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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TODO:

1. (All) Should we define *gentrification* somewhere?
2. (Shash) Review sections 2-6
3. ~~(Shash) Intro: review that the order matches the rest of the document; perhaps shorten it; perhaps add roadmap para (there are many sections); maybe mention self-driving cars earlier in intro~~
4. (Bernardo) Add moving-in results; fix misc typos in tables across paper
5. ~~(All) Data section could be shortened a bit; check that we are still using all of those sources~~
6. (All) Go through all the red items
7. (All) Think if we want to rename some tables or figures
8. (Sergio) Review latex errors; get rid of all the ??
9. (All) Reorder Appendix Tables/Figures so they appear in the same order as they are referenced.
10. (Open question) use less terms in-migration and out-migration and use more relocation or something more colloquial?
11. (Open question) Figures and tables have different number of coefs (11 vs 7). That might bother the referees, particularly if they don't match (EG Figure B.1 has potentially a higher pretrend than Table 5 column 3)
12. (Open question for later) Move Fig1 and Fig2 to the appendix
13. (All) Make sure there are no red comments left anywhere (not even in appendix)

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.

The paper is guided by a simple spatial-sorting mechanism. Ridesharing reduces transportation frictions, especially in dense urban environments where it is most heavily used and where avoiding car ownership is most valuable. As commuting and access costs fall, central-city neighborhoods become relatively more attractive to households

with a higher willingness to pay for urban amenities. The result is an inflow of more affluent residents into urban neighborhoods, rising housing demand and prices there, and pressure on lower-income households to relocate toward less central areas. This logic implies that ridesharing should affect urban and suburban neighborhoods very differently, which is the central comparison in our empirical analysis. Appendix C presents a simple model that formalizes this mechanism.

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 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

[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.

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]

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

[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 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.

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 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.

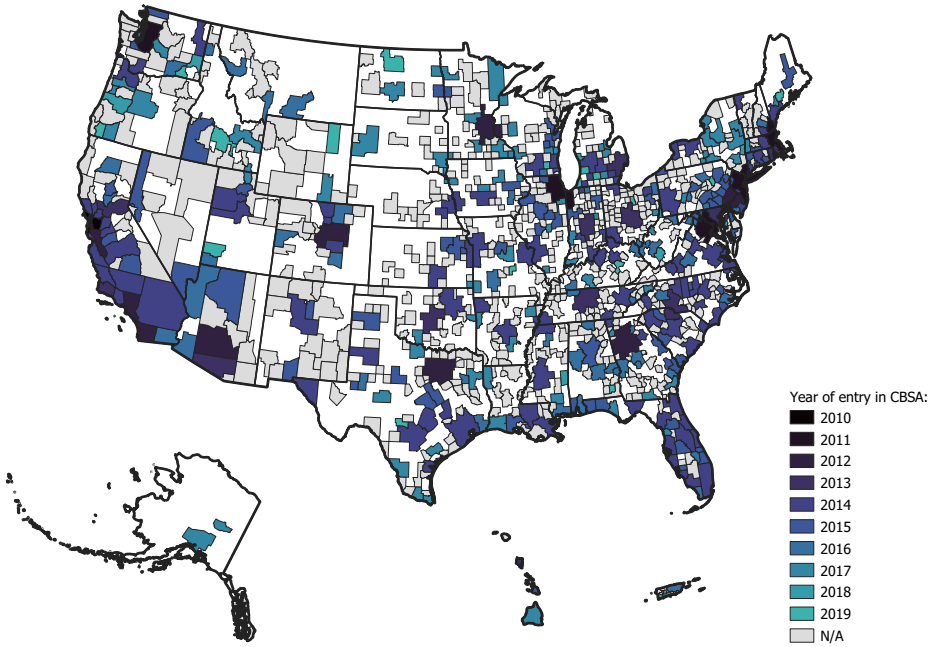
2 Data and Summary Statistics

We construct a ZIP-year panel of U.S. MSAs from 2009 to 2019 linking 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 while limiting outliers related to the Global Financial Crisis, and 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 for 312 MSAs between 2010 and 2019, as shown in Figure 1, which displays their geographical and temporal distribution. As we discuss in more detail in Section 4.1, entry was staggered over time, with ridesharing companies prioritizing larger MSAs.

To measure differential exposure to ridesharing within MSAs, we use two auxiliary

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).

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.

data sources. First, 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. Second, we collect Google Trends data on searches for the terms *Uber*, *Lyft*, and *Rideshare app*. Summary statistics for both measures are reported in the third panel of Table 1.

Our measure of local urbanicity is the Urbanization Perceptions Small Area Index (UPSAI), compiled by the U.S. Department of Housing and Urban Development. This index measures the perceived urbanization of ZIP codes based on resident assessments of whether an area is urban, suburban, or rural. For comparability, we exclude predominantly rural ZIP codes, defined as those with a rural share above 50 percent. We then split the urbanicity index into within-MSA quartiles and classify ZIP codes in the top quartile as urban and those in the bottom quartile as suburban. Table 1 reports summary statistics for this measure, while Table B.2 in Appendix B contrasts the characteristics of urban and suburban ZIP codes. 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.

Our main outcome variables come from several sources. Housing prices are obtained from CoreLogic, rental prices from Zillow, and vacant-address information from HUD-USPS data. Information on the number of households by income group and ZIP code, as well as child tax credits and related variables, comes from the Internal Revenue Service's Statistics of Income. Mortgage originations and applications are drawn from the confidential Home Mortgage Disclosure Act data set, and additional mortgage-level information is obtained from McDash. Information on consumer credit usage and performance is obtained from the Equifax Consumer Credit Panel of the Federal Reserve Bank of New York; we use fourth-quarter data from 2009 to 2019. Finally, ZIP-code-level measures of poverty and racial composition are obtained from the Census Bureau, while Walkscore and TransitScore data are obtained from Redfin. Summary statistics for these

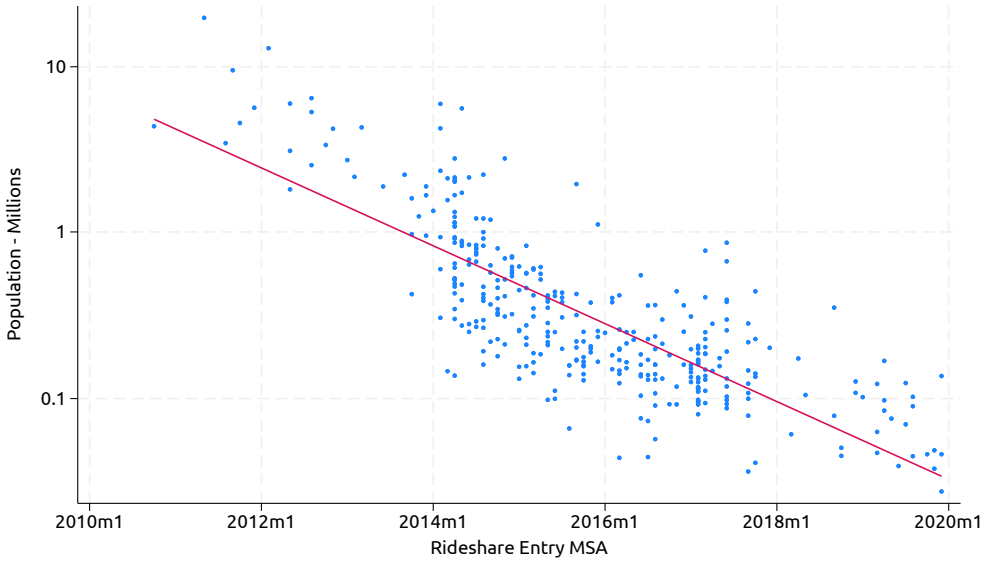
variables are reported in the remaining panels of Table 1, and detailed variable definitions are provided in Table B.1.

3 Ridesharing Rollout and Differential Exposure

3.1 Entry of Ridesharing Services Across MSAs

Ridesharing entered MSAs in staggered fashion, with substantially earlier entry in larger markets (Figure 2). This pattern is natural for a two-sided platform: larger MSAs offer thicker rider and driver markets, and expansion within a state may become easier once regulatory and operational fixed costs have been incurred. Consistent with this view, prior work identifies market size as a central determinant of rollout timing (Hall et al., 2018; Barrios et al., 2022; Fos et al., 2023; Buchak, 2024).

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 that MSA.

Appendix Table B.4 reports a Cox proportional hazards model relating entry timing to MSA characteristics. Entry is strongly associated with MSA population and, to a

lesser extent, with prior entry elsewhere in the same state. By contrast, we find little evidence that short-run local economic conditions predict entry timing. Taken together, these patterns suggest that rollout was driven primarily by market size and within-state expansion rather than by contemporaneous local housing-market conditions.

3.2 Differential Exposure Within MSAs

The effects of ridesharing entry need not be uniform within an MSA. They should be larger in the most urban neighborhoods, where trip distances are shorter, rider–driver matching is more efficient, and the costs of car ownership—especially parking—are higher (Cramer and Krueger, 2016). If ridesharing reduces transportation frictions, it should therefore do so most strongly in dense urban locations.

We provide direct evidence on this differential exposure using detailed trip data from four jurisdictions for which Zip code-level ridesharing data are available: Massachusetts, Chicago, San Francisco, and New York City. Specifically, we regress ridesharing trips per capita on the HUD Urbanization Perceptions Small Area Index (UPSAI), our measure of Zip code urbanicity. In alternative specifications, we add Zip code controls such as household income and MSA fixed effects. Because trip data are available only for a limited set of jurisdictions, we also use Google searches for *Uber*, *Lyft*, and related terms as an additional proxy for local ridesharing demand.

Table 2 shows a strong and robust positive relationship between urbanicity and ridesharing use. A one-standard-deviation increase in perceived urbanicity is associated with roughly a 30 percent increase in trips per capita, and this relationship changes little after controlling for Zip code characteristics and MSA fixed effects. Ridesharing use also increases monotonically across urbanicity quartiles: trips per capita in the top urbanicity quartile are more than twice as high as in the bottom quartile. Columns 5 through 8 show the same pattern using Google search intensity as a proxy for ridesharing demand. Although broader and noisier, this measure likewise indicates substantially

higher ridesharing demand in more urban Zip codes.

These patterns imply that MSA entry should not be interpreted as a uniform treatment across neighborhoods within the same metropolitan area. They also motivate our focus on comparing urban and suburban Zip codes within the same MSA.

Table 2: ***Urbanicity of Zip code and Ridesharing Use***

	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 reports regressions of ridesharing use on perceived Zip code urbanicity. The sample is restricted to Zip codes in metropolitan statistical areas (MSAs) in which ridesharing services operate. *Trips per Capita$_z$* is the number of ridesharing trips per capita in Zip code z. These data are available only 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 Google searches for the terms *Uber*, *Lyft*, or *Rideshare app* in Zip code z in the month following ridesharing entry in the corresponding MSA. *Urban$_z$* is the perceived urbanicity of Zip code z, measured using the Census Bureau's Urbanization Perceptions Small Area Index. *Urban$_{z,Qn}$* is an indicator for whether the urbanicity measure of Zip code z falls in quartile n. *Zip code controls* include household income, home value, the share of commuters using a personal car, commute time, walk score, and transit score. Standard errors clustered at the Zip code level. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 for detailed variable definitions.

4 Empirical Strategy

We estimate the effects of ridesharing entry using the imputation-based difference-in-differences estimator of Borusyak et al. (2021). This estimator is well suited to our setting because entry occurred at different times across MSAs and the effects of entry may

evolve dynamically. In such environments, conventional two-way fixed-effects estimators can be biased when already-treated units serve as controls for later-treated units under heterogeneous treatment effects.

Our baseline specification is

$$y_{z,t} = \alpha_z + \gamma_{r(z),t} + \sum_{j=-5}^{5} \beta_j \mathbf{1}\{t - T_{m(z)} = j\} + \epsilon_{z,t}, \tag{1}$$

where $r(z)$ and $m(z)$ denote the census division and MSA of Zip code z, $y_{z,t}$ is a Zip code-level outcome, α_z are Zip code fixed effects, $\gamma_{r(z),t}$ are census-division-year fixed effects, and $T_{m(z)}$ is the year in which ridesharing first entered MSA m. The coefficients $\{\beta_j\}$ trace out the dynamic effects of entry, while the pre-entry coefficients provide evidence on anticipatory responses and differential pre-trends.

Including census-division-year fixed effects implies that identification comes from variation across MSAs within the same census division that experienced ridesharing entry at different times. This absorbs regional shocks that could otherwise confound the estimates while preserving a broader pool of control MSAs than a specification with state-year fixed effects.[6]

Our main question, however, is not whether ridesharing affected an MSA uniformly, but whether it increased the relative attractiveness of urban locations within the same metropolitan area. We therefore present separate event studies for urban and suburban Zip codes in the main text. These estimates provide a transparent description of where the response to MSA entry is concentrated.

We also estimate pooled specifications that combine urban and suburban Zip codes

[6]Using state-year fixed effects is considerably more demanding, particularly for smaller states and in later years when the pool of untreated MSAs is limited. All of our main results remain qualitatively unchanged under this more stringent set of controls.

and include MSA-year fixed effects:

$$y_{z,t} = \alpha_z + \gamma_{m(z),t} + \sum_{j=-5}^{5} \delta_j \left(Urban_z \times \mathbf{1}\{t - T_{m(z)} = j\} \right) + \epsilon_{z,t}, \tag{2}$$

where $\gamma_{m(z),t}$ are MSA-year fixed effects and $Urban_z$ is an indicator for whether Zip code z is urban. In this specification, the coefficients $\{\delta_j\}$ capture the dynamic response of urban Zip codes relative to suburban Zip codes within the same MSA and year, thereby absorbing all metropolitan-area-wide shocks.

4.1 Threats to Identification

The central identification challenge is that ridesharing rollout across MSAs was not random. Entry occurred earlier in some markets and this may reflect baseline MSA characteristics associated with how urban neighborhoods evolve relative to suburban neighborhoods. If so, estimates based on staggered entry could confound the effect of ridesharing with other forces that would have caused urban areas in some MSAs to grow faster than suburban areas even in the absence of ridesharing.

In our setting, this is fundamentally a parallel-trends concern. In conventional staggered-adoption terms, the relevant comparison is between earlier- and later-entry MSAs, and a standard assumption is that these markets would have evolved similarly on average absent ridesharing. For the within-MSA analysis emphasized in this paper, however, the more relevant assumption is that the urban-suburban differential within earlier-entry MSAs would have evolved similarly to the urban-suburban differential within later-entry MSAs absent ridesharing.

Two features of our baseline design speak to this concern, but do not fully eliminate it. First, the event-study specifications allow us to inspect pre-entry dynamics directly. In the benchmark figures, the estimated lead coefficients are generally small and statistically indistinguishable from zero for up to five years before entry. Second, the pooled

specification with MSA-year fixed effects absorbs all metro-wide shocks common to Zip codes within a given MSA-year. Even so, neither approach rules out the possibility that urban and suburban neighborhoods in earlier-entry MSAs were already on systematically different trajectories for reasons correlated with entry timing.

We therefore supplement the baseline design with four additional checks aimed directly at this concern. First, we re-estimate the results in a restricted sample of smaller and more comparable MSAs, where the identifying comparison is more credible and less likely to be driven by systematic differences between early- and late-entry markets. Second, within this same restricted sample, we estimate instrumental-variables specifications that uses prior ridesharing entry elsewhere in the same state to predict entry in a given MSA.[7] Third, we allow urban-suburban trends to vary flexibly with baseline MSA characteristics, so that differential urban growth in, for example, larger, richer, or more cyclically sensitive MSAs does not mechanically load onto the ridesharing coefficients. Finally, we exploit the regulatory suspension and subsequent re-entry of ridesharing services in Austin, Texas, as a reversal test. While informative about timing and reversibility, this episode is necessarily limited to a single market and therefore serves as supporting rather than primary evidence.

A separate assumption is *no anticipation*: future ridesharing entry should not affect outcomes prior to entry. This assumption would be violated if households, lenders, or developers adjusted behavior in advance—for example, if households relocated in anticipation of lower commuting costs or if lenders expanded credit supply in anticipation of stronger housing demand. The absence of systematic pre-entry movements in the event-study estimates provides little evidence of such anticipatory responses.

[7]The idea is that, once ridesharing has entered other markets in the state, subsequent entry into a focal MSA may be accelerated by common regulatory and operational expansion factors.

5 Ridesharing and Spatial Sorting Within Cities

This section examines whether ridesharing entry changed the composition of neighborhoods within metropolitan areas. Because ridesharing is used disproportionately in dense urban neighborhoods and is more valuable to households with a higher willingness to pay to avoid car ownership and access urban amenities, its entry may induce spatial sorting within an MSA. We therefore ask whether, following ridesharing entry, urban Zip codes become relatively more affluent and younger, while suburban Zip codes absorb relatively more lower-income and older households.

The evidence points in that direction. Table 3 shows that, following ridesharing entry, urban Zip codes shift toward a higher-income and younger population, while suburban Zip codes tilt toward lower-income and older households. We then turn to individual-level evidence from the Equifax CCP and show that mobility rises in urban Zip codes after entry, with the increase driven primarily by renters rather than homeowners (Table 5). Taken together, these results are consistent with ridesharing entry contributing to spatial sorting within cities and increasing displacement pressure on incumbent renters in the most urban neighborhoods.

For our first set of results, we define *high-income households* as tax returns with annual income above $50,000, as reported in the IRS Statistics of Income.[8] Columns 1 and 2 of Table 3 show that the number of high-income households increases steadily in urban Zip codes after ridesharing entry, reaching about 5 percent above the counterfactual three years after entry. By contrast, we find no meaningful change in the number of high-income households in suburban Zip codes. Columns 3 and 4 show the opposite pattern for low-income households: their number declines in urban Zip codes—by roughly 1 percent over the first three years after entry—and increases in suburban Zip codes by around 1 to 2 percent, although the suburban estimates are not always statistically precise. Across these specifications, the pre-treatment coefficients are small and statistically insignificant,

[8] High-income households account for 41 percent of households in our sample.

providing no evidence of differential pre-trends.

These patterns suggest that ridesharing entry is associated with an inflow of higher-income households into urban neighborhoods and an outward shift of lower-income households toward suburban locations. As we show in Section 6, one likely mechanism is that ridesharing raises the relative attractiveness of urban neighborhoods, increasing local housing demand and, in turn, house prices and rents.

To further characterize these compositional changes, columns 5 through 8 of Table 3 examine the average age of residents and the share of households claiming the child tax credit, which we use as a proxy for households with children.[9] Column 5 shows that the average age of residents in urban Zip codes declines after ridesharing entry, by as much as 1.5 percent in the years following entry—equivalent to roughly half a year at the U.S. median age. Column 6 shows no comparable effect in suburban Zip codes. Columns 7 and 8 show that the share of households claiming the child tax credit falls in urban Zip codes, by up to 1.2 percent, while remaining largely unchanged in suburban Zip codes. These findings are consistent with ridesharing entry increasing the appeal of urban neighborhoods to younger, more affluent households and reducing their relative affordability for households with children. We view the latter channel as suggestive rather than definitive.

To sharpen the comparison between neighborhoods within the same metropolitan area, we next estimate a triple-difference specification that pools all Zip codes within an MSA and replaces state-year fixed effects with MSA-year fixed effects. Specifically, we estimate

$$y_{z,t} = \alpha_z + \gamma_{m(z),t} + \sum_{j=-2}^{4} \beta_j \, \text{Urban}_z \, \mathbf{1}_{t-j=T_{m(z)}} + \epsilon_{z,t} \tag{3}$$

where the dynamic treatment indicators are interacted with an indicator for urban

[9] Average age is constructed from the Equifax CCP, and child tax credit claims are obtained from the IRS Statistics of Income.

Table 3: ***Entry of Ridesharing Services and Neighborhood Composition***

	Number of Households - High Income$_{z,y}$		Number of Households - Low Income$_{z,y}$		Young$_{z,y}$		Child Credit$_{z,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PreEntry 2-Years	-0.001	0.003	-0.002	0.008	0.001	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	-0.003	0.003	-0.002	0.011	0.001	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	0.001	0.000	-0.001	-0.000
	(0.007)	(0.002)	(0.005)	(0.008)	(0.001)	(0.000)	(0.001)	(0.000)
PostEntry 1-Years	0.030***	-0.003	-0.015***	0.015	0.001	-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*	0.004***	-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	0.062***	-0.007	-0.010	0.026***	0.007***	-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	0.085***	-0.008	0.011	0.014*	0.010***	-0.003	-0.012***	0.001
	(0.019)	(0.008)	(0.011)	(0.008)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	20,327	14,232	20,327	21,559	14,232	10,424	20,327	14,232
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	0.36	0.26	0.13	0.17

This table reports the relation between ridesharing entry and neighborhood composition in urban and suburban Zip codes. *Urban (Suburban)* Zip codes are those in the top (bottom) quartile of the Urbanization Perceptions Small Area Index. *Number of Households – High Income*$_{z,y}$ (*Low Income*$_{z,y}$) is the number of tax returns (in logs) in Zip code z and year y with household income above (below) \$50,000. *Age*$_{z,y}$ is the average age of individuals with a credit report in Zip code z and year y, measured in logs, using the Equifax CCP. *Child Credit*$_{z,y}$ is the share of tax returns in Zip code z and year y claiming the child tax credit, from the IRS Statistics of Income. Standard errors are clustered at the MSA level. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table B.1 for detailed variable definitions.

Zip codes. This specification absorbs any shocks common to all neighborhoods within an MSA-year and identifies whether urban neighborhoods change differentially relative to suburban neighborhoods in the same local housing market.

The results, reported in Table B.5, are quantitatively similar to those in Table 3. In particular, following ridesharing entry, the number of high-income households rises by as much as 7.8 percent more in urban Zip codes than in suburban Zip codes. Likewise, average age declines by up to 1.1 percent more in urban areas, while the share of households claiming the child tax credit declines by about 0.8 percentage points (5.3 percent) relative to suburban neighborhoods. These results reinforce the interpretation that ridesharing entry changes neighborhood composition within cities rather than simply tracking broader MSA-level trends.

Although these findings are consistent with spatial sorting, they do not by themselves distinguish between changes in the composition of incumbent residents and actual relocation across neighborhoods. For example, existing residents could experience income changes, or households could change fertility behavior without moving.

To address this, we turn to individual-level data from the Equifax CCP and construct two related indicators. One for whether an individual moved into a Zip code (i.e., resides in a different Zip code in year y than in year $y-1$) and another for whether an individual moved out of a Zip code (i.e., resides in a different Zip code in year $y+1$ than in year y). We then estimate Equation (1) using these mobility measures as the outcome.

We start by analyzing whether there have been pressure for individuals to live

Table 5 reports the results. Column 1 shows that ridesharing entry increases the probability that residents move out of urban Zip codes. The effect averages about 1.2 percentage points in the years after entry, or roughly 11 percent relative to the pre-entry mean. By contrast, column 2 shows no economically meaningful change in suburban Zip codes. Columns 3 and 4 further show that the increase in urban out-migration is driven almost entirely by renters rather than homeowners. This pattern is important: it suggests

Table 4: ***Entry of Ridesharing Services, Newcomers and their Creditworthiness***

	Moving Into of Zip-Code$_{i,y}$			
	(1)	(2)	(3)	(4)
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 reports the relation between ridesharing entry and the probability that an individual moved into of their current Zip code of residence. *Urban (Suburban)* Zip codes are those in the top (bottom) quartile of the Urbanization Perceptions Small Area Index. *Moving Into Zip code*$_{i,y}$ is an indicator equal to one if individual i lived in a different residential Zip code in year $y-1$ than in year y. *Homeowner (Renter)* indicates whether the individual has (does not have) a mortgage or home equity loan tied to the current Zip code. *Controls* include age (in logs), FICO score, and an indicator for late repayment. Standard errors are clustered at the MSA level. *, **, 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.

that the compositional changes documented above reflect genuine residential sorting, and that the households most exposed to the resulting pressure are incumbent renters in urban neighborhoods.[10]

[10] Table B.11 reports analogous estimates from the triple-difference specification in Equation (3). The results remain qualitatively similar and of comparable magnitude.

Table 5: ***Entry of Ridesharing Services and Residential Mobility***

	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 reports the relation between ridesharing entry and the probability that an individual moves out of their current Zip code of residence. *Urban (Suburban)* Zip codes are those in the top (bottom) quartile of the Urbanization Perceptions Small Area Index. *Moving Out of Zip code*$_{i,y}$ is an indicator equal to one if individual i lives in a different residential Zip code in year $y+1$ than in year y. *Homeowner (Renter)* indicates whether the individual has (does not have) a mortgage or home equity loan tied to the current Zip code. *Controls* include age (in logs), FICO score, and an indicator for late repayment. Standard errors are clustered at the MSA level. *, **, 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.

6 Ridesharing and the Housing Market

The previous section showed that ridesharing entry changed neighborhood composition within cities and increased residential mobility, especially among renters. We now examine whether this reallocation of households translated into greater demand for urban housing and, ultimately, into higher house prices and rents.

6.1 Mortgage Originations

As higher-income households are attracted into urban areas, we expect demand for housing there to increase, including demand for owner-occupied units. This could prompt landlords and developers to convert rental units to condominiums or to build higher-end housing to meet the increase in demand (Boustan et al., 2023). Since housing purchases are financed mainly through mortgages (Garriga and Hedlund, 2020), we expect mortgage originations to increase in urban areas, particularly among higher-income borrowers.

We study this margin using the universe of mortgage loans reported in the confidential Home Mortgage Disclosure Act (HMDA) data, aggregated to the ZIP code-year level. Table 6 reports the results. We find an economically and statistically significant increase in mortgage originations in urban ZIP codes of treated MSAs after the entry of ridesharing services (column 1). The effect grows over time and averages about 9 percent over the five years following entry, while the pre-treatment coefficients are small and statistically insignificant. In contrast, the effect on suburban ZIP codes is much smaller and imprecisely estimated (column 2). These results are consistent with an increase in demand for owner-occupied housing in urban areas following ridesharing entry.[11]

[11] Mortgage originations are an imperfect proxy for housing demand. First, some wealthy households may purchase homes without a mortgage. To address this concern, we estimate analogous regressions using home vacancy rates as outcomes. The results, reported in Table B.7, show that vacancy rates decline sharply after ridesharing entry. Table B.8 shows that the same conclusion holds in a pooled urban–suburban specification with MSA-year fixed effects. Second, originations reflect both mortgage demand and loan approval decisions. To assess whether our results are driven by changes in lender risk appetite, we estimated similar regressions using approval rates as the outcome and found no meaningful effects.

We also examine whether the composition of mortgage borrowers changes after ridesharing entry. Column 3 shows an immediate increase in the income of loan applicants in urban areas averaging 7 percent in the five years following the entry of rideshare services. Column 4 shows smaller and less stable increases in suburban areas. Finally, 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 as being correlated with low-income or low-wealth borrowers. Finally, in the five years following the entry 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, the suburban estimates are much smaller and generally not statistically distinguishable from zero (column 6).

Finally, we also estimate a pooled specification combining urban and suburban ZIP codes and including MSA-year fixed effects. The results, reported in Table B.6, are qualitatively similar to the separate urban and suburban specifications. Mortgage originations increase by 8.6 percent in urban ZIP codes relative to suburban ones, average applicant income rises by 2.2 percent, and the fraction of FHA-insured loans falls by 1.9 percentage points (10.2 percent).

6.2 Housing and Rental Prices

The previous results indicate that ridesharing entry increased demand for housing in urban areas. We now examine whether this increase in demand translated into higher house prices and rents in a setting with limited short-run housing supply elasticity (**?**).

The results of our benchmark specification for house prices and rental prices are shown in Table 7 and Figure 3. 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

Table 6: ***Entry of Ridesharing Services, Mortgage Originations, and Characteristics of Applicants***

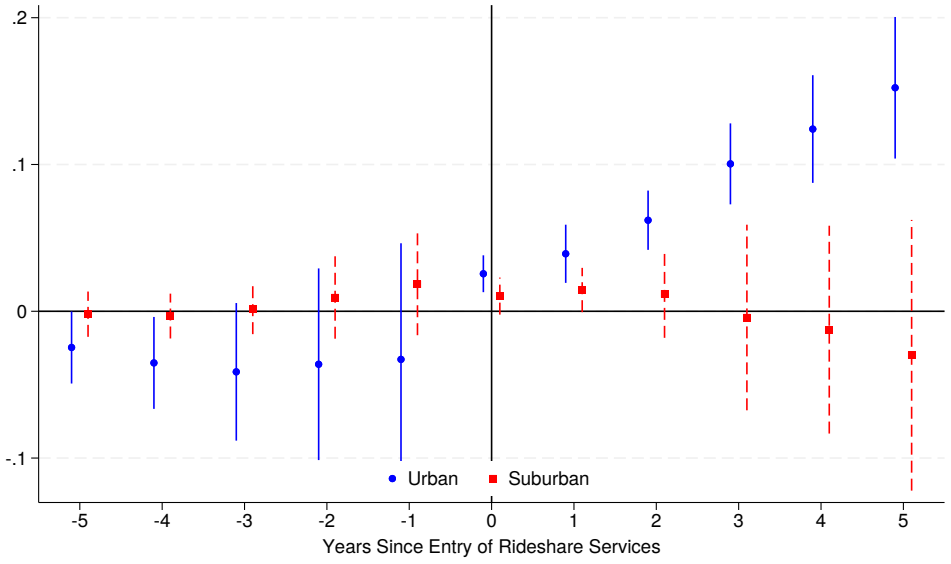
	#Mortgage Originations$_{z,y}$		Applicant Income$_{i,y}$		FHA-Insured$_{i,y}$	
	(1)	(2)	(3)	(4)	(5)	(6)
PreEntry 2-Years	-0.003	-0.001	0.005	0.005	-0.002	-0.009
	(0.025)	(0.023)	(0.004)	(0.005)	(0.009)	(0.015)
PreEntry 1-Years	0.023	-0.011	0.001	0.016**	-0.008	-0.025**
	(0.033)	(0.021)	(0.005)	(0.005)	(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 and the number of mortgage originations, as well as the 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 are obtained from confidential Home Mortgage Disclosure Act (HMDA) data. *, **, 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.

treatment, consistent with stronger demand for urban housing following ridesharing entry. In contrast, the coefficients in column 2 indicate that the effect on suburban prices is muted.

The rental price results are shown in columns 3 and 4. In line with the results on house prices, rental prices also rise after ridesharing entry. The effect is substantially larger in urban ZIP codes, where rents rise by about 6 percent on average, than in suburban ZIP codes, where they rise by about 1.8 percent.[12] Results from the pooled urban–suburban specification are reported in Table B.10. These results are qualitatively similar to those obtained when urban and suburban ZIP codes are estimated separately. In the pooled specification, house prices and rental prices rise by 2.5 percent and 1.9 percent, respectively, in treated urban ZIP codes relative to suburban ZIP codes.

Figure 3: ***Entry of Ridesharing Services and House Prices***



This figure displays the evolution of yearly coefficients from regressions relating ridesharing entry to housing prices in urban and suburban ZIP codes, shown 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 95 percent confidence intervals. See Table B.1 in the appendix for detailed variable definitions.

[12]One possible explanation is that some of the households displaced from urban areas move into rental housing in suburban locations. If these households are relatively liquidity constrained, they may be less able to bid up suburban house prices, but can still increase demand in suburban rental markets.

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 ridesharing entry to house 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.

In summary, the results in this section indicate that ridesharing entry increased demand for urban housing, particularly from higher-income households, and contributed to higher house prices and rents in urban areas.

7 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.

Shouldn't this indicator be delinquency between t and t+2 ie if he reaches delinq at any point in this period?

Given that the appreciation in urban house prices shown earlier in Figure 3 is likely to affect renters and homeowners differently (Autor et al., 2014), and that on Table 5 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.[13] The main characteristics of homeowners and non-homeowners are displayed in Table B.14. Consistent with Wolff (2000), we find that

[13]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).

homeowners tend to be older, have higher credit scores, move less frequently, and live in wealthier Zip codes.

This said YOUNGER before, is this fix correct?

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 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.

Shouldn't we define urban vs suburban based on pre-entry status?

Move columns 2-3 to columns 3-4 and rename to renter

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)
PreEntry 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.

8 Additional Identification Evidence

The main threat to our interpretation is that ridesharing entry may be correlated with unobserved changes in the relative demand for urban neighborhoods. While the baseline results already address this concern through event-study evidence, within-state comparisons, and within-MSA urban–suburban contrasts, this section provides two additional pieces of evidence. First, we study the high-profile regulatory suspension and subsequent re-entry of Uber and Lyft in Austin, Texas, which provides a reversal test for our main findings. Second, we exploit the tendency of ridesharing firms to expand across multiple MSAs within the same state over a short period of time, using state-level rollout as an instrument for MSA-level entry in a restricted sample of smaller and more comparable metropolitan areas.

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 most high-profile episode taking place in Austin. Uber and Lyft entered the MSA in 2014 but suspended operations in April 2016 following a regulatory dispute. More concretely, in December 2015, the Austin City Council passed an ordinance requiring drivers of rideshare companies to receive fingerprint-based background checks. After a *Ridesharing Works* campaign was organized—with financial support from both Uber and Lyft—to create 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 re-entry occurred only in mid-2017, after the Texas state legislature passed House Bill 100, which overrode local regulations and implemented a statewide framework for ridesharing companies.

We use this exit and subsequent re-entry to examine whether the baseline patterns reverse when ridesharing services temporarily disappear. Focusing on a short window around the exit and re-entry events, we study quarterly housing and rental prices in Texas

Zip codes using ZIP code and state-month fixed effects. The results, shown in Figure B.4, are consistent with our baseline findings: the suspension of ridesharing services led to a 2 percent decline in housing prices and a 4 percent decline in rental prices in urban areas, while re-entry reversed those declines and resumed their previous growth. In suburban areas, the effects are small and statistically indistinguishable from zero (not shown).[14]

Instrumenting Ridesharing Entry. As an additional robustness exercise, we address the concern that our results may reflect a spurious relation between ridesharing entry and unobserved changes in the relative demand for urban areas. For example, if the attractiveness of denser neighborhoods was rising for reasons unrelated to ridesharing, and if such changes were correlated with the timing of MSA entry, then the baseline estimates could overstate the causal effect of ridesharing. Although the absence of pre-trends is inconsistent with a gradual shift in preferences of this kind, we further address this concern by instrumenting ridesharing entry in an MSA with prior entry elsewhere in the same state.

This strategy is motivated by our finding in Subsection 4.1 that the presence of ridesharing services in a state is a strong predictor of entry into the state's MSAs, consistent with firms expanding locally once they have established operations in a region. For instance, the entry of Lyft in all Alabama MSAs in our sample took place within a span of two months, beginning with Birmingham in February 2017 and followed shortly thereafter 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.

To reduce heterogeneity in underlying trends, we restrict the sample to MSAs with fewer than 1 million residents and with income per capita and density in the middle three quintiles. We do this for two reasons. First, entry into smaller MSAs is more likely to be a by-product of broader state-level rollout rather than a response to idiosyncratic

[14]The larger response of rental prices is consistent with Anenberg and Ringo (2022), who show that rental prices tend to respond more immediately to demand shocks than house prices because rental agreements are relatively short-term and involve lower transaction costs.

demand conditions in a particular city. Second, neighborhood trends are more likely to be comparable across these more similar MSAs.[15] The relationship between state entry and MSA entry in smaller markets is illustrated in both panels of Figure **??**. In the left panel, we relate entry in an MSA to population, restricting the sample to MSAs with fewer than 1 million residents in states in which ridesharing services entered in 2010 (circles) and states in which they entered after 2014 (crosses). For MSAs in states in which ridesharing services entered in 2010, smaller MSAs were entered in September 2014, on average, and in June 2016 for the remaining sample. In the right panel, we further improve comparability by restricting to MSAs with income per capita and density in the middle three quintiles.

The corresponding estimates are reported in Table B.13. In columns 1 and 3, we restrict the sample to smaller and more comparable MSAs without instrumenting for entry; the results remain strong and similar to our benchmark findings. In columns 2 and 4, we use state entry as an instrument for MSA entry in the same sample. The IV estimates are again similar in sign and magnitude to the baseline results.

9 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 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

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

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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Deepa Mani, and Bernardo Morais*

March 26, 2026

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

A Rideshare Entry and the Supply of Ridesharing Services across MSAs

This is a bit of an orphan section; need to update or delete if not used

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.[16] The evolution of Figure 4 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 4 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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[16] 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.

Do we even use it, besides what we moved to appendix?

Figure 4: ***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.

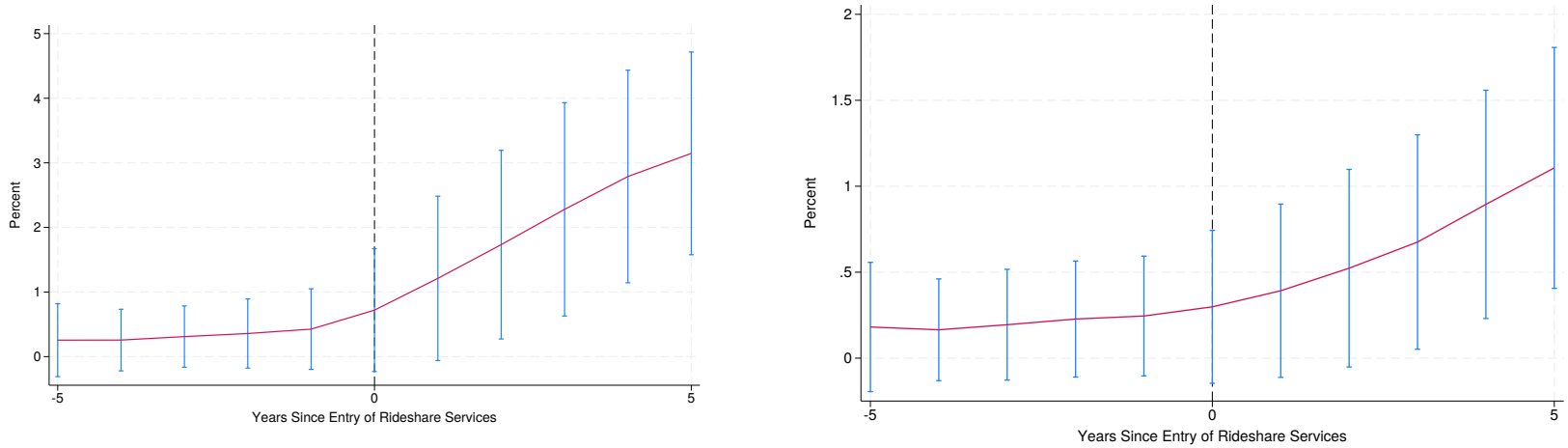


Table 9: ***Impact of Rideshare Services on Supply of Drivers***

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)

STATE THAT THIS IS A HAZARD MODEL AND WHAT TYPE OF MODEL; CHANGE TITLE TO MAKE IT LESS GENERAL

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)
PreEntry 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)
PreEntry 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.

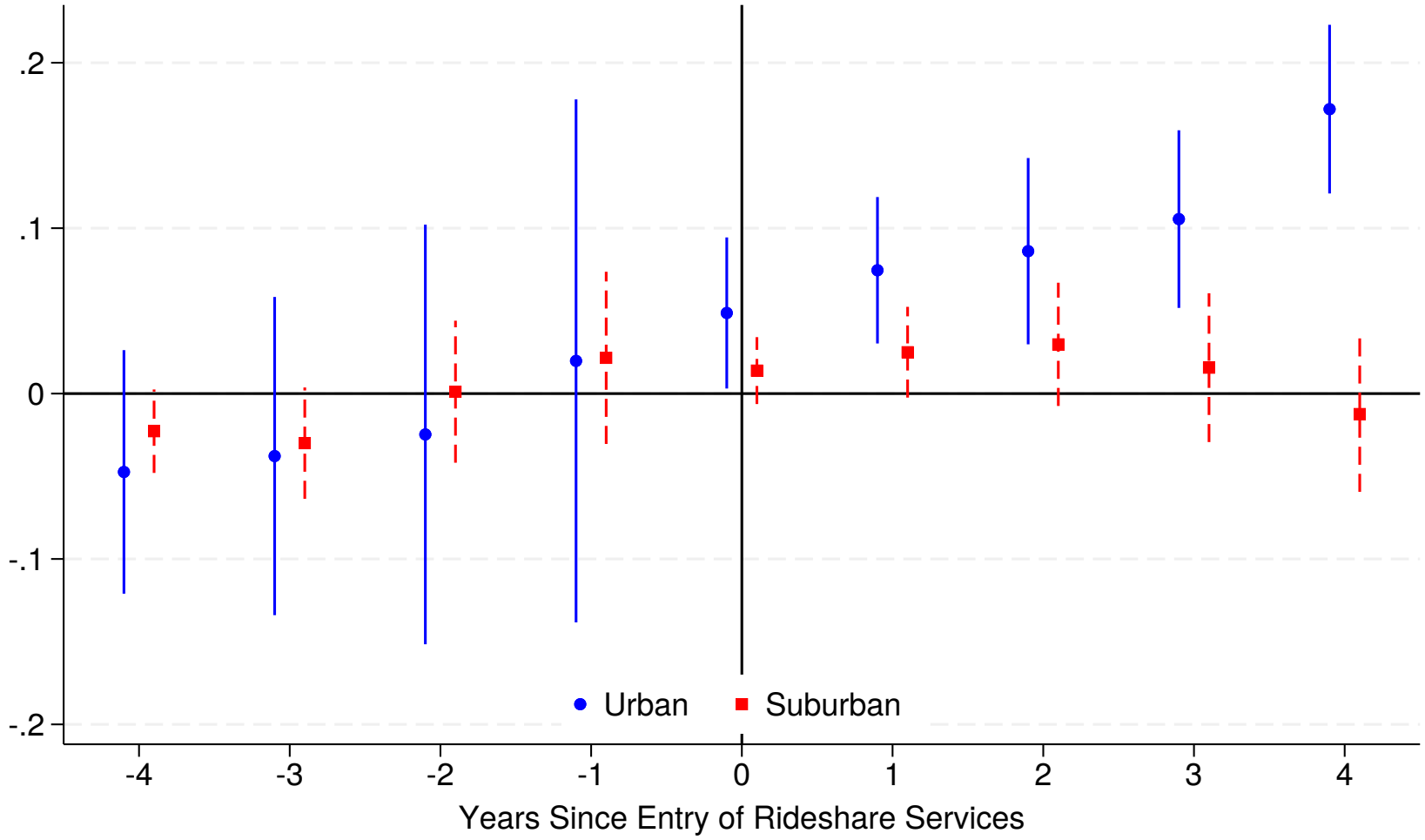
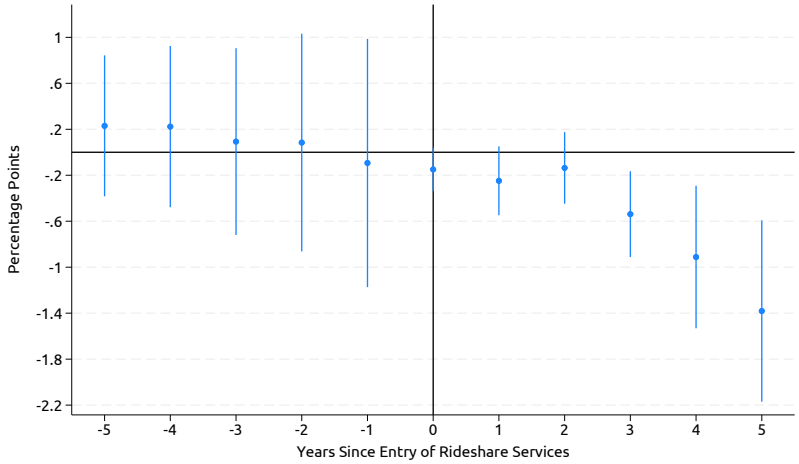


Figure B.2: ***Entry of Rideshare Services and Vacancy Rates***

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

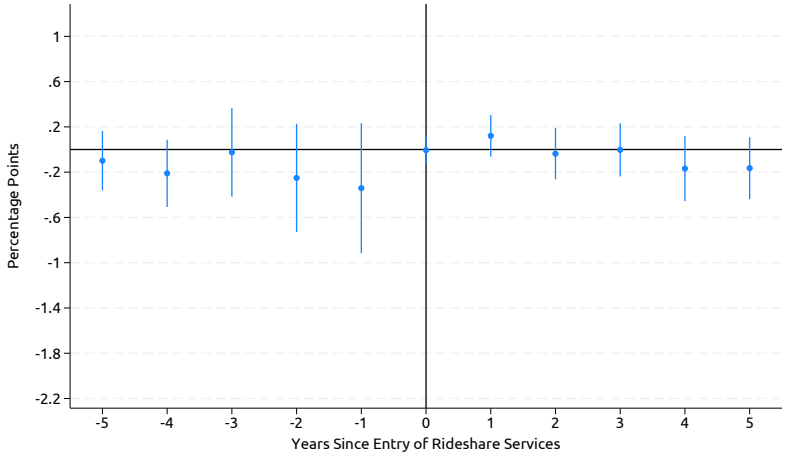
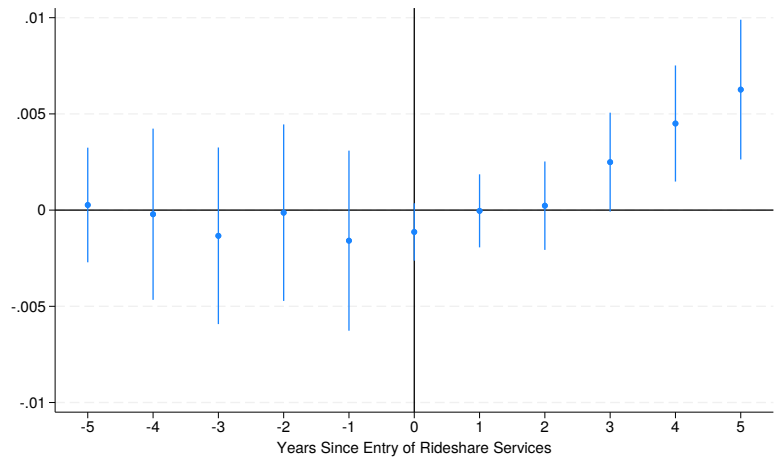


Figure B.3: ***Entry of Rideshare Services and Poverty Rate of ZIP codes of Mortgage Originations***

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

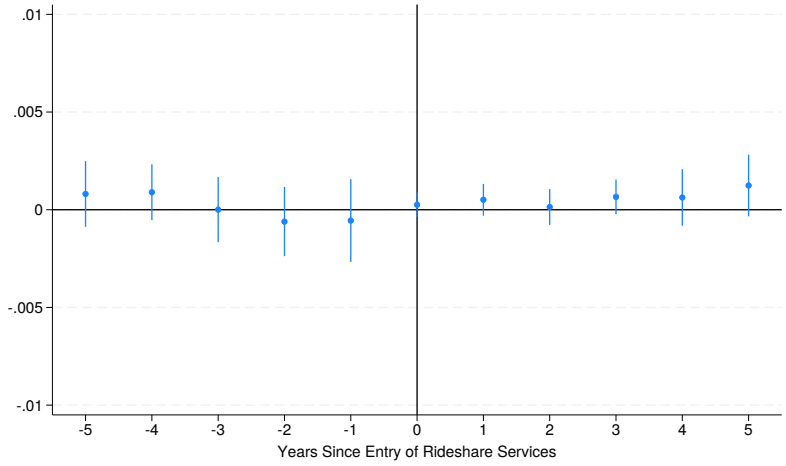
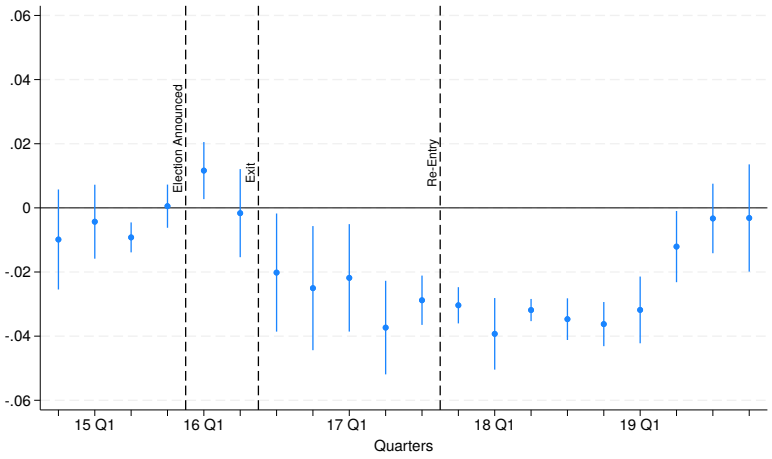


Figure B.4: ***Exit of Rideshare Services and Housing and Rental Prices - The Case of Austin***

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

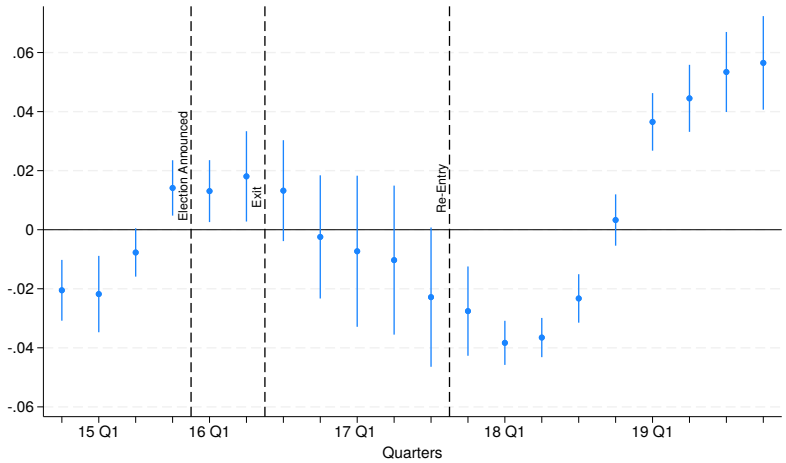


Table B.14: ***Characteristics of Homeowners vs non-Homeowners***

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*.

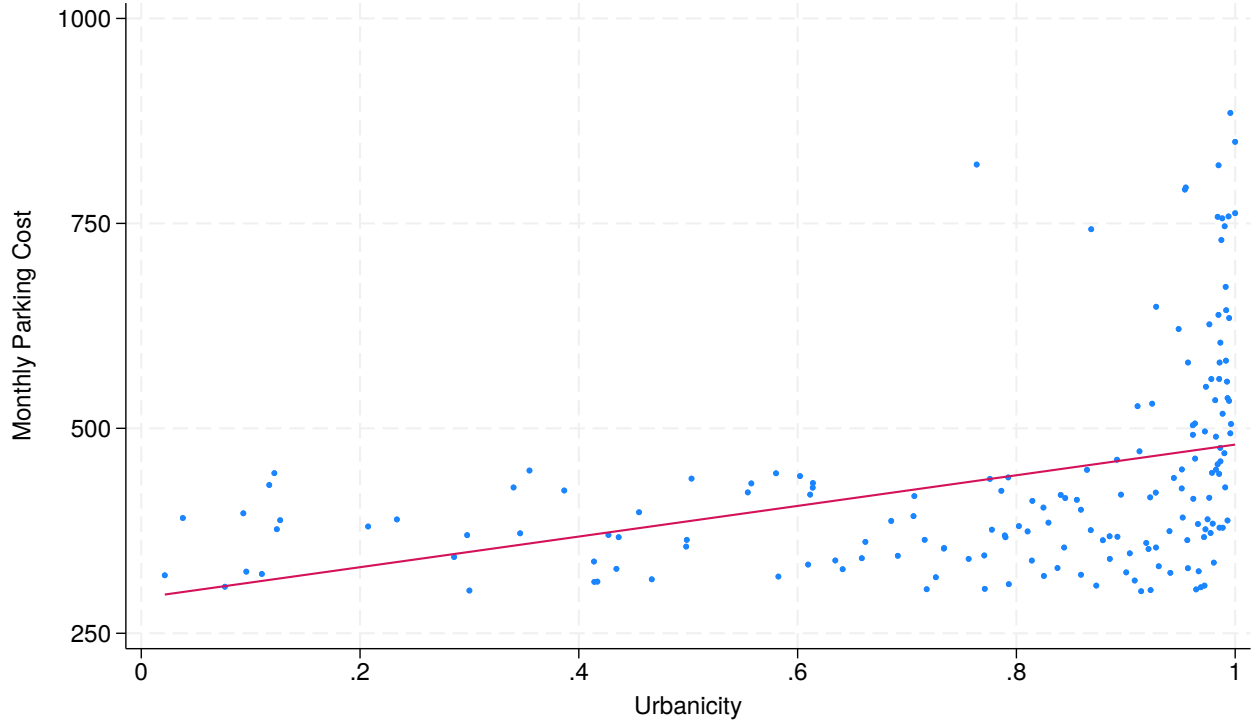
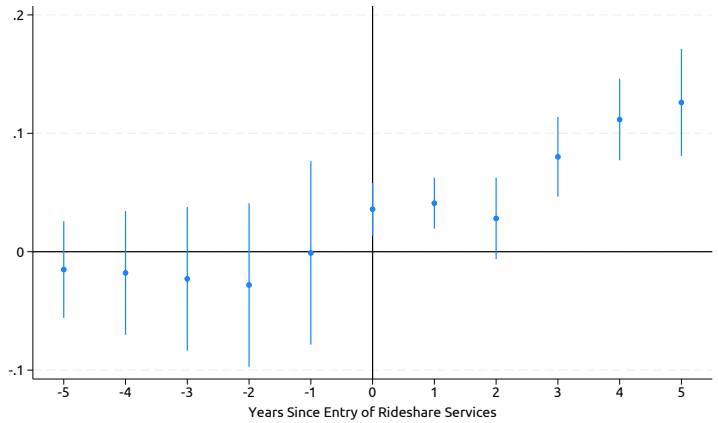


Figure B.6: ***Entry of Rideshare Services and Value of Originated Mortgages***

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

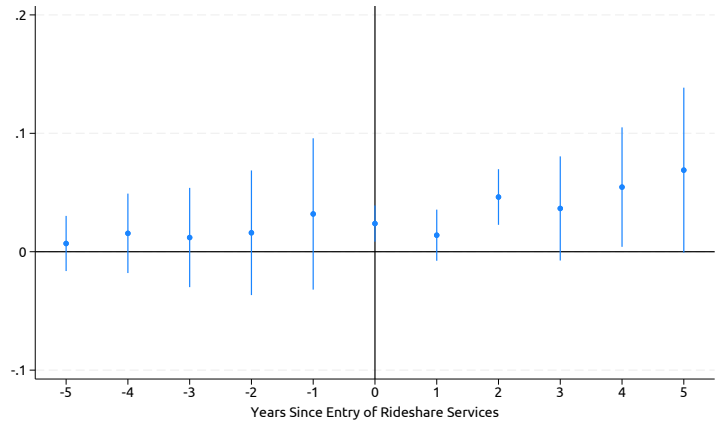
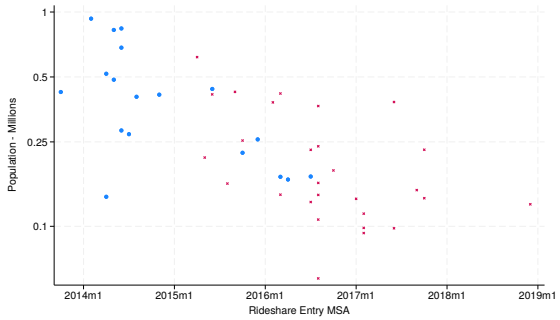


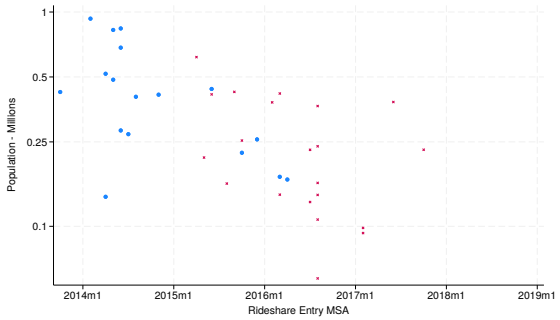
Figure B.7: ***Entry of Rideshare Services in MSAs given Entry in State - MSAs w/ Population <1 Million***

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.[17] 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.[18] 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:

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

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

$$0 = \tau^{u,c} < \tau^{s,c} < \tau^{u,p} < \tau^{s,p} < \infty \tag{4}$$

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:

$$U(c_i; v, l) = g(c_i) - \tau^{l,v} c_i \tag{5}$$

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:

$$(1 + \lambda_{l,v}) h_l + f_v + c_i \leq w_i \tag{6}$$

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.

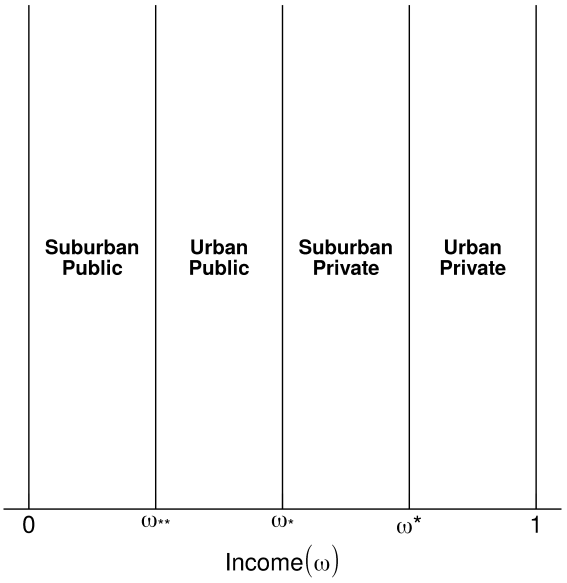
Proposition The entry of rideshare services incentivizes some higher income individuals in suburban areas to move to urban areas using private transportation. This leads to an increase in housing prices, and the out-migration of lower-income individuals in urban areas using public transportation.

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

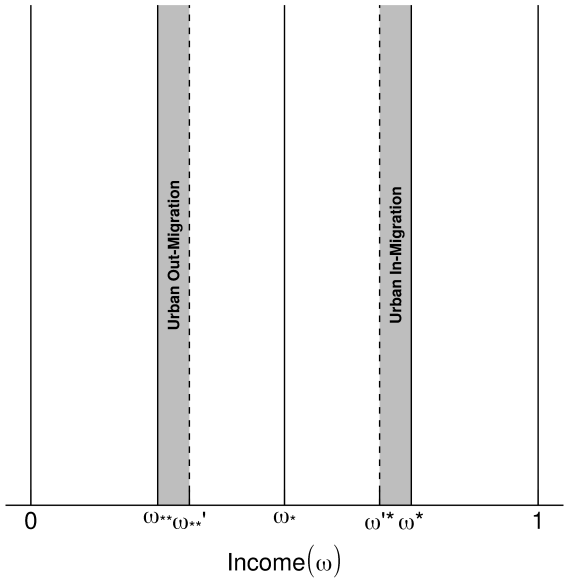
Figure C.8: ***Individuals Location and Mode of Transportation given Income***

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.