Transportation Technology and Gentrification: Evidence from Ridesharing Services

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March 12, 2025

Abstract

We analyze the staggered entry of ridesharing services across U.S. metropolitan areas, estimating its effect on spatial redistribution and real outcomes of households. By reducing the cost of personal transportation, ridesharing services incentivize the urban in-migration of higher income individuals, raising urban rents and housing prices by about 6 and 9 percent respectively. The effect on incumbent residents is conditional on ex ante homeownership. For homeowners, there is small displacement and a decline in delinquency rates. For non-homeowners, displacement and delinquency rates rise 11 percent and 42 percent, respectively. Our study emphasizes how the provision of high-end transportation technologies can increase urban gentrification and exacerbate inequality.

JEL codes: O33, J23

Keywords: Consumer Finance, Gig economy, Gentrification, Household Finance, Lyft, Mortgages, Residential real estate, Ridesharing services, Uber, Urbanization.

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We thank Harun Alp, Etienne Gagnon, Caitlin Gorback, Isaac Hacamo, Andrew Haughwout, Jose Luis Peydró, Wilbert van der Klaauw, Stijn Van Nieuwerburgh, Christopher Waller, and seminar participants at the Federal Reserve Board and New York Fed's System Equitable Growth Conference for comments and suggestions.

The opinions expressed in this paper do not necessarily reflect those of the Board of Governors of the Federal Reserve System.

1 Introduction

Urban areas in the United States have undergone remarkable gentrification over the past two decades, transforming from low-income, low-education to high-income, high-education zones (Couture and Handbury, 2023). This urban gentrification, a phenomenon in which higher-income individuals migrate to denser areas, has significant implications for social welfare, as the arriving high-income individuals can drive up prices of services (e.g., housing), potentially causing the displacement of lower-income residents. Such spatial sorting exacerbates wealth inequality, intergenerational mobility, and long-term life outcomes such as education, access to credit, income, and crime (Boustan et al., 2010; Boustan, 2010; Baum-Snow et al., 2019; Couture et al., 2024; Chyn and Katz, 2021; Kulkarni and Malmendier, 2022; Cook et al., 2024). Consequently, the causes and effects of urban gentrification are a subject of considerable academic and policy interest.

In this paper, we expand the literature relating transportation innovations with gentrification.[1] While previous research emphasizes the effect of low-cost mass public transit on the spatial redistribution of individuals (Baum-Snow, 2007; Glaeser et al., 2008; Gupta et al., 2022; Lee and Tan, 2024; Severen, 2023), we focus on the consequences of ridesharing services—a technology offering convenient personal transportation—on urban gentrification. We do so for three main reasons. First, the entry of rideshare services is likely to have higher impact in urban areas, given the lower costs of operation and service in denser cores (e.g., reduced matching costs and shorter trips) along with the higher costs associated with car-ownership (e.g., overnight parking and car insurance) in urban areas (Glaeser et al., 2008; Cramer and Krueger, 2016; Gorback, 2020; Li et al., 2022; Agarwal et al., 2023). Second, while the adoption of ridesharing services has been large and widespread across metropolitan statistical areas (MSAs), the use of these services has been largely driven by younger and higher-income individuals given technological requirements and relative high cost when compared to other alternatives like public transportation (Hall et al., 2018). Finally, the advent of autonomous taxis should further expand the supply of ridesharing services at a lower cost, potentially reinforcing the effects of the entry of driver-based ridesharing services.[2]

Summarizing our results, we find that the entry of ridesharing services increases urban gentrification. Upon entry the number of high-income individuals in urban ZIP codes gradually increases, with a smaller opposite effect for low-income individuals. This urban in-migration is driven by young individuals without dependents and is muted in suburban areas. Mortgage originations rise—especially in urban areas with lower housing values—as the increase in high-income mortgage applicants more than offsets the decline in lower-income applicants, boosting house prices. [3] The impact of the price appreciation on incumbent residents depends on their ex ante homeownership status. For homeowners, there is no impact on relocation and a significant

[1] See Boustan et al. (2013) and Couture and Handbury (2023) for a survey.

[2] For example, Waymo already operates an autonomous taxi service in Austin, Los Angeles, Phoenix and San Francisco. While the cost of autonomous taxi services is currently similar to those of equivalent driver-based ridesharing services, it is estimated that by 2030, the cost of these services is likely to be 50 percent lower per trip (McKinsey, 2022).

[3] Corroborating our identification strategy, we find that the impact of ridesharing services was reversed when Uber and Lyft temporarily exited Austin in early 2016, and resumed following their reentry in mid-2017.

improvement in their financial health. Conversely, non-homeowners experience a sharp increase in out-migration and credit delinquency. Collectively, these results point to a rideshare-driven urban gentrification within MSAs and an increase in inequality between incumbent homeowners and lower-income renters.

To examine empirically the impact of ridesharing services on urban gentrification, we use the staggered entry of Uber and Lyft (henceforth, ridesharing services) into MSAs across the United States and use the difference-in-differences (DID) estimator proposed by Borusyak et al. (2021). Specifically, we compare observations in MSAs with ridesharing services with not-yet-treated observations.[4] This DID specification is augmented with a multitude of detailed controls, granular location fixed effects at the ZIP code and MSA levels, and broader location*time (e.g., state*year) fixed effects. For additional robustness, we also control for time-varying factors at a local level using MSA time fixed effects, classifying urban ZIP codes as the treated group. These fixed effects help allay worries that our findings are influenced by unobservable time-varying confounders at the MSA level. Finally, a concern regarding our identification strategy is that the entry of ridesharing services may be correlated with time-varying factors influencing the local economy. However, we show that the entry of ridesharing services is mainly determined by the population in the MSA and is unrelated to local economic trends.[5]

To discipline our empirical strategy, we create a simple framework in which individuals trade-off consumption with travel time. Concretely, they choose mode of transportation—*public* or *private*, which faster but more expensive—along with location—*suburban* or *urban* which is costlier but closer to amenities. In equilibrium, and matching empirical regularities, highest-income individuals choose urban areas with private transportation, while slightly lower-income individuals live in suburban areas with private transportation. Lowest-income individuals use public transportation and live in both areas. The entry of rideshare services reduce the cost of private transportation, especially in urban areas where car-ownership costs (e.g. parking) are higher, thereby increasing the relative attractiveness of these areas. This leads to an inflow of higher-income individuals, and to an increase in housing prices forcing the out-migration of lower-income individuals away from urban areas. These effects are consistent with the recent gentrification patterns observed in urban areas (Baum-Snow et al., 2019).

We start our empirical analysis by uncovering the impact of rideshare entry on the composition of households across urban and suburban ZIP codes. In particular, we examine the effects of ridesharing services on the number of high- and low-income households in treated MSAs. Consistent with gentrification, we observe 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. Conversely, we find a slight reduction in the number of low-income households of around

[4]This method circumvents the recently documented limitations of two-way fixed effect (TWFE) models when treatment effects are heterogeneous and time to treatment varies (Borusyak et al., 2021; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Jakiela, 2021; Sun and Abraham, 2021).

[5]These findings are in line with literature documenting that entry decisions of ridesharing services are primarily based on population rank-order and orthogonal to economic activity (Hall et al., 2018; Barrios et al., 2022; Fos et al., 2023; Buchak, 2024).

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 given that younger individuals 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 are consistent with an in-migration of high-income and younger individuals into urban ZIP codes at the expense of a smaller out-migration of lower-income households.

We then examine the impact of ridesharing services at a more granular level. Starting with the impact on housing markets and given that a significant proportion of residential property acquisitions 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 following the entry of ridesharing services. Conversely, in suburban ZIP codes we find no effect.[6] 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 finding is consistent with the reduction in opportunities for lower-income groups to live in a gentrified area (Couture and Handbury, 2023) and indicates a decline in the inflow of low-income individuals into urban MSAs, further intensifying spatial economic segregation. Again, we detect no distinct pre-trends and no effect on suburban ZIP codes for all outcomes of interest.

Subsequently, we analyze whether 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, mortgages originated in ZIP codes with 2.2 percent lower house prices on average, suggesting that an improvement in amenities—like 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. Finally, we evaluate the impact that increased housing demand in urban neighborhoods has on home 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 importance robustness check on our identification strategy, we use the temporary exit of ridesharing services from Austin in May 2016 to examine if it led to a reversal in housing demand in urban areas. Focusing on rental prices, which tend to be more sensitive in the

[6]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.

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.

Finally, and given that gentrification tends to increase the price of amenities (Berkes and Gaetani, 2023; Couture et al., 2024), we conclude our paper by analyzing the effects that this wave of urban gentrification has on incumbent residents—more concretely, on their location and on their financial health. Given that gentrification led to an increase in house prices, we split our analysis into existing homeowners and non-homeowners. The underlying idea is that rideshare-led in-migration is likely to cause financial stress for low-income renters in urban areas due to increased housing prices, whereas homeowners are likelier to benefit from house price appreciation. 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. Furthermore, we find that the subsample of non-homeowners 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. We find a gradual increase in the likelihood of late repayments of incumbent residents in treated urban ZIP codes averaging 11 percent. However, this increase is driven by non-homeowners, which more than offsets the decline in late repayments of homeowners. More concretely, non-homeowners increased their late repayments by 42 percent, likely due to raising housing costs, whereas homeowners had a decline in their late repayments of around 36 percent, likely due to higher property values and net worth.

Overall, ours is the first study emphasizing the impact that the provision of high-end personal transportation by ride-hailing services has on the spatial reorganization of households and on residential mortgage and real estate markets. Specifically, ride-hailing services increased the relative desirability of poorer ZIP codes in treated urban MSAs, thereby 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 rise and displacement of low-income renters, which may further exacerbate inequality.

Our research contributes to multiple strands of the literature. First, we add to the literature examining the causes and consequences of urbanization and the spatial sorting of households. Prior work identifies changes in public transportation technology, natural amenities, and income distribution as significant determinants of spatial sorting (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 low and high incomes. Specifically, Baum-Snow (2007) finds that highway infrastructure in the United States contributed significantly to suburbanization, leading to a marked decline in higher-income population in core urban areas. Empirical evidence on the effects of urban public transit infrastructure is mixed. Glaeser et al. (2008) document that better access to public transportation in urban areas makes them more attractive to low-income individuals and explains the urbanization of poverty. By contrast, Lee and Tan (2024) find that the downtown transit line in Singapore resulted in spatial relocation of low-income jobs to less-attractive locations and exacerbated inequality, while Severen (2023) documents inelastic labor supply and housing supply response to Los Angeles Metro Rail construction and concludes that it had a negligible effect on individuals' willingness to relocate spatially. Moreover, Su (2022) concludes that the rising value of time is a significant driver of urban gentrification, particularly among high-skilled workers. By contrast, ours is the first study to document 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 spatial and gentrification. This literature collectively documents that rising income inequality (especially among the wealthy), 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. This exacerbated welfare inequality, with the rich benefiting from improved amenities and reduced commute times and the poor facing higher costs and consequent displacement (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). Our study expands this literature and documents that the entry of rideshare services led to an in-migration of higher-income households in urban areas, resulting in a sharp increase in housing prices with asymmetric welfare consequences for homeowners and non-homeowners. Homeowners experience a significant improvement in their financial health proxied by lower credit delinquency. By contrast, non-homeowners experience a sharp increase in out-migration and credit delinquency. Furthermore, rideshare entry exacerbated economic segregation by both displacing low-income residents and curbing the inflow of low-income individuals in urban MSAs.

Third, our work contributes to extant work on the factors influencing 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). Across the papers, a consistent theme emerges: Public infrastructure and investment in local amenities, such as transit systems and school facilities, 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 in local housing prices (Cellini et al., 2010). More directly related to our work, Gorback (2020) documents that the entry of UberX is associated with increased amenities (e.g. restaurants) along with higher housing prices and rental rates in previously inaccessible areas. In contrast, we investigate the effect of rideshare services on

urban gentrification and on residential real estate and mortgage markets. We find that rideshare entry leads to an average 9 percent increase in house prices and a 6 percent increase in rental prices in urban areas. Consistent with house price dynamics, mortgage originations increased by 8 percent. Importantly, these effects on house prices and mortgage origination are especially concentrated among treated urban regions with lower housing values, indicating an increase in gentrification in ex ante poorer neighborhoods.

Finally, we contribute to the novel theoretical literature analyzing the consequences of incoming autonomous vehicles on urban and non-urban spatial population organization, housing markets, and welfare (Zakharenko, 2016; Larson and Zhao, 2020; Gelauff et al., 2019). Two distinct and opposing effects are contingent upon the private ownership of automated vehicles and rideshare-operated autonomous vehicles. On the one hand, the automation of private vehicles will enhance the comfort of long-distance automobile travel, enabling drivers to participate in other activities during the commute. This decrease in the perceived cost of travel time may result in suburbanization as lengthier commutes become more acceptable. Consequently, there could be a population shift from urban centers to suburban and non-urban areas. On the other hand, shared-ride automated vehicles (SAVs) are likely to make public transit more convenient and efficient, especially in densely populated urban areas. This change could increase the attractiveness of urban centers, leading to population clustering and gentrification. Our findings speak to the public transit role of autonomous vehicles and indicate that SAVs are likely to exacerbate the trend of urban gentrification. This amplification can worsen housing affordability and result in greater economic segregation and inequality between the rich and the poor. Our study has important implications for policymakers: The overall welfare benefits and distributional consequences of vehicle automation are likely to vary significantly depending on how these technologies are implemented and the resulting shifts in population distribution.

2 Data and Summary Statistics

In this paper, we use data from a series of sources described below. Furthermore, given that ridesharing services started operating in 2010, we begin our analysis in 2009 to reduce potential outliers from the Global Financial Crisis. Similarly, given the large negative effects on demand for ridesharing services due to the COVID-19 pandemic, we stop our analysis at the end of 2019.

Data on the urbanness of ZIP codes are obtained from the Urbanization Perceptions Small Area Index (UPSAI) compiled in 2017 by the U.S. Department of Housing and Urban Development (HUD). The UPSAI is a metric used to quantify and assess the perceived level of urbanization in small geographic areas. This index incorporates various indicators (e.g., density, land use, and infrastructure) to gauge how *urban*, *suburban*, or *rural* a census tract is perceived to be.[7] For comparability purposes and given our focus in this paper on the use of ridesharing services, we restrict our sample to urban and suburban ZIP codes within MSAs. In this context, suburban areas

[7]We aggregate the census tract data at the ZIP code level, weighing tracts by population.

have lower population density, are primarily residential, have limited public services—such as public transportation and healthcare facilities—have higher car dependency, and have more green space and recreational facilities. The top panel of Table 1 reports the summary statistics of the urban perception index.[8] We define a ZIP code as urban (suburban) if it is in the top (bottom) quartile of the index of perceived urbanicity.[9]

Information on the entry of rideshare companies in MSAs was obtained directly from both Uber and Lyft. Overall, we have the entry of rideshare apps (Uber and Lyft) for 312 MSAs from 2010 to 2019. In Figure 1, we display the geographical and temporal distributions of the entry of rideshare apps across MSAs. As we discuss in more detail in subsection 3.1, the entry was staggered across time with rideshare-service providers sorting their entry by MSAs' population.

Information on the number and revenue of ridesharing services across time and MSAs is obtained from the Census Bureau's Nonemployer Statistics (NES). This annual series provides subnational economic data by industry. NES presents data for businesses with no paid employees (e.g., sole proprietorships, partnerships, and other forms of small businesses) and are subject to federal income tax. Data are available at the year and MSA levels and cover 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. We use the yearly data from 2009 to 2019. 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 subsection 3.2, 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 rideshare service drivers) operating in the MSA.

Data on the number of Uber trips within an MSA are compiled from regulatory data collected from five different areas—namely, Massachusetts, Chicago, New York, Los Angeles, and San Francisco. For more exhaustive coverage, we also include data on internet searches obtained from Google Trends on the terms *Uber*, *Lyft*, or *Rideshare app* in a ZIP code in the month before the entrance of the ridesharing services in the MSA. Summary statistics on both of these measures are displayed in the third panel of Table 1. As explained in subsection 3.3, within MSAs, ridesharing services are disproportionately used in urban areas compared to suburban ones.

Data on housing prices are obtained from CoreLogic. The CoreLogic home price data consist of yearly housing price indices at the ZIP code level using a weighted repeat-sales methodology. We use data from 2009 to 2019. Data on rental prices are obtained from Zillow using a smoothed yearly measure of the typical observed market rate rent in a ZIP code. It is a repeat-rent index that is weighted to the rental housing stock to ensure representativeness across the entire ZIP code, not just homes listed for rent. The index is calculated as the mean of listed rents in the 40th to 60th

[8] As we discuss in more detail in subsections 3.2 and 3.3, both the supply and demand for ridesharing services are relatively higher in urban areas relative to suburban ones.

[9] Table A.2 in Appendix A contrasts the main characteristics of urban and suburban ZIP codes. On average, urban ZIP codes have a population density nine times higher, its households have a 17 percentage point lower share of car ownership, a 20 percent lower commute time, 45 percent higher parking costs, significant higher amenities and transportation scores, and account for 63.6 percent of the population across MSAs.

percentile range for all homes and apartments in a given region. We use data from 2009 to 2019.

Finally, data on vacancies are obtained from the HUD Authority. Using information from the United States Postal Service (USPS), HUD compiles data on addresses identified as having been "vacant" in a given census tract. Vacant addresses include addresses that delivery staff have identified as being vacant for 90 days or longer. For this project, we will use data from 2012 (the earliest available data) to 2019. Data are compiled at the census-tract level, and we aggregate at a ZIP code level, weighing tracts by population. The summary statistics of these housing statistics are displayed in the *Housing Statistics* panel of Table 1.

Information on the number of households per income group and ZIP code is obtained from the Internal Revenue Service's (IRS) Statistics of Income, a yearly data set collected at the ZIP code*income-group level based on individual income tax returns filed from 2009 to 2019. Data include items such as the number of returns (which approximates the number of households), adjusted gross income and salaries, mortgage interest deductions, and child tax credits. The summary statistics of the main variables of interest from this data set are displayed in the *IRS Statistics* panel of Table 1.

Mortgage information is obtained from the confidential Home Mortgage Disclosure Act data set, containing regulatory information reported by depository institutions and certain for-profit nondepository institutions from 2009 to 2019. Data are compiled yearly by the Federal Financial Institutions Examination Council and include records on loan originations and loan applications that did not result in originations. Mortgage information includes property location, borrower demographics (e.g., applicant income, information on co-applicants, and race), whether the loan is government guaranteed (e.g., FHA), and loan amount. Further mortgage information on home value and on the credit score of the applicant is obtained from McDash. Summary statistics of the main variables of interest are shown in the *mortgage statistics* panel of Table 1.

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

ZIP code information on the level of poverty and racial composition is obtained from the Census Bureau's Current Population Survey (CPS). The CPS includes comprehensive yearly statistics from 2009 to 2019 on the percentage of individuals living below the poverty line and the demographic breakdown of minority populations within each ZIP code. Summary statistics of the main variables of interest are displayed in the *Other Statistics* panel of Table 1.

Walkscore and Transitscore data sets are obtained from Redfin. Walkscore provides information

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

3 Empirical Strategy

In this section we describe the empirical strategy used to study the impact of rideshare services. To motivate and discipline the analysis, we present in Appendix B a simple model where individuals trade-off consumption for transportation time associated with consumption. For brevity, in this paragraph we summarize its main assumptions and predictions. Individuals vary in income and decide their location (urban/suburban) and mode of transportation (private/public). Urban areas have higher (endogenous) housing prices but more efficient transportation.[10] This setup replicates a series of regularities like the fact that urban areas have higher income inequality, lower car-ownership rates and higher public transit utilization. The entry of rideshare services, modeled as a reduction in the cost of private-transportation, leads to an inflow of some higher-income individuals to urban areas, causing an increase in housing prices, which forces an out-migration of lower income individuals. These effects are larger in regions with larger ex ante car-ownership costs.

Empirically, we use a staggered DID approach to estimate the effects of the entry of ridesharing services in an MSA. Based on the estimator proposed by Borusyak et al. (2021), we compare observations in MSAs with ridesharing services with not yet treated observations. This method circumvents the recently documented limitations of two-way fixed effect (TWFE) models when treatment effects are heterogeneous and the time to treatment varies (Borusyak et al., 2021; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Jakiela, 2021; Sun and Abraham, 2021). When units are treated at different points in time, the canonical TWFE regressions make *clean* comparisons between treated and not-yet-treated units as well as *forbidden* comparisons that can receive negative weights, which are differences-in-differences that use early-treated units as a control group. In the presence of dynamic treatment effects, such comparisons can lead to biases and erroneous conclusions about the impact of an intervention (Baker et al., 2022; Goodman-Bacon, 2021; Rambachan and Roth, 2023). In our context, diagnostics indicate that such limitations are likely to be present (Jakiela, 2021) with the effects of the rideshare entry varying over time, as the supply of drivers gradually increases following the entry of ridesharing services as operations become more established (Figure A.1).

[10] As noted in Table A.3 walkscores and transitscores are significantly higher in urban ZIP codes indicating that both amenities and public transit options are more readily available in these areas.

To overcome these limitations, the main building block of the staggered DID approach involves calculating the average effect of the entry of ridesharing services t for the cohort of ZIP codes in the MSAs starting the program in each period g, ATT(g,t). Identification is obtained by comparing the expected change in outcomes between periods *g-1* and t of two groups: MSAs in cohort g and a control group of not-yet-treated MSAs. The estimated ATT(g,t) cohort-time parameters avoid "forbidden comparisons" and can be aggregated using specified weights to obtain the overall average effect of the program as well as its impact over time. We use the *did_imputation* command in Stata, described in Borusyak et al. (2021). Here, an MSA remains in the control group until the entry of ridesharing services into the MSA.

Formally, our baseline DID specification examines whether MSAs associated with the entry of ridesharing services experience differential changes in our variables of interest using the following specification:

$$Y_{z,m,y} = \beta_0 + \sum_{-1}^{-2} \theta_k \times Pre[k]_{z,m,y} + \sum_{0}^{4} \theta_k \times Post[k]_{z,m,y} + \delta_z + \gamma_{s,y}. \quad (1)$$

$Y_{z,m,t}$ is the dependent variable in a ZIP code z located in MSA m in year y. $Post[k](Pre[k])$ is an indicator that year y is k years from (to) rideshare entry into the MSA m. The coefficient θ_0 measures the immediate DID effect of a rideshare's entry. The *marginal* coefficients θ_1 (θ_2) measure the *additional* marginal responses one year (two years) after rideshare entry. Similarly, coefficients θ_{-1}, and θ_{-2} capture the difference in the dependent variables between the treatment group and the control group in each of the two pretreatment years. Finally, δ_z are ZIP code fixed effects that control for time-invariant characteristics of the ZIP code, while $\gamma_{s,y}$ are state*year fixed effects that control for average movements at the state*year level.

Given that ride-sharing services are used overwhelmingly in urban areas (as we discuss in Subsection 3.3), our benchmark analysis compares the effect of the entry of ridesharing services in urban and suburban ZIP codes—akin to our treatment and control ZIP codes. In particular, *urban* and *suburban* ZIP codes are defined as being in the top and bottom quartiles of our measure of perceived urbanicity, respectively. Finally, as a robustness check for all outcomes of interest, we also include a specification in which we group all ZIP codes and include MSA*year fixed effects $\gamma_{m,y}$ to control for average changes in the outcome variable at the MSA*year level. Therefore, this specification tests for variations *within* the MSA in urban and suburban ZIP codes. For this specification, we assume that ridesharing services only operate in urban ZIP codes within the MSA. In other words, suburban ZIP codes are the untreated control group.

As with the canonical DID methodology, there are two key identifying assumptions for MSAs in the control group (i.e., not-yet-treated MSAs) to provide a valid counterfactual for the evolution of outcomes that treated MSAs would have followed in the absence of the entry of ridesharing services. The first assumption requires that the average outcomes of MSAs with ridesharing services entering at different points in time follow parallel trends in the absence of rideshare entry. The second identifying assumption is that of no anticipation, which implies that ridesharing services have no

causal effect before their entry. In the next two subsections, we provide evidence that suggests that these assumptions hold in our setting.

3.1 Entry Decision of Ridesharing Services

The left panel of Figure 1 displays the frequency and geography of the entry of ridesharing services—Uber and Lyft—across U.S. MSAs. It shows a large variation in the timing and geography of the entry of ridesharing services across MSAs.

Given that our estimation exploits this staggered entry, a concern could be that the entry decision may be correlated with time-varying factors related with our variables of interest (e.g., in housing or rental markets). Previous work relying on the same identification strategy has shown that the entry decision of ridesharing services was primarily based on the population size of the MSA and was orthogonal to other dynamics like economic or population growth (Hall et al., 2018; Barrios et al., 2022; Fos et al., 2023; Buchak, 2024). This relation between population size and entry is graphically displayed in the right panel of Figure 1.[11] The timing of entry of ridesharing services in an MSA is strongly negatively correlated with the MSA's population size, with ridesharing services entering areas with larger populations first. For robustness, we use a hazard model to verify the relationship between rideshare entry and the population of an MSA, as well as other economic and demographic variables of interest. The results of this test are shown in Table A.5. The dependent variable $Entry_{m,y}$ is a yearly indicator of whether a ridesharing service entered MSA m in year y. Observations of an MSA are dropped for all years after entry. We find that the entry of ridesharing services is mainly determined by the population in the MSA and, to a lesser extent, by whether ridesharing services were already operating in the state.[12]

We find no evidence that the timing of ridesharing services was systematically driven by the economic conditions of the MSA, such as average income or unemployment. This finding suggests that not-yet-treated observations should be a valid counterfactual for treated observations.

3.2 Rideshare Entry and Supply of Ridesharing Services across MSAs

In this subsection, we examine the effect of ridesharing services' entry on the overall supply and revenue of cab drivers. The idea is to use the total cab drivers' supply in an MSA as a proxy for the supply of ride-hailing services.[13] The evolution of Figure A.1 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.

[11] Anil and Fisher-Ellison (2022) also find that Uber is more likely to enter MSAs with higher regulatory barriers for entry of conventional cab services. Insofar as ex ante regulations governing the entry of taxi operators are orthogonal to local economic conditions, this finding adds another layer of exogenous variation in the entry decision of ridesharing services.

[12] This last result is consistent with the findings that companies expand locally, benefiting from familiar regulations and infrastructure, before entering new regions (Holmes, 1998; Duranton and Puga, 2001).

[13] 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 rideshare-service drivers and taxi and limousine drivers.

We start by noting that the number and revenues of cab drivers only increase after the entry of ridesharing services (Figure A.1 and Table A.4), 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, 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 A.4 report the point estimates for impulse responses using the specification in 3, 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.

3.3 Use of Ridesharing Services within MSAs

Previous research has shown that the use of ridesharing services is especially higher in urban areas (Gorback, 2020; Li et al., 2022). There are several reasons for this phenomenon. The shorter distances in urban areas lead to lower prices per trip, resulting in higher demand for rides (Cramer and Krueger, 2016). This higher demand, combined with higher density, increases passenger turnover therefore reducing operational costs (e.g., matching drivers with passengers)(Cohen et al., 2016). Ridesharing services also help avoid costs associated with car ownership (e.g., parking), which are larger in urban areas (Glaeser et al., 2008).[14] Finally, ridesharing services can provide last-mile connectivity for public transit, which predominantly serves urban areas (Hall et al., 2018). For all these reasons, we expect the effect of the entry of ridesharing services to be relatively stronger in urban areas.

Next, we verify the positive relation between the use of ridesharing services and the perceived urbanness of a ZIP code. The main outcome of interest is the number of rideshare trips per capita. However, for regulatory reasons, this measure is only available for ZIP codes in Massachusetts, Chicago, San Francisco, and New York City. The explanatory variable is a $Urban_z$ is a continuous variable of the perception of whether ZIP code z is urban, using data compiled by the Census' Urbanization Perceptions Small Area Index. To control for additional drivers of demand, we control for characteristics at the ZIP code level (e.g., income). Furthermore, to control for local characteristics (e.g., urban sprawl), we also include MSA fixed effects. The results of this exercise are shown in Table 2. Focusing on column 1, we find that one standard deviation in the measure of urban perception of a ZIP code is associated with a 30 percent increase in the number of trips per capita. In column 2, we include a series of controls at the ZIP code level (e.g., average household income,

[14] In Figure A.6 of Appendix A, we display the positive relation between our measure of perceived urbanicity of ZIP codes in New York City and its monthly parking costs.

home value, walk score, and transit score), and in column 3, we include MSA fixed effects. In both specifications, the results remain qualitatively similar, showing a robust correlation between ZIP code urbanization and ridesharing usage. Finally, in column 4, we divide the sample of ZIP codes into four quartiles of $Urban_z$. We then compare rideshare usage for MSAs in the top three quartiles with those in the bottom quartile. Rideshare usage is monotonically increasing in urbanness, with the number of trips per capita in the top urban quartile more than double that of the bottom quartile.

Since data on trips per capita is only available for a small subset of MSAs, for robustness, in columns 5 to 8 of Table 2, we use Google queries for the terms *Uber*, *Lyft*, or *Rideshare app* in a ZIP code as a proxy for rideshare demand. Specifically, $GoogleSearches_z$ indicates the relative number of Google queries for the terms *Uber*, *Lyft*, or *Rideshare app* in ZIP code z in the month following the entry of ridesharing services in the MSA. Consistent with the results reported in columns 1 to 4, rideshare-related Google searches are significantly more prevalent in urban ZIP codes.

Overall, the results in this subsection suggest that the usage of ridesharing is significantly higher in urban areas.

4 Main Results

Given that usage is more cost-effective in urban areas (Cramer and Krueger, 2016), in this section, we analyze the relative effect of the entry of ridesharing services into an MSA in both urban and suburban ZIP codes.

4.1 Entry of Ridesharing Services and Gentrification

Considering that the adoption of ridesharing services has been primarily driven by high-income and young individuals (Hall et al., 2018), in this section, we evaluate the effect that the entry of ridesharing services had on any in-migration of individuals in these groups.

In particular, we start by examining the effects on the number of high- and low-income households in urban and suburban ZIP codes of treated MSAs. We use IRS dataset of Statistics of Income to analyze the evolution of the number of households in a given ZIP code z and year y, classifying them as having a higher (lower) income if they have an annual income above (below) 50,000 dollars (high income).[15] Our benchmark results, splitting the sample into *urban* and *suburban* ZIP codes, are displayed in columns 1 to 4 of Table 3. The results on the number of high-income households in urban and suburban ZIP codes are displayed in columns 1 and 2. Consistent with gentrification, we observe a gradual increase averaging 3.5 percent in the number of high-income households in *urban* ZIP codes in the years after the entry of ridesharing services. We do not observe a similar pattern in our control group of suburban ZIP codes. In columns 3 and 4, we display the evolution of low-income households in both urban and suburban locations. In column 3, we find a slight decline in the number of low-income households of around 0.8 percent in urban

[15] Higher-income households represent, on average, 41 percent of total households in our study.

ZIP codes in the years following the entry of ridesharing services. In contrast, the results in column 4 indicate that the number of low-income households increased in suburban ZIP codes roughly 2 percent following the entry of ridesharing services. Reassuringly, we do not find any differential pre-trends for the number of both high- and low-income households. Overall, these results support the hypothesis that the entry of ridesharing services is associated with an *in-migration of high-income individuals* into urban ZIP codes and an out-migration of lower-income individuals into suburban areas. This out-migration of lower-income individuals is likely partly driven by the increase in housing prices that we document in Subsection 4.2.2.

To shed further light on changes in the demographic composition of treated MSAs, we examine the average age of individuals living in a ZIP code, as well as the fraction of households claiming a child tax credit, which we use as a proxy for being a household with children.[16] Starting with the average age, column 5 shows a decrease in the average age of individuals of around 0.8 percent in treated urban ZIP codes, while column 6 indicates no effect on suburban areas. These findings are consistent with previous literature documenting a large increase in the number of younger, high-income individuals in urban areas over the past two decades (Couture and Handbury, 2023). Finally, column 7 indicates that rideshare entry is associated with a decline in the fraction of households claiming child tax credit of 0.8 percentage point (around 6 percent), while results in column 8 suggest that this effect is not present in suburban areas. Therefore, urban gentrification—which tends to increase the price of services (Gorback, 2020)—appears to be reducing the affordability of urban areas for families with children.

As we mentioned in the empirical section 3, to allay concerns that our findings may be driven by variations in local economic conditions, we test all our outcomes of interest using a specification with MSA*year fixed effects, pooling all observations within an MSA using urban ZIP codes as the treatment group. Results of this specification are displayed in Table A.6. All results are quantitatively similar to the previous specification comparing urban and suburban ZIP codes separately. In particular, the number of high-income (low-income) households increases by 4.7 percent (decrease of 4.7 percent) in treated urban ZIP codes relative to suburban ZIP codes. The average age of individuals declines by 0.9 percent in urban ZIP codes, whereas the fraction of households reporting a child tax credit declines by 0.3 percentage point (1.9 percent).

Overall, results in this section suggest that the entry of ridesharing services has contributed to urban gentrification.

4.2 Entry of Ridesharing Services and the Housing Market

As results in the previous section suggest that the introduction of ridesharing services is leading to the gentrification of urban areas, we now examine its effect on housing markets. More concretely, we analyze the effects on the demand for housing, on the demographics of mortgage applicants, on characteristics of the neighborhoods where new homeowners are moving into, and on the prices of

[16] Information on the average age of individuals in a ZIP code comes from the Equifax Consumer Credit Panel, while information on children's deductions is obtained from the IRS's Statistics of Income

homes and rents.

4.2.1 Demand for Housing

Given that a significant proportion of residential property acquisitions are financed through mortgages (Garriga and Hedlund, 2020), our analysis in this section focuses mainly on them. In particular, we analyze the number of mortgages (and of vacant homes), the characteristics of mortgage applicants (e.g., applicant income), and the characteristics of the neighborhoods in which homes are located.

Mortgage Originations. We begin by examining the evolution of mortgage originations, collapsing the number of mortgage originations at the ZIP code*year level. The results of this exercise are displayed in Table 4.[17] We find an economically and statistically significant increase in the number of mortgages originated in urban ZIP codes of treated MSAs after the entry of ridesharing services (column 1). Mortgage originations increase gradually over time, averaging around 8.1 percent in the five years following their entry. In contrast, the effect on suburban ZIP codes is muted (column 2). These results are consistent with the relative increase in the demand for housing in urban areas following the introduction of ridesharing services. Importantly, these results are not driven by preexisting differential trends.[18]

Vacant Homes. As a robustness check on the increase in demand for housing in urban areas, we also examine whether the urban ZIP codes in the treated MSAs also experienced a decline in vacant homes. The results of this test are shown in Table A.8 of Appendix A. Consistent with an increase in housing demand, in column 1, we observe a drop in vacancy rates in urban areas by 0.5 percentage points (11 percent) in the five years after treatment. Reassuringly, the impact estimates of the vacancy rates before rideshare entry are close to zero and do not show a discernible trend. This effect is muted for suburban areas (column 2). In columns 3 and 4, we use the yearly number of vacant residences (in logs) in a ZIP code as the dependent variable and obtain qualitatively similar results.[19] Finally, in Table A.9, we display the results of the specification pooling urban and suburban ZIP codes using MSA*year fixed effects. The results are quantitatively similar to the specifications, which analyze urban and suburban vacancies separately. All in all, these results suggest that the introduction of ridesharing services in an MSA led to a sharp reduction in vacant homes in urban areas.

Characteristics of Mortgage Applicants. Since urban gentrification is associated with the in-migration of high-income individuals into these areas (Baum-Snow et al., 2019), we expect new mortgage applicants will have relatively high incomes. Therefore, we test the variation of the income of households across urban and suburban ZIP codes. The results on the income of households

[17] In Figure A.2 we display the dynamics of the coefficients.

[18] A concern regarding this effect on number of originations is that some unobservable time-varying characteristics at the MSA level, which are correlated with rideshare entry, may have led to an increase in the approval rate for new mortgage applications. We conducted a similar test to analyze whether there was any change in approval rates after the entry of the ridesharing services and found no change.

[19] Figure A.3 plots the entire path of the coefficient of DID treatment effect estimates for vacancy rates.

with new mortgages are displayed in columns 3 and 4 of Table 5.[20] We find that an increase in the average income of households who contracted new mortgages in treated urban ZIP codes relative to the control group of MSAs. Consistent with the evidence in Table 3, this effect gradually increases with time. In column 3, we see that new mortgages in urban ZIP codes are taken out by households with 6.5 percent higher income in treated MSAs, with no distinct pre-trends. In column 4, we see a relatively modest and short-lived increase in the income of households contracting new mortgages in treated suburban ZIP codes compared to the control group of suburban MSA.

A common consequence of gentrification is the reduction of opportunities for lower-income groups to live in the area due to the increase in the price of services (Couture and Handbury, 2023). Therefore, we also test the effect that ridesharing services have on the number of subsidized mortgages. More concretely, we examine whether the frequency of FHA-insured mortgage origination, a proxy for poor households, has changed.[21] Results of this test are displayed in columns 5 and 6 of Table 5. Consistent with the increase in the average income of households with mortgages, we see a very sharp reduction in the number of FHA-insured loans in urban ZIP codes. In the five years following the introduction of ridesharing services, the share of FHA-insured loans decreased by an average of 6.4 percentage points (around 30 percent) in urban ZIP codes. In contrast, we do not see any effect in the suburban areas of the treated MSAs.

As before, as a robustness test, we pool urban and suburban ZIP codes using MSA*year fixed effects using urban ZIP codes as a control group. The results of this specification are shown in Table A.7. All results are qualitatively similar to the specifications, comparing urban and suburban ZIP codes separately. The number of mortgage originations increases 8.6 percent in urban ZIP codes compared to suburban ones. The average income of mortgage applicants rises 2.2 percent, while the fraction of FHA-insured loans decreases 1.9 percentage points (10.2 percent).

Characteristics of Locations of Mortgage Originations. In this section, we analyze the characteristics of the neighborhoods of the properties of the originated mortgages. In particular, we test whether these new mortgages cluster in more affordable areas, proxied by median housing prices, within urban and suburban ZIP codes in line with the mechanism proposed in Guerrieri et al. (2013). Furthermore, in the context of gentrification, we also check whether new mortgages are concentrated in areas with higher poverty rates and a larger share of minorities. In this specification, we still split the sample into urban and suburban ZIP codes, but we now use MSA fixed effects to absorb time-invariant characteristics of urban (suburban) ZIP codes in an MSA, as well as state*year fixed effects. Therefore, all our results compare urban (suburban) ZIP codes *within* an MSA.

The results relating mortgage originations to the median value of homes in the ZIP code are shown in Table 5 and Figure 3. In columns 1 and 2, we display the results for median house prices in urban and suburban ZIP codes. They show that within urban areas in an MSA, mortgages are originated in ZIP codes with 2.2 percent lower median house prices in the five years following the

[20] The dynamics of the coefficients are displayed in Figure 2.

[21] FHA insurance is a government-run program that provides insurance to lenders on behalf of borrowers, thereby reducing the risk associated with lending to higher-risk individuals. It is designed to help low-income people with limited credit access obtain financing for the purchase of a home.

entry of ridesharing services. Furthermore, this effect is gradual, with the demand for lower-priced ZIP codes increasing over time. By the fifth year after entry, mortgage originations in urban areas are for ZIP codes with 5 percent lower home values. The results of the average poverty rate are displayed in columns 3 and 4. After the introduction of ridesharing services within urban areas, more mortgages tend to originate in ZIP codes with higher poverty. The average poverty rate of these ZIP codes is 0.3 percentage point (1.5 percent) higher. Again, the effect is gradual, and we find no effect on suburban ZIP codes. Finally, in columns 5 and 6, we analyze the composition of minorities. In urban ZIP codes, new mortgages originated in ZIP codes with a 0.7 percentage point (1.5 percent) higher fraction of minorities. Again, effects on suburban areas are significantly lower and exhibit pre-trends. The results of the pooled specification are displayed in Table A.10. They show that the urban ZIP codes of mortgage originations have 1.1 percent lower house prices, 1.8 percent higher poverty rates, and a 2.7 percent higher share of minorities.

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

4.2.2 Housing and Rental Prices

So far, our results are suggestive of an increase in the demand for housing in urban areas. In this section, we analyze whether this higher demand leads to higher home and rental prices given the low elasticity of housing supply in the short run (Glaeser and Gyourko, 2018). The results of our benchmark specification for house prices and rental prices are shown in Table 6 and in Figure 4. Columns 1 and 2 report the results on house prices for the subsamples of urban and suburban ZIP codes, respectively. The coefficients in column 1 indicate a gradual increase in house prices of around 9 percent in the five years after treatment, consistent with higher demand for ridesharing in urban areas. Conversely, coefficients in column 2 indicate that the effect on suburban prices is muted. The rental prices results are shown in columns 3 and 4. In line with the results on house prices, we find an overall differential increase in rental prices in treated MSAs. Following the introduction of ridesharing services, rental prices in urban ZIP codes increase 6 percent on average. We also find a small but statistically significant effect on suburban ZIP codes averaging 1.8 percent.[22] Results of the specification that group urban and suburban ZIP codes are displayed in Table A.11. Qualitatively, the results are similar to those that split urban and suburban ZIP codes. We find that housing prices and rental prices rise 2.5 percent and 1.9 percent, respectively, in the treated urban ZIP codes compared to suburban ZIP codes.

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

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

Exit of Ridesharing Services: The Case of Austin As a robustness check, we check whether the patterns observed after the entry of ridesharing services are reversed after the (temporary) exit of these services. Although there are only a few cases of ridesharing services leaving an MSA, the longest and highest-profile case occurred in Austin, where ridesharing services—who had entered the MSA in 2014—decided in April 2016 to leave the region due to regulatory concerns. More concretely, in December 2015, the Austin City Council passed an ordinance requiring drivers of rideshare companies to receive fingerprint-based background checks. After this ordinance, a *Ridesharing Works* campaign was organized—with financial support from both Uber and Lyft—creating a citizen-initiative ballot to repeal the ordinance. The vote took place in May 2016, and the ordinance was not repealed (i.e., Uber and Lyft lost). Immediately after the announcement of the results, Uber and Lyft suspended their operations in Austin. Their subsequent reentry only occurred in mid-2017, after the Texas state legislature passed a bill (House Bill 100) which overrode local regulations and implemented a statewide framework for ridesharing companies. Therefore, we use the exit and posterior reentry of ridesharing services to examine whether it led to a relative decline, and later recovery, in housing demand in urban areas focusing on a short window around the exit and reentry events. In particular, we focus on the effect on housing and rental prices in urban areas using monthly rental price data controlling for ZIP code and state-month fixed effects. Therefore, our analysis focuses on the impact of exit/reentry of ridesharing services on quarterly housing/rental prices within the state of Texas. The results of this test are shown in Figure A.5. Consistent with our baseline results, the exit of rideshare services exit led to a 2 percent fall in housing prices and a 4 percent fall in rental prices in urban areas. Upon re-entry of rideshare services the decline in prices was reversed and resumed their growth. Therefore, these two exogenous shocks support our results that the entry of rideshare services has a relative positive effect on housing in urban areas within an MSA.[23] Importantly, in suburban areas, the effect was indistinguishable from zero (not shown).

4.3 Effect of Ridesharing Services on Residents

Taken together, the results in the previous sections suggest that the entry of ridesharing services led to urban gentrification, with the in-migration of high-income individuals leading to an increase in housing prices, causing the out-migration of lower-income residents.

In this section, we use granular data from the Equifax Consumer Credit Panel of the New York Fed to analyze changes in the real outcomes of incumbent residents—namely, relocation status and financial health. Furthermore, given that gentrification led to an increase in housing prices, we split

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

our analysis between homeowners and non-homeowners (e.g. renters), as generalized appreciation in housing prices is likely to affect renters and homeowners differently (Autor et al., 2014). In our context, low-income renters should be negatively affected by increasing rental prices and are more likely to be forced to move amid increased financial stress. For homeowners, the outcomes are less straightforward. While increased home values boost incumbents' wealth, which can be accessed either through outright sale or home equity loans, they are also likely to result in higher property taxes, which can place a financial strain on homeowners with limited incomes.

We define individuals as homeowners (non-homeowners) depending on whether they have (not) had a mortgage or a home equity loan in their current ZIP code since 1999 (the first year for which we have data). To limit the number of events in which individuals are misclassified as non-homeowners, since they might have fully paid their mortgage, we limit our analysis to individuals under age 55.[24] The main characteristics of homeowners and non-homeowners are displayed in Table A.15. Consistent with the findings in Wolff (2000), we find that on average homeowners are younger, have higher credit scores, move less frequently, and live in ZIP codes with higher median income and lower poverty.

4.3.1 Relocation

We start by analyzing whether the entry of ridesharing services increases the relocation of incumbent residents. For that, we use our benchmark specification and create a variable, *Moving Out of ZIP Code*$_{i,y}$, indicating whether individual i will be living in a different ZIP code by year y+1 relative to current in year y. The results of this exercise are exhibited in Table 7. Our first test, displayed in column 1, pools homeowners and non-homeowners in urban ZIP codes. We observe a significant increase in the likelihood of individuals moving out following the entry of ridesharing services. There is, on average, a 1.2 percentage point (11 percent) gradual increase in the number of people moving out of urban ZIP codes in treated MSAs. To understand whether non-homeowners are relatively more affected than homeowners, we then split our sample into these two groups. The results of this exercise are displayed in columns 2 and 3. We find that the subsample of non-homeowners drives the aggregate results. In columns 3 and 4, we do not find these patterns in the subsample of homeowners residing in treated urban regions and the full sample of individuals residing in treated suburban regions. Finally, we do not observe a statistically significant difference in the pretreatment period between the treated and control MSAs. Finally of the specification pooling urban and suburban ZIP codes together are displayed in Table A.12. Qualitatively, results are similar to the ones splitting urban and suburban ZIP codes. In particular, following the introduction of ridesharing services in an urban MSA, the rates of out-migration increased by 0.3 percentage point (3 percent). However, as displayed in columns 2 and 3, this increase is driven by the sample of non-homeowners. For this subsample, the rate of out-migration gradually rose by an average of 0.5 percentage points (almost 5 percent) in the years following the

[24] We do this given that roughly 85 percent of home acquisitions by individuals under age 55 are financed through mortgages (of Realtors, 2024).

entry of ridesharing services. Results for the sample of homeowners are almost indistinguishable from zero. For this subsample, moving-out rates increased 0.1 percentage points, or about 1 percent.

Insofar as homeownership and income are correlated, these results confirm and support the evidence discussed in Section 4.1 that the introduction of ridesharing services is associated with the displacement of incumbent renters, which tend to have lower incomes.

4.3.2 Financial Health

In this section, we investigate the effect of the introduction of ridesharing services on the short-term financial health of incumbent residents, in the context of a generalized increase in housing and rental prices. Again, we split our analysis into homeowners and non-homeowners. We proxy for the short-term financial health of residents using future information on credit delinquency. In particular, we create an indicator, $Late\ Repayment_{i,y+2}$, of whether an individual i is late on his or her payments in year y+2.[25] Results of this exercise are displayed in Table 8. In column 1, we present the results for the full sample of homeowners and non-homeowners in urban ZIP codes. Its coefficients indicate a slight gradual increase in the likelihood of late repayments following rideshare entry, averaging 0.3 percentage point (11 percent). However, as indicated by columns 2 and 3, this increase in future delinquency is driven by non-homeowners, which more than offset a decline in late repayments of homeowners. From column 2, we find that non-homeowners increase their late repayments by 0.9 percentage point (42 percent), likely due to increased rental costs. In contrast, results for homeowners, displayed in column 3, show that this group has a decline in their late repayments by 1.2 percentage points (36 percent), likely due to the increase in their property value and consequent net worth, which, in principle, allows them to expand their credit constraints. Results for the suburban sample of ZIP codes, our control group, show no effect of the entry of ridesharing services on delinquencies. As before, the results of the specification pooling urban and suburban ZIP codes together are displayed in Table A.13. 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). However, as displayed in columns 2 and 3, this increase in delinquency rates is driven by the sample of non-homeowners.

Overall, results in this section suggest that rideshare entry has uneven effects across residents of urban ZIP codes. 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 while increasing the probability that they will suffer financial stress in the near future in the form of late credit repayments.

[25] We create an indicator of future delinquency, in this case, two years ahead, as individuals may be moving locations before delinquency.

4.4 Robustness Checks - Sample of Small MSAs

In this section, we provide a final robustness check to ensure that our results are not driven by a spurious relation between the entry of rideshare services with unobserved changes in relative demand for urban areas. For example, the observed gentrification could be driven by a change in the preferences of younger individuals to live in urban areas. Furthermore, if this change in preferences is correlated with the size of the MSA (i.e., if the change in preferences for urban areas is stronger in large MSAs), it may be that the entry of rideshare services coincides with this increased attraction for denser areas. While all of our findings show the absence of any pre-trends, consistent with a gradual change in preferences, in this section we provide two robustness checks to verify the validity of our identification strategy. First, we instrument for the entry of rideshare services in an MSA. Second, we study an event in which rideshare services exited an MSA for regulatory reasons, to check whether our observed effects upon their exit. For brevity reasons, we focus on changes in housing and rental prices given their high frequency and availability.

In particular, we instrument for the entry of rideshare services in an MSA with their entry in the state. We do this following our findings in section 3.1 showing that presence of rideshare services in a state is a strong predictor of entry in the state MSAs (i.e., rideshare services tend to expand locally once already in a region). Furthermore, we limit our sample to MSAs with fewer than 1 million individuals and with income per capita and density in the three middle quintiles. We do this for two reasons, first, the entry decisions into smaller MSAs is likely to be a by-product of their decision to enter in a state. Second, gentrification trends are more likely to be similar in these subgroups of similar MSAs.[26,27]. The results of this refinement are displayed in Table A.14. In columns 1 and 3, we limit our sample to MSAs with a population under 1 million and income per capita and density in the three middle quintiles. The results for this subsample remain strong and similar to our benchmark findings. In columns 2 and 4, we continue with the same sample of MSAs, but instrument for the entry of rideshare services using the entry in the state. Again, the results remain similar.

5 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

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

[27] This relation can be seen graphically in both panels of Figure A.8. In the left panel, we relate the entry of rideshare services in an MSA with its population, restricting the sample to MSAs with fewer than 1 million individuals in states in which rideshare services entered 2010 (circles) and states in which they entered after 2014 (crosses). For MSAs in which rideshare services entered in 2010 in the states, rideshare services entered the smaller MSAs in September of 2014, on average, and in June 2016 for the remaining sample. In the right panel, we improve the comparability of MSAs, restricting to MSAs with income per capita and density in the three-middle quintiles

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

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

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

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Table 1: ***Summary Statistics***

This panel displays the summary statistics of the main variables of interest. See Table A.1 in the appendix for detailed variable definitions.

	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 Codes 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

Table 2: *Urbanicity of ZIP Code and Rideshare Usage*

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

	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

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

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

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

Table 4: ***Entry of Ridesharing Services, Mortgage Originations, and Characteristics of Applicants***

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

	#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

Table 5: ***Entry of Ridesharing Services and Characteristics of ZIP Codes of Mortgage Originations***

This table displays the results of a regression relating the entry of ridesharing services with the characteristics of ZIP codes of the properties for which the mortgages were issued in urban and suburban ZIP codes. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled by the Census Bureau's Urbanization Perceptions Small Area Index. *Median House Price in ZIP Code*$_{i,y}$ is the median house price (in logs) in the ZIP code of the property financed by mortgage i originated in year y. *Average Poverty Rate in ZIP Code*$_{i,y}$ is the average poverty rate of the ZIP code of the property financed by mortgage i originated in year y. *Average Minority Share in ZIP Code*$_{i,y}$ is the average share of minority individuals of the ZIP code of the property financed by mortgage i originated in year y. Mortgage information was obtained from Home Mortgage Disclosure Act confidential, while information on the dependent variables was obtained from Zillow and the Census Bureau.*, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. See Table A.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)	(4)	(5)	(6)
PreEntry 2-Years	0.001	-0.003	-0.001	0.001	0.001	-0.003**
	(0.003)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
PostEntry 1-Years	0.004	-0.001	-0.002	0.000	0.000	-0.004***
	(0.003)	(0.006)	(0.002)	(0.001)	(0.001)	(0.002)
PostEntry 0-Years	-0.004	-0.003	0.000	-0.000	0.000	0.002
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
PostEntry 1-Years	-0.009**	-0.006	0.000	-0.000	0.003**	0.000
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)
PostEntry 2-Years	-0.020***	-0.016***	0.003*	0.000	0.006***	0.002
	(0.005)	(0.005)	(0.002)	(0.001)	(0.002)	(0.002)
PostEntry 3-Years	-0.032***	-0.011***	0.004**	0.001	0.010***	0.003**
	(0.006)	(0.004)	(0.002)	(0.000)	(0.002)	(0.001)
PostEntry 4-Years	-0.050***	-0.019***	0.006***	0.001*	0.015***	0.004**
	(0.008)	(0.006)	(0.002)	(0.001)	(0.003)	(0.002)
Observations	2,295,577	3,534,990	2,295,577	3,534,990	2,295,577	3,534,990
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip codes	Urban	Suburban	Urban	Suburban	Urban	Suburban
Avg. Dep. Variable	12.3	12.4	0.20	0.06	0.43	0.18

Table 6: ***Entry of Ridesharing Services and House and Rental Prices***

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

	House Price Index$_{z,y}$		Rental Prices$_{z,y}$	
	(1)	(2)	(3)	(4)
PreEntry 2-Years	-0.004	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

Table 7: ***Entry of Ridesharing Services and Relocation Away from ZIP Code***

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

	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	Non-Homeowner	Homeowner	All
Avg. Dep. Variable	0.11	0.12	0.07	0.08

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

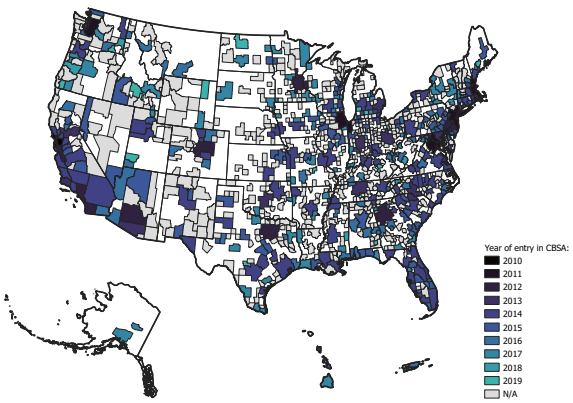
This table displays the results of a regression relating the entry of ridesharing services with changes in the financial health of incumbent residents, proxied by an indicator of credit delinquency. *Urban (Suburban)* ZIP codes are in the top (bottom) quartile of a measure of perceived urbanicity compiled 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(Nonhomeowner)* 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 A.1 in the appendix for detailed variable definitions.

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

Figure 1: ***Entry of Ridesharing Services across Metropolitan Statistical Areas***

Panel (a) displays the entry of ridesharing services across time by core-based statistical area (CBSA). Each CBSA is colored according to the year a ridesharing service (either Uber or Lyft) first appeared. CBSAs include both metropolitan statistical areas (MSAs) and micropolitan statistical areas. Panel (b) displays the population size of an MSA along with the month in which ridesharing services entered an MSA.

(a) *Entry of Ridesharing Services—Uber and Lyft*



(b) *Metropolitan Statistical Area Population and Entry of Ridesharing Services*

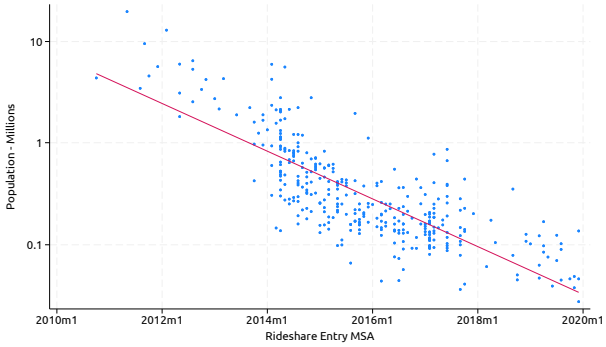
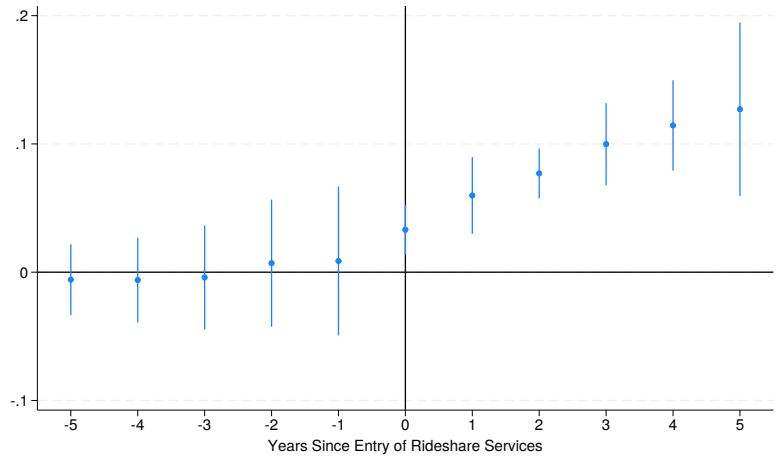


Figure 2: ***Entry of Ridesharing Services and Income of Mortgage Applicants***

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

(A) Urban ZIP Codes



(B) Suburban ZIP Codes

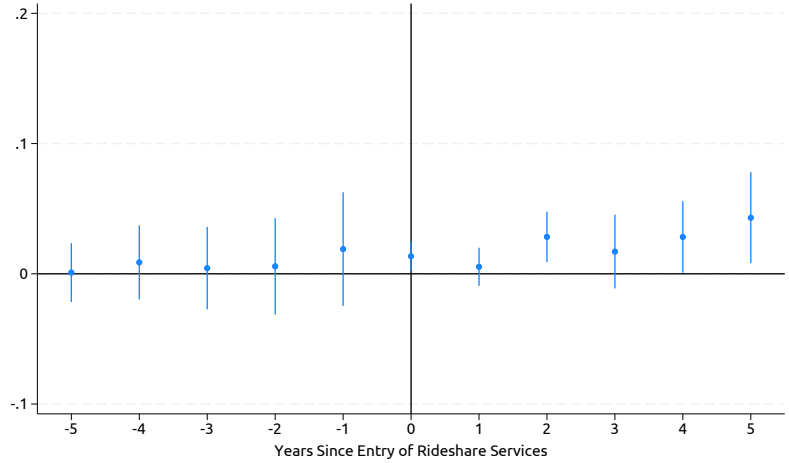
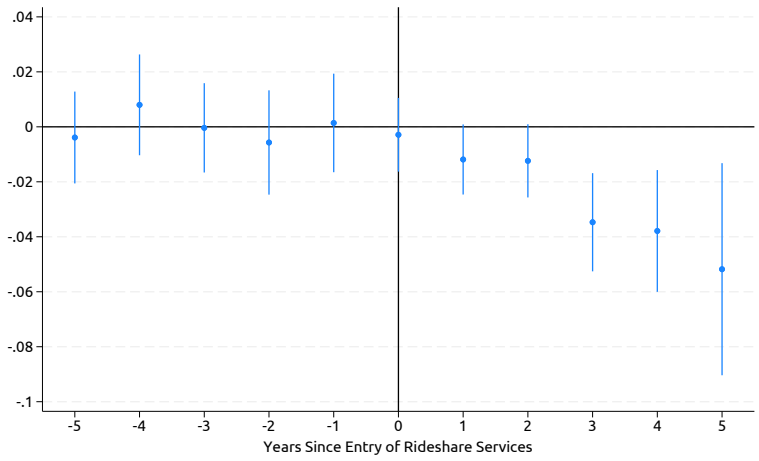


Figure 3: ***Entry of Ridesharing Services and Ex Ante Median Home Values of ZIP Codes of Mortgage Originations***

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

(A) Urban ZIP Codes



(B) Suburban ZIP Codes

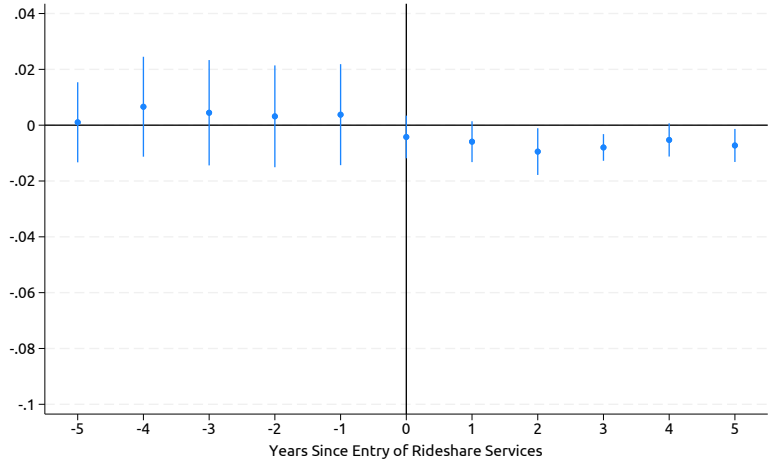
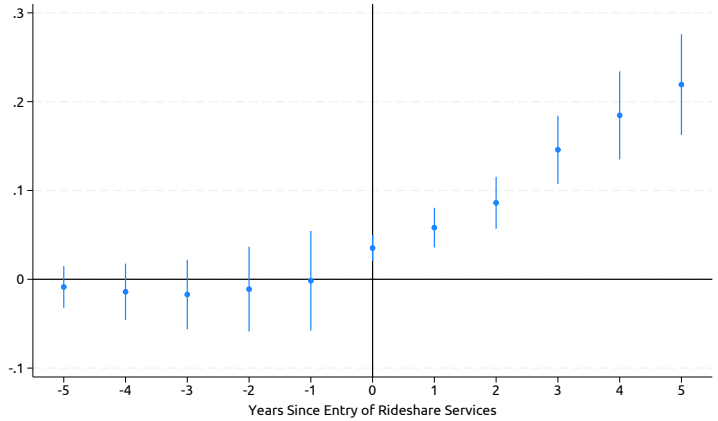


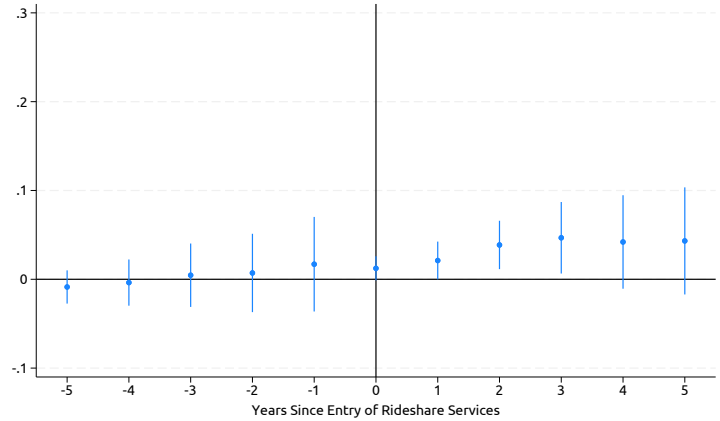
Figure 4: ***Entry of Ridesharing Services and House Prices***

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

(A) Urban ZIP Codes



(B) Suburban ZIP Codes



Transportation Technology and Gentrification: Evidence from Ridesharing Services Online Appendix

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March 12, 2025

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

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A Supplementary Figures and Tables

Table A.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*.
Car Ownership_z	Percent of individuals living in zip-code z who own a car. Data obtained from *American Community Survey*.

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

Variable	Definition
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 A.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 A.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 A.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 A.1 in the Appendix for detailed variable definitions.

	Urban	**Suburban**
Walkscore_z	95.8	82.4
	(3.7)	(11.8)
Transitscore_z	95.9	74.1
	(6.1)	(13.4)
Parking Costs_z		
	()	()
Car Ownership (High Income)	0.61	0.98
	()	()
Car Ownership (Low Income)	0.34	0.83
	()	()
Monthly Rent_z	95.8	82.4
	(3.7)	(11.8)
Income 90 percentile	500	225
	()	()
Income 10 percentile	23.1	33.6
	()	()
Poverty	11.1	3.4
	()	()

Table A.4: ***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 A.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

Table A.5: ***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 A.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 A.6: ***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 Consumer Credit Panel*. *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 A.1 in the Appendix for detailed variable definitions.

	Number of High-Income Households$_{z,y}$	Number of Low-Income Households$_{z,y}$	Age$_{z,y}$	Child Credit$_{z,y}$
	(1)	(2)	(3)	(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 A.7: ***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 A.1 in the Appendix for detailed variable definitions.

	#Mortgage Originations$_{z,y}$	Applicant Income$_{i,y}$	FHA-Insured$_{i,y}$
	(1)	(2)	(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 A.8: ***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 A.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 A.9: ***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 A.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 A.10: ***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 A.1 in the Appendix for detailed variable definitions.

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

Table A.11: ***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 A.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 A.12: ***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 A.1 in the Appendix for detailed variable definitions.

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

Table A.13: ***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 A.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

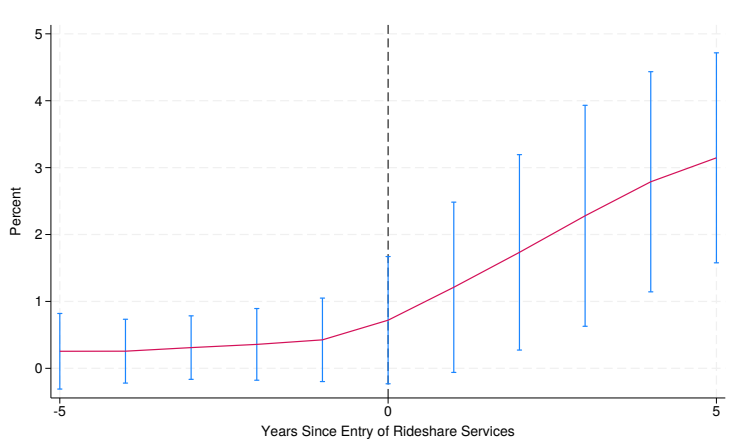
Table A.14: ***Entry of Rideshare Services and House and Rental Prices - Robustness***

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 A.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 A.1: ***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.



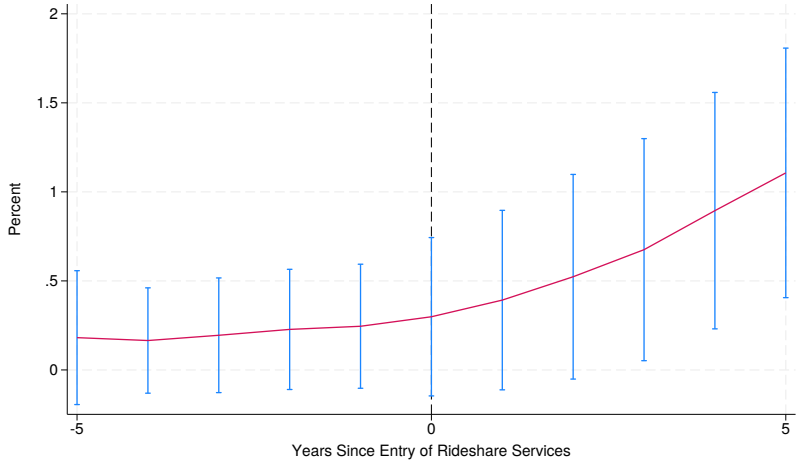
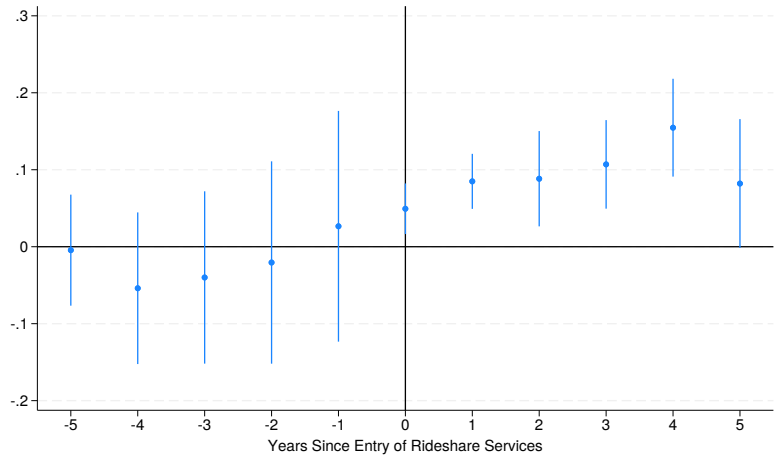


Figure A.2: ***Entry of Rideshare Services and Number of Mortgage Originations***

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 A.1 in the Appendix for detailed variable definitions.

(A) Urban ZIP codes



(B) Suburban ZIP codes

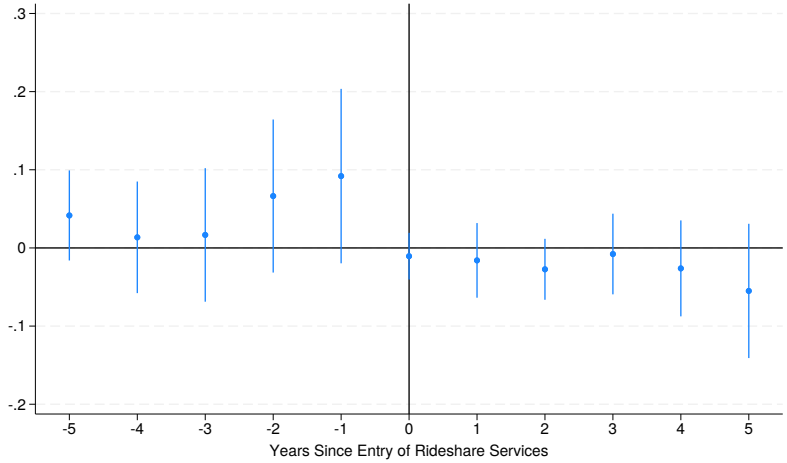
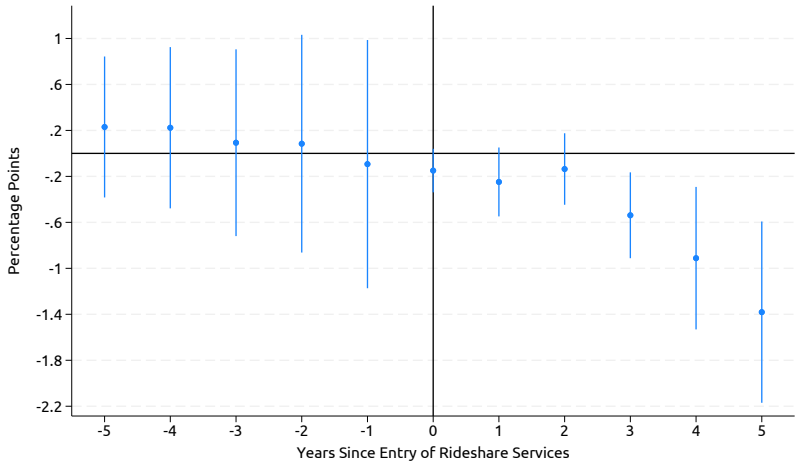


Figure A.3: ***Entry of Rideshare Services and Vacancy Rates***

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 A.1 in the Appendix for detailed variable definitions.

(A) Urban ZIP codes



(B) Suburban ZIP codes

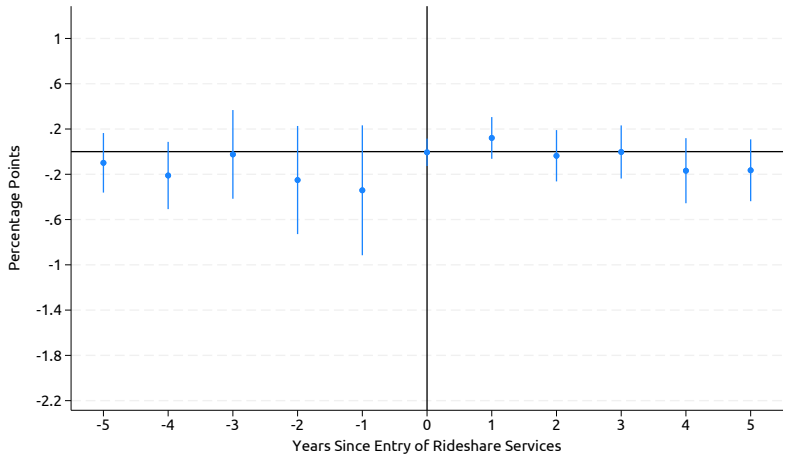
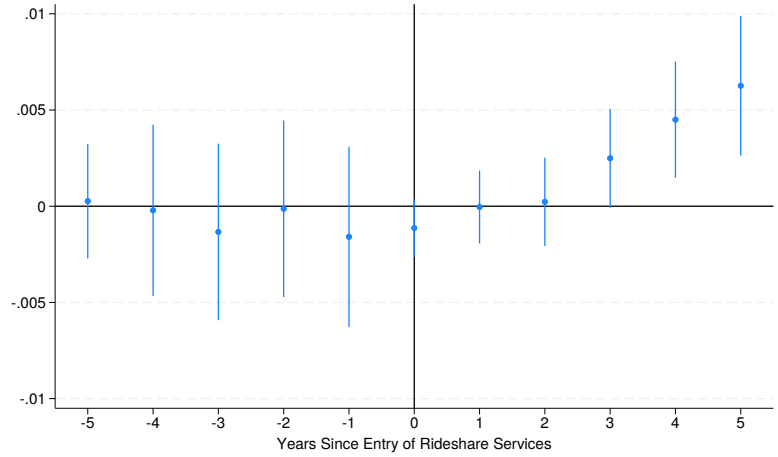


Figure A.4: ***Entry of Rideshare Services and Poverty Rate of ZIP codes of Mortgage Originations***

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 A.1 in the Appendix for detailed variable definitions.

(A) Urban ZIP codes



(B) Suburban ZIP codes

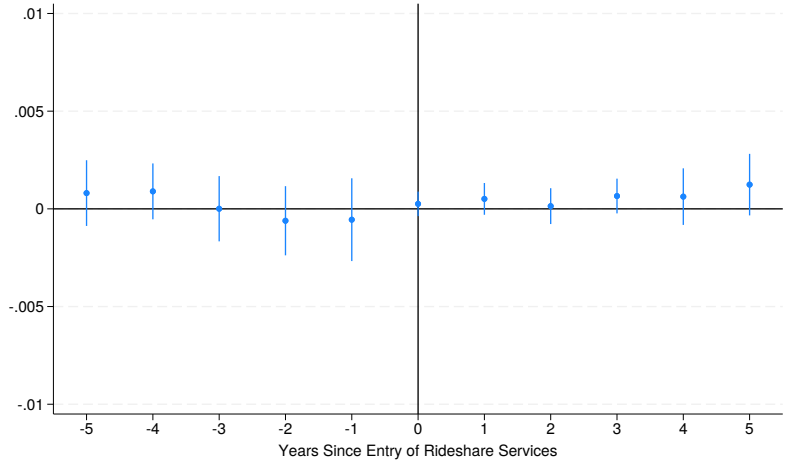
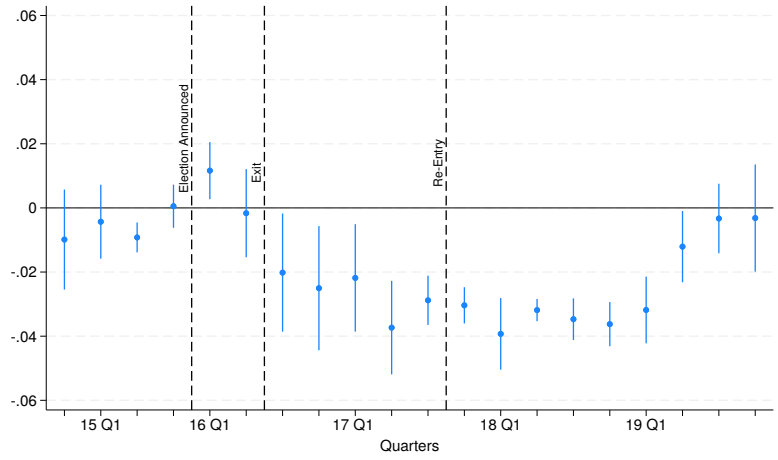


Figure A.5: ***Exit of Rideshare Services and Housing and Rental Prices - The Case of Austin***

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 A.1 in the Appendix for detailed variable definitions.

(A) Housing Prices



(B) Rental Prices

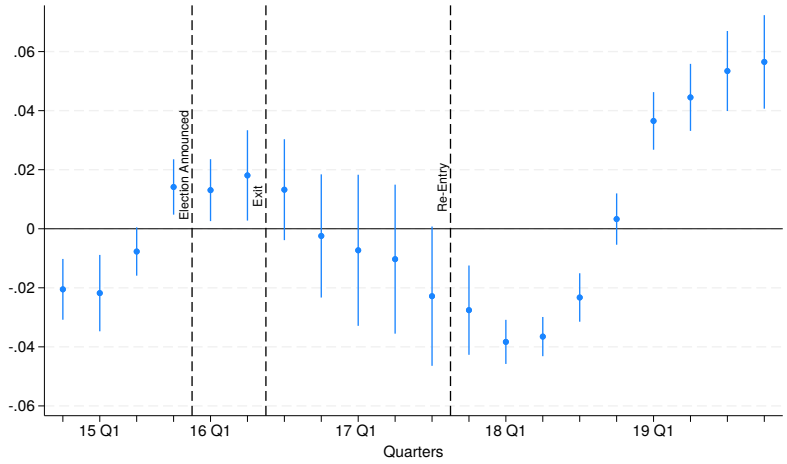


Table A.15: ***Characteristics of Homeowners vs non-Homeowners***

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 A.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 A.6: ***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*.

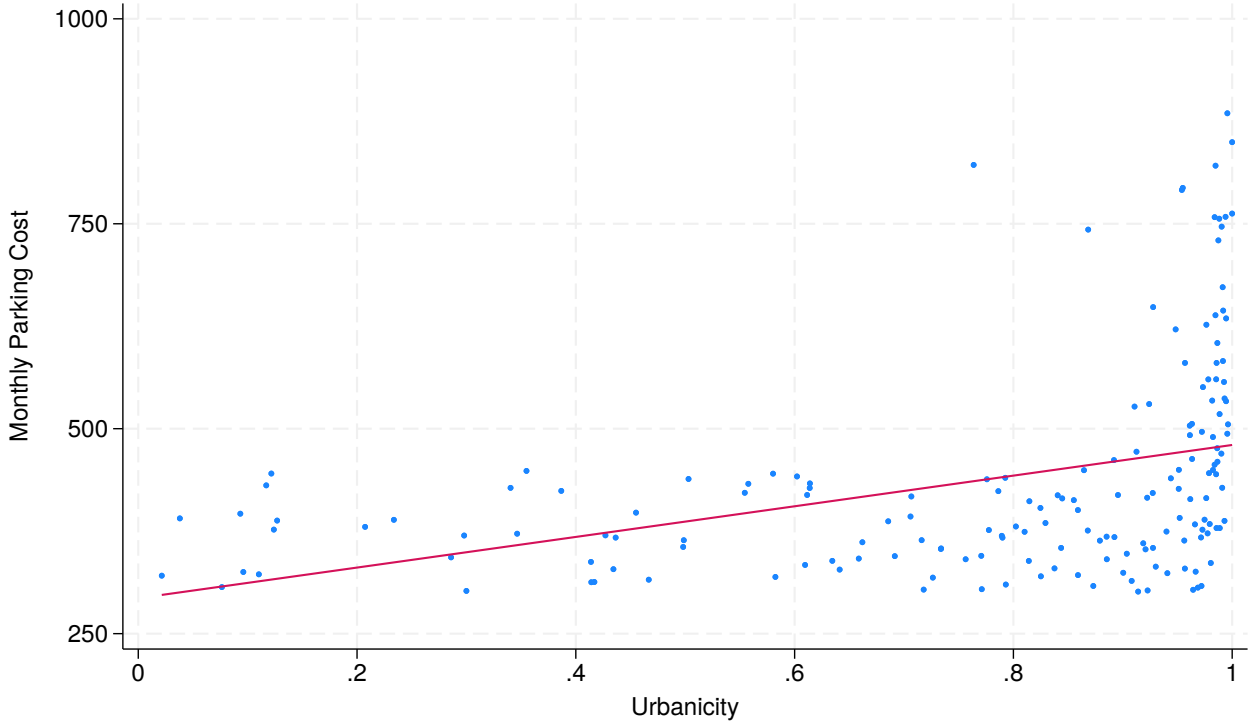
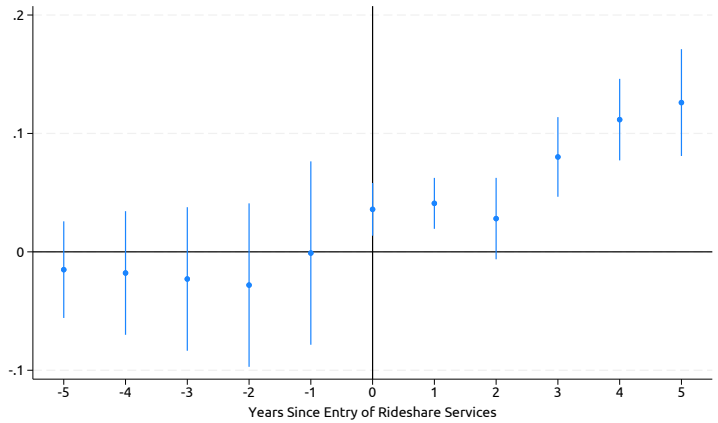


Figure A.7: ***Entry of Rideshare Services and Value of Originated Mortgages***

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 A.1 in the Appendix for detailed variable definitions.

(A) Urban Zip-Codes



(B) Suburban Zip-Codes

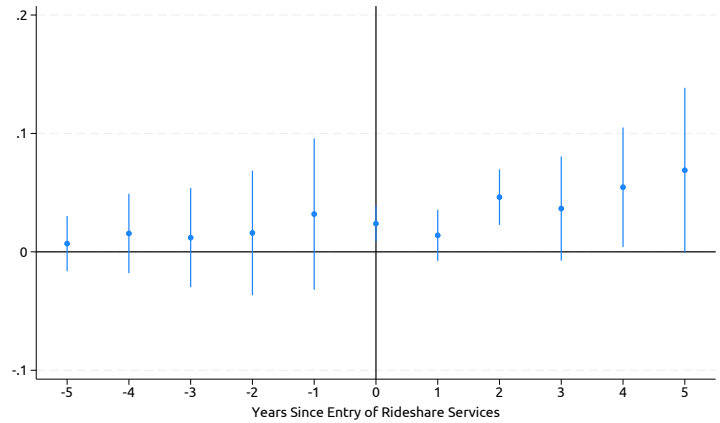
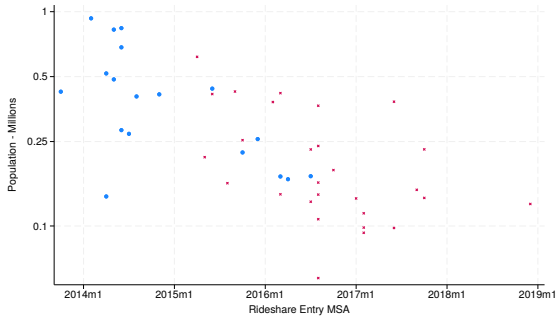


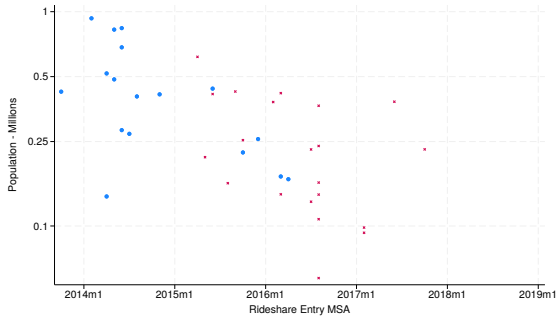
Figure A.8: ***Entry of Rideshare Services in MSAs given Entry in State - MSAs w/ Population <1 Million***

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



B 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.

B.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.[28] 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.[29] 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:

$$0 = \tau^{u,c} < \tau^{s,c} < \tau^{u,p} < \tau^{s,p} < \infty \tag{2}$$

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.

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

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

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:

$$U(c_i; v, l) = g(c_i) - \tau^{l,v} c_i \tag{3}$$

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:

$$(1 + \lambda_{l,v}) h_l + f_v + c_i \leq w_i \tag{4}$$

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

Table B.16: ***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.

B.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 B.16. 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.

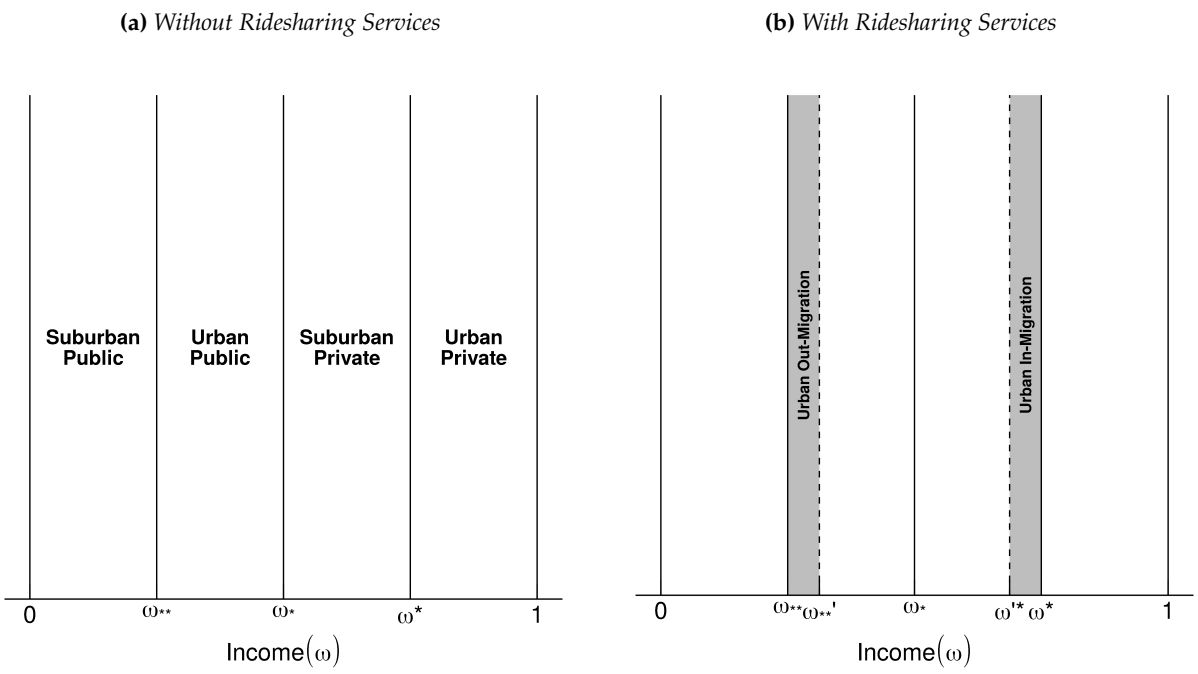
Result 4. Individuals with incomes w_i such that $w_i > w^*$ choose urban areas with private transportation. Individuals with income w_i such that $w_* < w_i < w*$ prefer suburban areas with private transportation with $w* < \mu$. Individuals with income w_i such that $w_** < w_i < w_*$ prefer urban 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 B.9. 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

Figure B.9: ***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



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 $1 - w^* + w_* - w_{**}$.

B.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 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 B.9. 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.