transportation decisions given individuals income following the entry of ridesharing services

(a) *Without Ridesharing Services*



(b) *With Ridesharing Services*



increases housing prices, resulting in the same number of lower-income individuals to move suburban areas using public transportation.

A graphical display of the impact that the entry of ridesharing services has on relocation of individuals given their income is present of the panel to the right of C.8. The reduction in the parking costs, reduces the cost of car-ownership in urban areas, making individuals with an income in the vicinity w^* to now prefer to live in urban areas and save on transportation time. However, this increase in individuals raises the housing prices, and forces individuals with an income immediately above w_{**} to benefit relatively more from saving on the increased housing cost and move to suburban areas.