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Abstract

We show that the intensity of "keeping up with the Joneses" behavior is largely determined by the extent to which a community is socially connected. Using a unique dataset on car purchases in Southern California, we find that social influence intensifies in suburban communities in which neighbors are likely to know each other well. The effect of connected communities is particularly apparent in higher price segments and cannot be fully explained by word-of-mouth as it spills across car makes. Our findings suggest that positional externalities from the consumption of visible status goods are higher in closer-knitted social networks.

JEL Classification: A14, D12

Keywords: Conspicuous consumption, neighbor effects, Population density, tight-knit community

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Heterogenous Peer Effects: How Community Connectivity Affects Car Purchases*

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"We asked him how he heard of Tesla and why he bought the car," said Rachel Konrad, a Tesla spokeswoman. "He said, 'Well, three other guys on my block have them.' " (*New York Times*, Feb. 15, 2010).[1]

1 Introduction

This quote from *The New York Times* provides an explanation of why someone had decided to buy a $190,000 fully electric Tesla sports car: namely, because of peer effects and conspicuous consumption. In this paper, we analyze how car purchase decisions of neighbors in a large area of Southern California affect an individual's own car purchase decisions. In particular, we examine how the purchase of a given car make affects subsequent purchases of *other* makes by people living nearby. We find that the spillover effect is stronger in higher-priced segments, as luxury makes are clearly more conspicuous. That is, if your neighbor buys a BMW, you are more likely to buy a Mercedes. We further show that status-driven consumption is stronger in suburban communities than in urban, more densely populated, areas. Indeed, our sample includes three counties with large and diverse populations mostly living in metropolitan areas with different degrees of density, from high (urban residency) to low (suburban community). We use this heterogeneity in local density as a proxy for the extent to which a community is socially connected. We find that the social influence of neighbors buying a luxury car increases when the population density decreases and is highest in suburban communities, where neighbors are likely to know each other well.

A major empirical challenge for our analysis is the existence of several potential reasons other than "keeping up with the Joneses" that might influence a car purchase. Arguably, one of the most important is the information channel or word-of-mouth. In our empirical analysis, we control for this "information" effect in several ways. First, we distinguish between different price segments, as the behavioral effect is expected to be stronger in luxury makes, which are clearly more conspicuous. Second, we study the effect across different

[1] "Cities Prepare for Life With the Electric Car" by Todd Woody and Clifford Krauss.

makes—i.e., how purchases of one make affects purchases of other makes that are different from the original. While it is possible that purchases of cars of the same model or even the same make are induced by a "bandwagon" effect, it is difficult to see how information exchange can create spillover effects across different car makes. In addition, since cars of different makes are often considered to be imperfect substitutes, crowding in specific car makes due to word-of-mouth is expected to come at the expense of other makes. As effects across different makes are less likely to be driven by information transmission, positive—rather than negative—peer effects across different makes are more likely driven by status signaling rather than by information transmission. In particular, positive effects across different *luxury* makes are consistent with a "snob" effect, representing a desire to distinguish oneself by purchasing not the same car but a better one (Leibenstein 1950). Third, we use population density as a proxy for the extent of social connections within a community and conjecture that more connected communities facilitate the signaling of income or wealth through the public display of consumption. We argue that the block group is a peer group sufficiently local to capture the association between density and social ties. Importantly, our empirical analysis interacts all of the abovementioned identification strategies. For example, we show that the density effect is strong even if the previous transaction involves a different luxury make.

Our data includes all car purchases, new and used, during 2004–2006 in three large adjacent counties in Southern California. While it is not possible to obtain the exact street address of each buyer, our data is broken down into the smallest geographical unit one can use in studying car purchases with U.S. data—i.e., census block groups (BG). Our objective is to compare purchase patterns across areas with different population densities within these three counties. Unlike thinly populated areas in which inhabitants may live too far apart to know one another, Southern California is highly populated. Low-density areas in our sample will thus typically represent a suburban neighborhood or a small community, usually with relatively high household incomes. We follow the identification strategy suggested by

Bayer, Ross, and Topa (2008) and include neighborhood fixed-effects. One concern is that neighbor effects are driven by the mobility of households into neighborhoods. That said, our focus is on recent car-purchasing patterns. While people definitely consider neighborhood characteristics such as nationality, religion, ethnicity, age, and wealth when they choose where to reside, recent car-purchasing patterns are not expected to play a significant role in the sorting of households into neighborhoods. Another concern is that neighbor effects are driven by the presence of unobserved individual attributes associated with a propensity to buy a car in general and luxury makes in particular. The granularity of our data allows us to control for the census tract to capture unobservable neighborhood characteristics. While each neighborhood is expected to have unobservable characteristics, blocks of 1,500 people are not expected to differ within the tract of 4,000. We thus argue that any remaining within-neighborhood effects, after including tract fixed-effects, stem from social interactions.

In our first exercise, we examine whether the decision of which car to buy is affected by recent decisions made by neighbors. We show that neighbor effects are stronger in luxury makes. This is consistent with a stronger behavioral effect in higher-priced segments, which are clearly more conspicuous. We further show that, in general, crowding in specific car makes comes at the expense of other makes. In luxury makes, however, we find that the likelihood of buying a different luxury make increases with recent transactions within the same BG, consistent with a desire to "get ahead of the Joneses" by which neighbors care more about distinguishing themselves by purchasing not the same luxury brand, but a different one. To tease out the mechanism, we introduce *local population density* as a proxy for neighbor anonymity. We find that the magnitude of the neighbor effect depends on its interaction with population density. The results hold after we control for the median family income in each BG (as a proxy for the general tendency to buy a luxury car) and include both calendar and neighborhood fixed-effects.

Next, we show that close neighbors matter more. We match each BG with its broader zip code and examine the effect of recent transactions by distant neighbors—that is, more distant residents within the same zip code but not residing in the same BG. Overall, the effect of distant residents is weaker and not affected by population density. For robustness, to ensure that the neighbor effects cannot be fully explained by either native car makes in Southern California or car dealerships serving the broader region, we control for the general prevalence of each make in our sample.

Our paper contributes to the literature on status-signaling behavior. Indeed, as documented by Heffetz (2011), cars are the single most visible expenditure category among 31 items that altogether include almost the entire range of consumer expenditures in the U.S. economy. Heffetz (2011) shows that car expenditures are not only the most visible but also the most luxurious (i.e., have the highest income elasticity). Choo and Mokhtarian (2004) provide more evidence of the purchase of luxury cars as status-signaling devices. Kuhn et al. (2011) identify the substantial social effects of the Dutch Postcode Lottery, in which one participating household in a randomly selected postal code receives a new BMW. The authors find robust evidence of the effects of lottery prizes on neighbors of winners, but only for one good—car consumption—which is likely to be easily, and repeatedly, visible to a household's neighbors.[2] Most recently, Bricker, Krimmel, and Ramcharan (2021) use data from the Survey of Consumer Finances (linked to tract-level proprietary data on car purchases) to show that a household's income rank relative to its close neighbors—those in the same census tract—is positively associated with the decision to buy a high-status car. Spending on high-status cars is positively associated with a reduced savings rate and greater household debt including credit card balances, the decision to file for bankruptcy, and riskier portfolios. The authors suggest that relatively richer households signal their higher status to their neighbors through the consumption of visible status goods.

Compared to this literature, our findings suggest that positional externalities from the consumption of visible status goods are higher in *closer-knitted social networks*. We docu-

[2]For example, an immediate neighbor winning the lottery raises the probability that a household will buy a car in the next six months by close to seven percentage points and reduces the mean age of its main car by half a year (about a 7% decline) within six months after the lottery date.

ment that in areas of relatively low-population density, consisting of suburban areas —as opposed to metropolitan areas of high density, or rural areas of little density—neighbors are more likely to influence each other's conspicuous consumption decisions. We show that purchases of luxury make cars have an effect on neighbors' luxury-make purchase decisions, and the effect is stronger in areas with lower population density, which represent suburban communities in our sample. By documenting a crucial determinant of status-driven behavior, this paper offers a better understanding of the underlying forces in economic decision making. The empirical research on social influence is divided as to why consumers appear compelled to "keep up with the Joneses." Our evidence shows that social influence results from status-signaling behavior—but to a varying degree. The effectiveness of status-signaling behavior depends on the extent to which a community is connected.

To the best of our knowledge, we are the first to examine the effect of population density on conspicuous consumption with such granular U.S. data.[3] De Giorgi, Frederiksen, and Pistaferri (2020) construct peer groups based on workplace (rather than neighborhood) using Danish longitudinal data. The authors distinguish between the status mechanism of "keeping up with the Joneses," and a more traditional risk-sharing view. More relatedly, Grinblatt, Keloharju, and Ikäheimo (2008) find social effects, which occur immediately (within days), of car purchases among Finnish neighbors. The authors argue that their results are consistent with information transmission as the primary source of social influence on consumption. We are interested in the extent to which car purchases can be used to signal wealth. In the U.S., pay is confidential and considered a very private and sensitive matter. As information on income and wealth becomes less transparent, status signaling plays a more important role. While it is possible that people have more information on each other in small communities, we believe that even in the most "connected" communities in our sample (wealthier small communities in Southern California), information is still far from transparent and status

[3]Hong, Kubik, and Stein (2008) and Gómez, Priestley, and Zapatero (2016) provide some indirect evidence of the effect of population density on relative wealth concerns through the equilibrium properties of security prices.

signaling plays an important role. The main limitation in using U.S. data is that we are unable to identify individuals and their immediate (as in literally next-door) neighbors, but only a pool of individuals residing in the same block. While this data restriction does give rise to alternative explanations for neighbor effects other than status, it has much less to do with our main research question, which is whether the status-driven part of neighbor effects is attenuated by population density.

The paper is structured as follows. Section 2 explores the conspicuous consumption and social capital literatures and motivates our main hypothesis. In section 3, we describe the data. Section 4.1 examines the decision of which (luxury) car to buy in light of recent transactions within the same BG; section 4.2 presents the effect of population density; and sections 4.3 and 4.4 provide falsification and robustness tests respectively. Section 5 concludes.

2 Hypotheses Development

The notion that individual agents are influenced in their economic decisions by the consumption or wealth of some comparison group (such as neighbors, co-workers, or relatives) has been present in the social sciences literature in general, and in the economics literature in particular, for a long time. This type of behavior has been labeled as "keeping up with the Joneses" and, arguably, it is at least partially motivated by the objective of signaling a certain level of economic status. In his path-breaking work, Veblen (1899) introduced the notion of "conspicuous consumption" and argued that individual agents spend resources on luxurious goods that indicate a certain status.[4] A related line of research has provided strong macroeconomic evidence of investment in conspicuous goods. Hirsch (1976) calls this type

[4]According to the Longman Dictionary of Contemporary English, conspicuous consumption is defined as: "The act of buying a lot of things, especially expensive things that are not necessary, in order to impress other people and show them how rich you are." (http://www.ldoceonline.com/dictionary/conspicuous-consumption)

of activity the "positional economy."[5] Duesenberry (1949) postulates that the utility of consumers depends on the ratio of their own consumption to a weighted average of a reference group. The inclusion of relative wealth concerns in the utility function has become a frequent device to explain asset prices since Abel (1990) first suggested it. In an influential paper, Campbell and Cochrane (1999) introduce the notion of "external habit formation." This additional parameter in the utility function has been interpreted as relative wealth concerns by most scholars. Bagwell and Bernheim (1996) examine conditions under which luxury brands are sold at a price above marginal cost to consumers seeking to achieve social status by signaling wealth through conspicuous consumption. More recently, Moav and Neeman (2012) show that a signaling equilibrium in which poor individuals tend to spend a large fraction of their income on conspicuous consumption can emerge. Using survey-experimental methods, Alpizar, Carlsson, and Johansson-Stenman (2005) find that most individuals are concerned with both relative income and relative consumption. The recent availability of data on individual consumption enables us to study how individual purchase decisions affect the consumption decisions of neighbors. Ravina (2019) finds that household consumption choices are influenced by both household past consumption and the consumption level of the city in which the household is located. Charles, Hurst, and Roussanov (2009) find that the share of expenditure devoted to visible goods (clothing, jewelry, and cars) is lower the larger the income of the reference group, defined (in that paper) as others of the same race living in the same state as the focal consumer. Using data from the German Socio-Economic Panel, Drechsel-Grau and Schmid (2014) find that household consumption is particularly affected by the consumption level of households who are perceived to be richer, which the authors describe as "keeping up with the *richer* Joneses" behavior.

We find that the use of car purchase data is an adequate setup to study conspicuous consumption. In particular, it allows us to distinguish between the two channels at play, namely

[5]Mason (2000) offers a survey of some of the literature on this topic, as well as recommended economic policies, and Heffetz and Frank (2011) provide a more recent and comprehensive survey with an analysis of some economic implications.

information transmission and status signaling. First, we distinguish between ordinary and luxury cars. Of course, cars do not necessarily fit the abovementioned definition of conspicuous goods: For many people, a car is as important for their normal participation in society as proper clothes or an adequate dwelling. However, it is also clear that above a certain threshold, the car becomes a luxury good, and some of the price is related to "unnecessary" car attributes. We conjecture that:

H1: Neighbor effects in car purchases are stronger in luxury makes, which are more conspicuous.

Second, we study the effect across different makes. Leibenstein (1950) distinguishes between the "bandwagon" effect and the "snob" effect. The bandwagon effect represents the desire to catch-up and conform by mimicking purchases of peers, while the snob effect represents the desire to be exclusive and distinguish oneself by purchasing a different brand from one's peers. Spillover effects across different car makes thus enable differentiating between the two channels at play—namely, information transmission and status signaling. If word-of-mouth induces purchases of cars of the same model or even the same make, we would expect that crowding in a specific car make would come at the expense of other makes. On the other hand, neighbors may find the purchase of a different make more appealing in an attempt to distinguish themselves. They will therefore consider alternative makes and purchase one that offers an even better set of features. This is consistent with an objective to not merely to get close to the average, but rather to surpass one's peers or "get ahead of the Joneses." Importantly, while both bandwagon and snob behaviors can be consistent with status signalling, the bandwagon effect is driven by information transmission while the snob effect is inconsistent with information transmission. We therefore conjecture that:

H2: Spillover effects across different car makes are primarily the result of status signaling and not information transmission.

While peer pressure can come from several reference groups, such as family and co-workers, our focus is on neighbors. Luttmer (2005) finds that controlling for an individual's own income, higher earnings of neighbors are associated with lower levels of self-reported happiness. Results are stronger for people who socialize more with neighbors, but not for those who socialize more with friends outside the neighborhood, which further suggests that the mechanism mediating this effect is most likely caused by interpersonal closeness. Following this insight, we want to move a step forward and study the effect of community on status-driven behavior. Duesenberry (1949) argues that "any particular consumer will be more influenced by the consumption of people with whom he has social contacts than by that of people with whom he has only casual contacts." The notion of "social contacts" in Duesenberry (1949) is at the core of our study, and related to another line of literature in sociology of "social capital." Social capital typically refers to social, economic, and political effects of a social network. The sociology literature provides several reasons why social capital appears to decline with population density. Jacobs (1961) was the first to argue that in big cities, strangers are far more common than acquaintances. In smaller towns and communities, controls on acceptable public behavior seem to operate through a web of reputation, gossip, approval, disapproval and sanctions, all of which are powerful if people know each other and word travels. Fischer (1982) directly measures interpersonal networks in areas with different population density and finds that urban life reduces the size of, as well as frequency of, socializing with one's local personal network. He also finds that social ties with nonrelatives who live nearby decrease with population density. Putnam et al. (2000) show that organizational forms of social capital—such as membership and participation in civic, social and fraternal clubs and societies—also collapse with urbanization.

This paper bridges the two lines of literature—namely, conspicuous consumption and social capital—by using local density to proxy for neighbor anonymity. In high density areas, it is more difficult to keep track of neighbors, and social interactions are more transitory and impersonal. Bumping regularly into the same people is also less likely, and thus fewer opportunities exist to form relationships. Neighbors in suburban communities, on the other hand, have the opportunity to chat or wave hello when coming and going from their residences, playing in the yard, or gardening.[6] Neighbors in suburban communities are likely to interact in multiple ways as a result of possibly having children who attend the same schools, shopping in the same stores, attending the same churches, and even working for the same employers. In his seminal analysis of social networks, Granovetter (1973) defines weak ties in terms of a lack of overlap of two individuals' networks. Sato and Zenou (2015) and Zenou (2015) define a weak tie when the social interaction between two persons is transitory (e.g., random encounters) rather than repeated over time (e.g., members of a small community).[7] According to both arguments, suburban neighbors who routinely interact in multiple ways with a relatively unchanging peer group become a "connected" community. Hong, Kubik, and Stein (2004) show that stock-market participation depends on the number of neighbors you know, how often you visit them, and whether you attend the same religious services. Using data from the Social Capital Benchmark Survey, Brueckner and Largey (2008) provide empirical evidence for a negative link between interaction and census-tract density. Low density neighborhoods are associated with higher friendship-oriented social interactions and various measures of group involvement. Arguably, driving a nice car in a densely populated city may attract more envious gazes than in a lower populated area. Status seeking, however, is not about such petty swagger but rather about being clearly identified with an upper class. That is, conspicuous consumption only has value as a signal if the receiver can clearly identity the sender. A connected community provides an obvious reference for its members, and the lack of "anonymity" gives more strength to the visibility and attribution of conspicuous consumption. We thus conjecture that:

H3: Neighbor effects in car purchases are stronger in connected communities, which are defined as low density areas in our sample.

[6]In our sample, "lower population density" refers to areas in which neighbors live close enough to interact, rather than areas in which people are so far apart that they might have to drive to interact. This will become clear when we describe our data.

[7]Sato and Zenou (2015) show that in denser areas, individuals seek weak ties in order to maximize their employment prospects.

The idea of using population density as a proxy for social network—but only the density of the local area—is not new to the literature. Bayer, Ross, and Topa (2008) were among the first to explicitly test the interactions between the urban and the social space and their impact on individuals' outcomes. The authors find that block-level sorting on observables does not appear to be directly related to employment outcomes. The findings are also robust to the inclusion of individual fixed-effects, which essentially control for a type of sorting on unobserved attributes. Bayer, Ross, and Topa (2008) thus suggest that a significant portion of interactions with neighbors are very local in nature—i.e., the interactions occur among individuals on the same block. It is therefore important to note that the validity of density as a proxy for the extent of a community's social connections is crucially dependent on the geographical level used in the empirical analysis. Our analysis is performed on the census block group level—that is, peer groups sufficiently local to capture the association between density and social interactions.[8] Topa and Zenou (2015) further provide an extensive survey on the extent of overlap between the social space spanned by individual social networks and the geographic space described by neighborhoods.

3 Data and Descriptive Statistics

3.1 Data

We use information from a data set from R. L. Polk & Co. that records all new and used car purchases from most U.S. Departments of Motor Vehicles (DMVs) offices. For each purchase, we have the car model, make, and year, as well as date of purchase. For privacy reasons, it is not possible to obtain the exact address of the buyer; however, we have information on the census block group (BG), which comprises a household's geographically localized community. We merge the Polk data set with data from the 2000 U.S. Census, which

[8]See also Wahba and Zenou (2012), Patacchini and Zenou (2012), and Biavaschi, Giulietti, and Zenou (2021) who proxy the social network of individuals by the local area where they live.

includes demographical information at the BG level. BGs are delimited by the U.S. Census Bureau. and they contain between 600 and 3,000 people, with an average size of only 1,500 people. A BG is the smallest geographical unit for which the Bureau publishes data, making it the finest level of analysis one can use in studying car purchases in the U.S. BGs provide much greater granularity than U.S. Postal Service ZIP Codes, as the population of a single zip code can exceed 100,000. Furthermore, BGs are defined on the basis of population and not area, meaning that BGs with different population densities will only differ in geographic size, while having similar population levels. This provides the statistical uniformity required for small-area demographic and economic analyses.

We have information on all car purchases for three years, 2004–2006, in three large, adjacent counties in Southern California: Los Angeles, Orange, and Riverside (Orange County is contiguous to both Los Angeles and Riverside Counties, but the last two are separated by a narrow sleeve of land belonging to San Bernardino County). The three counties in our sample are heavily populated, with nearly 14 million inhabitants according to the 2000 census. While downtown Los Angeles is not very densely populated, the neighborhoods west of downtown (e.g., Koreatown, Westlake, and so forth) are very dense. Overall, the city of Los Angeles has the highest population density in the U.S., housing nearly 7,000 people per square mile (U.S. Census 2010). As the Los Angeles metropolitan area is surrounded by numerous smaller cities and communities, it enables us to study the effect of population density in our sample. Even within some areas in the Los Angeles metropolitan area—Santa Monica and Hollywood, for example—there is a mix of high-rise and residential housing, and thus population density can be diverse within a relatively small neighborhood, and thus can change dramatically from one BG to the next. Overall, Southern California is a highly populated area, and "low density" typically represents a suburban neighborhood, usually with relatively high household incomes. Therefore, in what we call "low population density," neighbors are likely to know each other and have the opportunity to communicate easily (as opposed to areas in which neighbors are so far apart that direct communication might require an extra effort). In addition, neighbors in suburban areas are likely to see each other's cars more often, as they park in a driveway rather than in a parking garage. Our objective is to compare car-purchasing patterns across different areas with different population densities within these three counties. Importantly, a car is virtually a strict necessity throughout Southern California, as public transportation options are limited even in the most populated areas.

3.2 Descriptive Statistics

Panel A of Table I includes descriptive statistics on all three counties. In total, we have over 7 million car observations with a population of nearly 14 million people and nearly 9,000 BGs. In Figure I, we show that the BGs delimitation is based on population, not area.[9] Although there is some variation in population across BGs (1,500 people on average), we note that it should not affect our analysis as population and area across BGs are uncorrelated.

[Table I about here.]

[Figure I about here.]

In Panel B of Table I, we present median BG characteristics within each county. We see that BGs span across various areas depending on the county, with Riverside BGs having a much larger area. Importantly, the distance between neighboring block groups (roughly the square root of the BG area) is less than a mile even in the least populated areas, attesting for the granularity of our data. Another important observation is that, in our sample, low density represents small communities, high density represents cities, and medium density represents urban sprawl. Figure II provides histograms of the distribution of population density across BGs.[10] Clearly, we have enough density dispersion across our sample to test

[9]In this histogram, we have used the number of households per BG, but population per BG displays a similar graph.

[10]Population density is measured per 1,000 square meters, however, one can easily convert this density metric into population per square mile by multiplying by 2,590.

whether population density affects how agents' purchase decisions influence the decisions of their neighbors. Similarly, Figure III shows that we have sufficient dispersion in the distribution of household income across the BGs. Given that income is a main factor in the types of cars people buy, it can be used to control for the baseline probability of buying a luxury car.

[Figure II about here.]

[Figure III about here.]

To examine car-purchase patterns within a BG over time, we first aggregate all car purchases within each BG and calendar quarter (note that we have 12 quarters during our 3-year sample period), and then report median BG-quarter characteristics within each county. Given the geographical granularity of our data, calendar quarters represent the shortest interval to provide an informative indication of car-purchasing patterns (that is, the number of car registrations of a particular make within one BG during only three months is around one). Most importantly, focusing on calendar quarters minimizes the effect of limited-time promotions as a possible source for lumping. Limited-time promotions, whether initiated by the actual carmaker or a local representative, can produce transitory lumping of purchases of (luxury) cars independent of communication and/or status signaling, and might give the false impression of influence in purchase decisions. As such promotions typically last no longer than one month, calendar quarters are sufficiently long to span over limited-time promotions. The bottom part of Panel B of Table I shows that while a total of 66 different car makes exist in our sample (63 non-luxury and 3 luxury), the typical BG-quarter combination involves purchases within less than 20 car makes (with the reminder of makes involving zero transactions within the same BG-quarter combination). That is, each of the currently-bought car makes accounts for around 5% of the overall flow of car purchases (within the same BG during the same calendar quarter), on average. Yet the individual portion of each currently-bought car make ranges from zero to potentially much higher than the 5% average, and can alternate significantly from one quarter to the next. These observations facilitate our main empirical specification in which we examine how changes in car make composition can be attributed to recent purchases by neighbors. Finally, we see that the portion of luxury makes is significantly smaller than that of non-luxury makes, consistent with the higher prices and exclusivity that define luxury makes. Luxury cars account for 5%–10% of all car purchases. Among the currently-bought car makes, each non-luxury make will typically involve around three transactions, while each luxury make will involve around one to two transactions, at the BG-quarter level.

4 Main Results

Our exercises aim to examine the magnitude of status-driven behavior (conspicuous consumption). In particular, we focus on crowding in specific makes. One concern is that crowding is the result of a common local shock, which will affect neighbors similarly even if no peer effect exists. We address this simultaneity issue by examining whether the decision to buy a car is affected by recent (but not contemporaneous) decisions made by neighbors. As previously noted, calendar quarters are long enough to span over limited-time promotions as a possible source for lumping. Because peer effects create lumping/clustering in specific makes, our analysis is make-specific. We are interested not in the decision to buy a car, but in the decision of *which* car to buy. We therefore focus on the propensity to buy a particular car make. Importantly, we want to capture not only peer effects within the same car make, but also in a different make. While effects within the same make are consistent with both "keeping up with the Joneses" and word-of-mouth, effects across different makes capture a clean peer effect through the notion of "*getting ahead* of the Joneses." To be able to capture peer effects within as well as between car makes, the level of analysis in our panel data is the triplet BG-Date-Make, or more elaborately BlockGroup-CalendarQuarter-CarMake.

4.1 The Decision of which (Luxury) Car to Buy

Our main regression model estimates the effect of recent transactions within the same BG on the subsequent car turnover involving either the same, or a different, car make. The OLS model we estimate is

$$\begin{aligned} MakePortion_{i,j,q} \;&=\; \alpha + \beta_1 SameMake_{i,j,q-1} + \beta_2 DifferentMake_{i,j,q-1} + \\ &\quad \beta_3 Income_i + Quarter_q + Tract_i + \varepsilon_{i,j,q}, \end{aligned}$$

where i is a block group, j is a car make, and q is a calendar quarter. We reiterate that we include observations for all makes that exist at some point in the sample, including makes that experienced zero transactions in the BG-Quarter level.

The dependent variable is *Make Portion*$_{i,j,q}$, defined as the number of car-make transactions j in block group i at a calendar quarter q, divided by the overall number of transactions of all makes in a block group i during a calendar quarter q in percentage terms (i.e., multiplied by 100).[11] Observe that both the numerator and denominator are based on the flow—as opposed to the stock—of car registrations. Effectively, *Make Portion* represents the probability that a car buyer chooses a particular car make within a BG-Quarter, which should not be confused with the preexisting and cumulative "market share" of a car make. We focus on car make and not on specific models because model effects may be driven by information exchange to a larger degree than the make of the car.[12] Cars of different makes are often considered to be imperfect substitutes for their purpose of transportation. As such, crowding in specific car makes does not require an increase in the total number of transactions, but rather a transition from one brand to another. Importantly, we still normalize the depen-

[11] We note that our results are almost identical when we use a logit model instead of OLS, in which the dependent variable equals 1 if at least one car of a specific make was purchased in a specific block group within a period of three months. However, the logit specification does not allow for the same straightforward interpretation of the coefficients and marginal effects.

[12] Because the car make is the most obvious attribute that signals status, we do not distinguish between new and used nearby car purchases. Any differences in add-ons and special features (such as sound systems and safety measures) are not distinguishable from the outside.

dent variable by the overall number of transactions in the same BG and calendar quarter to control for local shocks. One example would be a shock to housing prices cascading to car turnover. The remaining variation in our dependent variable thus captures crowding in specific makes at the expense of other makes.

The independent variables include indicators for purchases of either the same make or a different make within the same block group within the previous quarter.[13] *SameMake* is equal to 1 if at least one car of the same make was purchased within the same block group in the previous quarter. Since even make-level effects may be driven by information exchange, we also explore only transactions that follow a car of a different make. *DifferentMake* is equal to 1 if at least one car of a different make was purchased within the same block group within the previous quarter.[14] Importantly, *DifferentMake* is immune to any clustering in specific car makes due to unobservable variables. One such unobservable variable is car dealerships, many of which are associated with one particular make. Another example would be a local employer purchasing a batch of new company cars of the same model. As *SameMake* may capture such local clustering unrelated to status, we consider *DifferentMake* a much cleaner proxy for a "keeping up" or the "getting ahead of the Joneses" effect.

We include the median family income in each BG as a proxy for the general tendency to buy a car, and a luxury car in particular. We also control for seasonal effects that tend to lump car purchases around certain times of the year. It is widely known certain times of the year are more popular for car purchases (e.g. before Christmas, before summer for vacation traveling, and at the beginning of fall when new models are rolled out). The regression model therefore includes calendar quarter fixed-effects in order to control for within-year seasonality.

[13] We use indicators rather than counts to facilitate interpretation. It seems more intuitive that the existence of a recent purchase is triggering status concerns, while any additional purchase(s) have a diminishing marginal effect. We also note that in most cases, the number of car registrations within one BG within only 3 months will not exceed 1. The raw counts are thus not expected to behave differently than indicator variables.

[14] Specifically, we subtract the number of recent transactions of the same make from the total number of recent transactions of all makes and indicate whether the excess is positive.

We follow Bayer, Ross, and Topa (2008) and include broader neighborhood fixed-effects. Specifically, we use one level above BGs: census tract.[15] According to the U.S. Census Bureau: "Census tracts generally have between 1,500 and 8,000 people, with an optimum size of 4,000 people. Census tracts are designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions." One concern is the mobility of households into neighborhoods, as well as the presence of unobserved individual attributes associated with a propensity to buy a particular car style. It is possible, for example, that specific ethnic groups tend to buy specific car brands and also tend to gravitate to neighborhoods with a particular type of dwelling (e.g., single-family homes or apartments). Tract fixed-effects will absorb all time-invariant lumping in car makes—i.e., the tendency to purchase a smaller set of car makes—whether it is driven by correlated unobservables and/or endogenous selection into neighborhoods. We argue that the within-neighborhood effects, after controlling for the neighborhood, stem from social interactions. Our underlying assumption, the same as in Bayer, Ross, and Topa (2008), is that no block-level correlation exists in unobserved attributes among block residents after taking the broader neighborhood reference group into account. In our sample, this assumption seems reasonable: When you choose where to reside in Southern California, or even in L.A., you do care about the neighborhood, and each neighborhood does have unobservable characteristics; however, the particular block you live on within the neighborhood is relatively unimportant (specifically, in which BG of 1,500 people within the tract of 4,000). Table II displays the results.

[Table II about here.]

[15] Note that we cannot include BG-level fixed-effects, as doing so would remove the same cross-sectional variation we would like to capture in this study. It would also require us to drop all time-invariant place-specific variables, including local density, which is our main variable of interest. Econometrically, our data includes roughly 9,000 BGs but only 12 calendar quarters. This granularity results in a "short panel" with many individual units and few time periods. Even with 15 years rather than just 3, we would still have over 100 times more BGs than calendar quarters. As Nickell (1981) shows, fixed-effect models in short panels are not estimable, as they result in inconsistent estimators—i.e., estimators which do not converge to the true value even if the sample size goes to infinity.

Although Models 1–4 in Table II use different combinations of fixed effects, the R-Square remains at the same level—around 22% in all specifications. When we add quarter fixed-effects in Model 2, the explanatory power of the model does not improve, suggesting that seasonality is not responsible for much of the clustering in specific car makes. This is not surprising as our dependent variable is by definition normalized by the total number of transactions of all makes in the same block group during the *same calendar quarter*. In Model 3, we add tract fixed-effects.[16] Interestingly, the effect of income changes sign. Recall that income is a BG-level characteristic, and thus its coefficient measures the average make portion within a BG. Because people living in richer areas can afford a wider variety of car makes, each make will have a lower weight in the flow of car purchases. When we add tract fixed-effects, income becomes positively associated with lumping in specific makes, consistent with a stronger peer effect in richer communities. Most importantly, tract fixed-effects do not add significantly to the explanatory power of the model. This is not surprising because neighborhoods tend to be homogenous (in nationality, religion, ethnicity, age, wealth, and so forth), which makes it far from obvious that individual BGs within each neighborhood will differ in their car-purchasing patterns. Still, in all subsequent specifications we include neighborhood fixed-effects. This reassures us that the mobility of households into neighborhoods, as well as the presence of unobserved individual attributes associated with a propensity to buy a particular car make—which we capture via the tract fixed-effects—do not drive much of the clustering in specific car makes.

Our explanatory variables of interest are *SameMake* and *DifferentMake* in the previous quarter. We find that the probability of buying a particular car make is significantly *positively* affected by purchases of the same car make within the same BG in the previous calendar quarter. For every car make bought in the previous quarter, the likelihood of a neighbor buying it increases by around 4%. Conversely, the probability of buying a particular car

[16] We use the absorb option in SAS proc GLM. The absorption technique enables us to address the massive number of tracts. Rather than including individual dummies, this computational technique adjusts each observation for the absorbed effects in one pass of the data. An additional advantage of absorption is that the R-squared does not need to be adjusted.

make is *negatively* affected by purchases of a different car make in the previous quarter. Importantly, the peer effects remain strong within the local neighborhood after taking the broader neighborhood reference group into account. The positive effect of *SameMake* and the negative effect of *DifferentMake* are consistent with crowding in specific makes at the expense of other makes. However, crowding at this stage could still be driven by either word-of-mouth or peer effects, or some combination of the two.

In Models 5–6, we examine luxury makes separately from non-luxury ones. Because luxury cars are more conspicuous by definition, non-luxury cars are expected to elicit less envy and motivation to imitate and/or surpass thy neighbor. The non-luxury subsample may thus serve as a "placebo" test for status-driven peer effects in the luxury subsample. Luxury car makes include BMW, LEXUS, and MERCEDES-BENZ.[17] Note that when we split the sample into Luxury vs. Non-luxury makes, *DifferentMake* is naturally defined with respect to the reference group. That is, in the (non-)luxury analysis, *DifferentMake* equals 1 if at least one (non-)luxury car of a different make was purchased within the same block group within the previous quarter. This subtle yet crucial distinction enables us to test whether neighbors try to distinguish themselves by purchasing not the same luxury car, but rather a better one. Model 5 shows that non-luxury car makes behave much like the pooled sample. When we focus on luxury car makes in Model 6, the R-Square almost doubles (spikes from around 22% to around 36%). This is consistent with a stronger peer effect in luxury makes. The effect of *SameMake* seems smaller than that of non-luxury makes, yet this does not mean lower economic significance. Recall from Panel B of Table I that the the baseline portion of luxury makes is significantly smaller than that of non-luxury makes. Most interestingly, the effect of *DifferentMake* is no longer negative. While the negative effect in the pooled sample as well as in non-luxury makes seems intuitive and consistent with crowding in specific car makes at the expense of other (substitute) makes, different

[17] We confirm that these are the most popular makes within the higher price segment in our sample. While there are much more expensive luxury brands (such as Aston Martin, Bentley, Lamborghini, Maserati, and Rolls-Royce), we are after luxury brands that are not uncommon as well as available to neighbors.

luxury makes are more than just substitutes. The latter result is consistent with luxury transactions adding positional externalities, such as the desire to "get ahead of the Joneses." It is likely that permanent differences exist across BGs in the mean luxury purchase rate, and so one may argue that the autocorrelation that we find (between the decision to buy a luxury car and previous transactions involving luxury cars within the same BG) may be capturing this tendency rather than our social effect. Recall that we include the median family income in each BG as a proxy for the general tendency to buy a luxury car. By controlling for income, we mitigate any concern that the effect of past decisions made by neighbors is merely driven by the propensity to buy a luxury car in a BG.

4.2 Peer Effects in Connected Communities

Our next exercise directly examines "keeping up with the Joneses" behavior and its intensity in areas with different population density. In particular, we examine the interaction between local density and a recent nearby purchase. In the absence of status-driven behavior, we expect that information transmission merely by observation would be stronger in high density areas in which neighbors are closer to each other.[18] If, on the other hand, local density is associated with neighbor anonymity, we expect that status-driven behavior would be stronger in low density areas—that is, connected communities. Local density will thus assist in teasing out which mechanism prevails.

Table III follows our main specification and adds local density. The OLS model we estimate is

$$\begin{aligned} MakePortion_{i,j,q} &= \alpha + \beta_1 SameMake_{i,j,q-1} + \beta_2 DifferentMake_{i,j,q-1} + \\ & \beta_3 Density_i + \beta_4 Density_i^2 + \\ & \beta_5 SameMake_{i,j,q-1} Density_i + \beta_6 DifferentMake_{i,j,q-1} Density_i + \end{aligned}$$

[18] Recall that BGs are defined on the basis of population and not area, and so density corresponds to one over area. High density thus means much closer distance between neighbors.

$$\beta_7 Income_i + Quarter_q + Tract_i + \varepsilon_{i,j,q},$$

Density is the population density of the car buyer's BG and is defined per square meter as in the U.S. census. To explore a non-linear relation between peer effects and local density, we include density, first only by itself and then squared. This allows us to test whether the effect is convex, in which case it is concentrated in low-density areas. The interaction terms between our explanatory variables, *SameMake* and *DifferentMake*, and density will allow us to directly test whether the effects of recent nearby transactions differ in connected communities. Recall that we include the median family income in each BG as a proxy for the general tendency to buy a luxury car. In controlling for income, we mitigate any concern that the effect of past decisions made by neighbors, *and thus its interaction with density*, is merely driven by the propensity to buy a luxury car in a BG.

[Table III about here.]

Model 1 in Table III shows that local population density at the BG level is negatively correlated with lumping in specific car makes. Recall that density is a BG-level characteristic, and thus its coefficient measures the average car make portion within a BG (roughly the inverse of the number of non-zero car makes). Population density thus translates into concentration in specific makes, consistent with *stronger peer effects in low-density areas.* Importantly, while we control for local shocks both by normalizing our dependent variable by total transactions as well as with the inclusion of census tract fixed-effects, one may still argue that very localized shocks other than status can explain neighbor effects. If local shocks are confined to a very small geographical area, however, they will have a stronger effect on narrower BGs—i.e., BGs that are more densely populated. Since we report higher clustering in low-density areas, the effect of local shocks is not an alternative explanation because it goes against our findings. Model 2 shows that the relation is non-linear. In particular, lumping is concentrated in the lowest density areas. Recall that the lowest density areas in our sample typically represent a suburban neighborhood characterized by a high degree of "connectedness."

In Models 3–5, we add interactions between density and our two peer effects. Model 4 focuses on non-luxury makes while Model 5 focuses on luxury ones. When we focus on luxury car makes, several interesting findings arise. First, density per se is not correlated with lumping in non-luxury makes, indicating that the positive effect in the pooled sample is driven by luxury car makes. Second, the interaction term of *SameMake* with density flips sign. In non-luxury makes, *SameMake* increases with density, consistent with information transmission merely by observation. High density thus means much closer distance between neighbors. In luxury makes, *SameMake* decreases with density. The latter result suggests that in low density areas—connected communities—neighbors distinguish themselves by purchasing not the same luxury car but a better one. Finally, the coefficient of *DifferentMake* becomes positive. Recall that if word-of-mouth induces purchases of cars of the same model or even the same make, we would expect that crowding in specific car makes would come at the expense of other makes. A positive spillover effect among luxury makes, on the other hand, is consistent with the notion of "getting ahead of the Joneses" by which neighbors care more about distinguishing themselves by purchasing not the same car but a better one. That is, if your neighbor buys a BMW, you are more likely to buy a Mercedes. Importantly, this "getting ahead of the Joneses" effect in luxury makes is concentrated in suburban communities. To demonstrate, we can report that the joint effect of *DifferentMake* and its interaction with density drops monotonically with density and is no longer positive and significant when local density exceeds 6 people per 1,000 square meters.[19] Referring to the distribution of local density in Figure II, the "getting ahead of the Joneses" effect in luxury makes is expected to go away in many BGs in our most populated county of Los Angeles.

[19] A more crude yet straightforward calculation is that the joint effect of *SameMake* (*DifferentMake*) equals zero when local density exceeds 16 (8) people per 1,000 square meters.

4.3 Do Proximate Neighbors Matter More?

One of our core arguments in this paper is that the effect of community on status-driven behavior crucially depends on socialization among close neighbors in connected communities. We thus next examine whether more distant residents matter less. In particular, we use people residing in the same zip code as "fake neighbors." That is, we examine the effect of recent transactions within the same zip code rather than the same BG. While BGs contain only 1,500 people on average, a single U.S. Postal Service ZIP Code can exceed 100,000. Our data includes the zip code of the buyer; however, since zip codes are delimited by the U.S. Postal Service and not by the U.S. Census Bureau, we occasionally have BGs associated with multiple zip codes (that is, close neighbors residing in the same BG but with a different associated zip code). In such cases, we attribute the entire BG to the zip code with the highest number of transactions within the BG.

Table IV displays the results of our "fake neighbors" specification. We redefine *SameMake* and *DifferentMake* based on the same zip code rather than the same BG. *SameMake* equals 1 if at least one car of the same make was purchased within a different BG in the same zip code during the previous quarter. Specifically, we count the number of car purchases in each make and calendar quarter within each zip code and each BG, and then subtract the BG total from the zip code one. This allows us to exclude the center block group so that we can capture "fake neighbors". *DifferentMake* equals 1 if at least one car of a different make was purchased within a different BG in the same zip code during the previous quarter. Specifically, we start from the total purchases of all makes within the zip code, and subtract the total purchases of the all makes within the center BG. This subtotal however still includes purchases of the same make within the zip code but outside the center BG, and thus we further subtract the number of cars defining *SameMake* as above (the number of car purchases in each zip code, make and calendar quarter minus the number of car purchases in the center BG, same make and calendar quarter).

We again include interaction terms between *SameMake* and *DifferentMake* and local density. With peer effects now based on distant neighbors, however, the interpretation of these interaction terms no longer captures the connectedness of one's local community. Recall that BGs are defined on the basis of population and not area, and thus density corresponds to one over area. High density thus becomes a proxy for information transmission merely by observing one's not-so-distant resident, while low density means that distant residents are too far apart. Given that our independent variables of interest are now at the zip-code level, which is larger than census tract, we do not include tract fixed-effects in this exercise.

[Table IV about here.]

We find that the R-Squared drops significantly when we consider residents outside the buyer's block group. In all specifications, *SameMake* is positive and *DifferentMake* is negative. This suggests that some information transmission, that induces crowding in specific car makes at the expense of other makes, persists even outside the block group. Importantly, this study does not argue that neighbor effects in general are purely status-driven, but rather that the status-driven part of the effects is attenuated by population density. Consistently, we find that the interactions between *DifferentMake* and density becomes insignificant, suggesting that only information transmission but not status signaling drive the broader zip-code effect.

Overall, although more distant residents matter less, effects in car purchases do not entirely decay with distance. This is consistent with Grinblatt, Keloharju, and Ikäheimo (2008), who show that effects in car purchases among Finnish neighbors do not decay with distance. The remaining effect from distant residents may be driven by the presence of unobservable control variables—e.g., the level and quality of public transportation in the broader region.

4.4 Robustness Test: Car Dealerships

The remaining effect that we find among distant residents may stem from car dealerships. Dealerships typically serve large areas and may thus create a broader effect by offering specific brands or special promotions. In Southern California, even in the most suburban areas in our sample, the nearest dealership is not more than a 30-minute drive. The average consumer would thus only have to exert minimal effort to buy a specific brand or respond to a sales promotion. Dealerships are thus expected to have a broader effect rather than a local one. If this is the case, then some of the local clustering in specific car makes that we find may be mechanically driven by promotions. Another concern is that there are fewer dealerships in suburban areas and thus fewer makes available, which could mechanically create more clustering in specific car makes in low-density areas. More broadly, it is possible that particular makes are naturally more prevalent in Southern California (e.g., SUVs more suitable for hilly areas), thus creating a spurious effect even if residents are distant.

In this section, we add make fixed-effects to control for the general prevalence of each make in our sample. If peer effects are driven by the broader neighborhood or general market trends, a BG's dominant make would typically be the same as the one in the broader neighborhood. If, on the other hand, it is the more immediate neighbors that drive clustering into particular makes, we should then expect some extrinsic uncertainty in a BG's dominant make. Table V presents the results.

[Table V about here.]

As expected, the magnitude of the two peer effects is smaller, as with make fixed-effects they capture only the residual variation over and above the sample means. *DifferentMake* is positive and significant in all makes, suggesting some level of "getting ahead of the Joneses" even outside luxury makes. Most interestingly, local density (our proxy for neighbor anonymity) now only plays a role in luxury makes.

Overall, results with make fixed-effects are qualitatively the same as in our main specification (Models 3–5 in Table III). The neighbor effects that we find therefore cannot be fully explained by native makes to Southern California (and/or car dealerships serving the broader region). Rather, car-purchasing patterns in a BG deviate from the profile of purchases in the broader area. In particular, BGs not only tend to cluster into a particular make, but also the particular make that each BG clusters into is uncorrelated, or at least not perfectly correlated, across BGs. This extrinsic uncertainty in a BG's dominant make is consistent with clustering into particular makes driven by immediate neighbors.

5 Conclusion

In this paper, we show that the extent to which a community is socially connected has a strong effect on conspicuous consumption. We use a unique database of car purchases in areas with different population densities and find strong evidence that car purchases influence the purchase decisions of neighbors. This effect is stronger in suburban communities in which neighbors are likely to know each other well. In principle, our evidence is consistent with two possible channels of influence: information transmission and status signaling. To distinguish between the two, we examine different price segments, since the behavioral effect is expected to be stronger in luxury makes. We also examine spillovers across different makes, which are more likely driven by status signaling than by positive word-of-mouth. We show that the purchase of luxury cars—identified in the literature as the quintessential conspicuous good—has a strong effect on neighbors' purchases of luxury cars *even across different makes* (as opposed to "bandwagon"). The effect is significantly stronger in suburban areas than in urban areas.

We argue that the stronger effect of peer pressure on conspicuous consumption in areas with lower population density is driven mainly by status-signaling behavior. Conspicuous consumption only has value as a signal if the receiver can clearly identity the sender. Suburban communities in our sample are characterized by a high degree of "connectedness," which has been widely studied in the sociology literature. The "connectedness" and lack of "anonymity" in suburban communities gives more strength to the visibility and attribution of conspicuous consumption.

To clarify, this study does not argue that neighbor effects in general are purely status-driven, but rather that the status-driven part is attenuated by population density. This notion, that social influence results from status-signaling behavior yet to a varying degree, has implications for different social sciences such as sociology and psychology, managerial subfields like marketing and organization science (for example, the impact on compensation incentives), and economics and its subfields, including financial economics. Moav and Neeman (2012), for example, show that the intensity of conspicuous consumption can play a crucial role in explaining saving rates and poverty. In particular, a signaling equilibrium could emerge in which poor individuals spend a large fraction of their income on conspicuous consumption. This equilibrium gives rise to a scenario in which saving rates that increase with income might generate a poverty trap. Future research may also explore novel proxies for connectedness other than density—e.g., the number of Facebook friends in online communities and so on, in many other fields.

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Table I: Descriptive Statistics

Panel A: Counties	Los Angeles	Orange	Riverside	All counties
		Census 2000		
Number of Block Groups	6,351	1,826	804	8,981
Total population	9,519,338	2,846,289	1,545,387	13,911,014
Total household units	3,270,909	969,484	584,674	4,825,067
Area in sq. meters (millions)	10,517	2,044	18,667	31,229
		Car registrations in 2004-2006		
Used	2,720,491	787,919	554,287	4,062,697
New	2,038,502	610,846	362,885	3,012,233
All	4,758,993	1,398,765	917,172	7,074,930

Panel B: Block Group medians	Los Angeles	Orange	Riverside
Area in sq. meters	318,407	454,918	1,353,677
Population density (per 1,000 sq. meter)	3.81	3.08	1.26
Per capita income in 1999	17,296	25,738	16,761
Median family income in 1999	46,685	64,710	44,829
Cars purchased per calendar quarter	46	53	71
Non-luxury cars purchased per calendar quarter	42	47	67
Non-luxury makes per calendar quarter (out of 63)	15	16	19
Luxury cars purchased per calendar quarter	3	5	3
Luxury makes per calendar quarter (out of 3)	2	3	2

Notes: The sample includes all car purchases, new and used, for the 2004–2006 period in three large, adjacent counties in Southern California: Los Angeles, Orange, and Riverside. Block Groups (BG) are delimited by the U.S. Census Bureau, and demographical information at the BG level is from the 2000 U.S. census. In Panel B, we present median BG characteristics within each county. Luxury makes are BMW, LEXUS, and MERCEDES-BENZ.

Table II: Lumping in Car Makes following Recent Local Car Purchases

	Model 1 All makes	Model 2 All makes	Model 3 All makes	Model 4 All makes	Model 5 Non-luxury	Model 6 Luxury
SameMake_{t-1}	4.149***	4.149***	4.216***	4.217***	4.301***	0.351***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.015)
$\text{DifferentMake}_{t-1}$	-0.172***	-0.172***	-0.082***	-0.083***	-0.077***	0.025
	(0.025)	(0.025)	(0.028)	(0.028)	(0.027)	(0.019)
Family income (100K)	-0.063***	-0.063***	0.066***	0.066***	-0.039***	2.98***
	(0.004)	(0.004)	(0.010)	(0.010)	(0.010)	(0.047)
Quarter fixed-effects	No	Yes	No	Yes	Yes	Yes
Tract fixed-effects	No	No	Yes	Yes	Yes	Yes
R-Square	0.22	0.22	0.223	0.224	0.228	0.364
Observations Used	6,511,494	6,511,494	6,511,494	6,511,494	6,215,517	295,977

Notes: The sample includes all car purchases, new and used, for the 2004–2006 period in three large, adjacent counties in Southern California—Los Angeles, Orange, and Riverside. The level of analysis in our panel data is the triplet BG-Date-Make. The dependent variable is the number of car-make transactions divided by the overall number of transactions of all makes in a BG during a calendar quarter in percentage terms (i.e., multiplied by 100). *SameMake* equals 1 if at least one car of the same make was purchased within the same block group within the previous quarter. *DifferentMake* equals 1 if at least one car of a different make was purchased within the same block group within the previous quarter. Quarter fixed-effects control for within-year seasonality, while census tract fixed-effects control for neighborhood characteristics. Block Groups (BG) and Tracts are delimited by the U.S. Census Bureau, and demographic information at the BG level is from the 2000 U.S. census. Family Income is scaled to 100,000. In Models 5–6 we examine non-luxury and luxury makes, respectively. Luxury makes are BMW, LEXUS, and MERCEDES-BENZ. In these subsamples, *DifferentMake* equals 1 if at least one car of a different make but *of the same type* (luxury/non-luxury) was purchased within the same block group within the previous quarter.

Table III: Recent Car Purchases and Local Density

	Model 1 All makes	Model 2 All makes	Model 3 All makes	Model 4 Non-luxury	Model 5 Luxury
SameMake_{t-1}	4.219***	4.22***	4.105***	4.085***	0.504***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.023)
$\text{DifferentMake}_{t-1}$	-0.041	-0.018	0.035	0.046	0.095***
	(0.028)	(0.028)	(0.029)	(0.029)	(0.028)
Density	-22.145***	-38.387***	-16.508**	-10.018	-144.437***
	(0.725)	(1.267)	(7.098)	(7.099)	(7.065)
Density^2		794.776***	785.239***	595.167***	3,387.274***
		(50.858)	(50.855)	(51.371)	(237.093)
$\text{SameMake}_{t-1} \times \text{Density}$			26.124***	49.597***	-31.254***
			(0.794)	(0.815)	(3.782)
$\text{DifferentMake}_{t-1} \times \text{Density}$			-28.861***	-33.404***	-11.561***
			(7.026)	(7.027)	(4.297)
Family income (100K)	0.005	-0.01	-0.009	-0.1***	2.608***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.049)
Quarter fixed-effects	Yes	Yes	Yes	Yes	Yes
Tract fixed-effects	Yes	Yes	Yes	Yes	Yes
R-Square	0.224	0.224	0.224	0.229	0.366
Observations Used	6,511,494	6,511,494	6,511,494	6,215,517	295,977

Notes: The sample includes all car purchases, new and used, for the 2004–2006 period in three large, adjacent counties in Southern California—Los Angeles, Orange, and Riverside. The level of analysis in our panel data is the triplet BG-Date-Make. The dependent variable is the number of car-make transactions divided by the overall number of transactions of all makes in a BG during a calendar quarter, in percentage terms (i.e., multiplied by 100). *SameMake* equals 1 if at least one car of the same make was purchased within the same block group within the previous quarter. *DifferentMake* equals 1 if at least one car of a different make was purchased within the same block group within the previous quarter. Quarter fixed-effects control for within-year seasonality, while census tract fixed-effects control for neighborhood characteristics. Block Groups (BG) and Tracts are delimited by the U.S. Census Bureau, and demographic information at the BG level is from the 2000 U.S. census. Density is defined per square meter as in the U.S. census. Family Income is scaled to 100,000. In Models 4–5 we examine non-luxury and luxury makes respectively. Luxury makes are BMW, LEXUS, and MERCEDES-BENZ. In these subsamples, *DifferentMake* equals 1 if at least one car of a different make but *of the same type* (luxury/non-luxury) was purchased within the same block group within the previous quarter.

Table IV: Recent Car Purchases of Distant Residents

	Model 1 All makes	Model 2 Non-luxury	Model 3 Luxury
SameMake_{t-1}	2.483***	2.346***	0.82***
	(0.004)	(0.005)	(0.152)
$\text{DifferentMake}_{t-1}$	-1.38***	-1.211***	-0.919***
	(0.028)	(0.028)	(0.172)
Density	20.836	17.543	256.443***
	(15.980)	(16.202)	(73.125)
Density^2	52.654	-10.993	1095.902***
	(32.465)	(32.915)	(154.360)
$\text{SameMake}_{t-1} \times \text{Density}$	2.74***	18.484***	-245.466*
	(0.774)	(0.780)	(128.721)
$\text{DifferentMake}_{t-1} \times \text{Density}$	-25.113	-30.264*	-16.535
	(15.995)	(16.216)	(145.327)
Family income (100K)	-0.044***	-0.35***	6.454***
	(0.005)	(0.005)	(0.025)
Quarter fixed-effects	Yes	Yes	Yes
R-Square	0.097	0.095	0.224
Observations Used	6,511,494	6,215,517	295,977

Notes: The sample includes all car purchases, new and used, for the 2004–2006 period in three large, adjacent counties in Southern California—Los Angeles, Orange, and Riverside. The level of analysis in our panel data is the triplet BG-Date-Make. The dependent variable is the number of car-make transactions divided by the overall number of transactions of all makes in a BG during a calendar quarter, in percentage terms (i.e., multiplied by 100). *SameMake* equals 1 if at least one car of the same make was purchased within a different BG in the same zip code during the previous quarter. *DifferentMake* equals 1 if at least one car of a different make was purchased within a different BG in the same zip code during the previous quarter. Quarter fixed-effects control for within-year seasonality. Zip codes are delimited by the U.S. Postal Service. Block Groups (BG) are delimited by the U.S. Census Bureau, and demographic information at the BG level is from the 2000 U.S. census. Density is defined per square meter as in the U.S. census. Family Income is scaled to 100,000. In Models 2–3 we examine non-luxury and luxury makes respectively. Luxury makes are BMW, LEXUS, and MERCEDES-BENZ. In these subsamples, *DifferentMake* equals 1 if at least one car of a different make but *of the same type* (luxury/non-luxury) was purchased within a different BG in the same zip code during the previous quarter.

Table V: Robustness: Native makes and/or Car Dealerships

	Model 1 All makes	Model 2 Non-luxury	Model 3 Luxury
$SameMake_{t-1}$	0.577***	0.312***	0.453***
	(0.004)	(0.004)	(0.023)
$DifferentMake_{t-1}$	0.684***	0.707***	0.124***
	(0.020)	(0.019)	(0.028)
Density	-3.364	5.295	-144.057***
	(4.842)	(4.636)	(7.032)
$Density^2$	56.238	-165.064***	3381.278***
	(34.692)	(33.551)	(235.986)
$SameMake_{t-1} \times Density$	17.773***	41.02***	-30.319***
	(0.542)	(0.533)	(3.765)
$DifferentMake_{t-1} \times Density$	-5.145	-9.414**	-12.538***
	(4.793)	(4.589)	(4.277)
Family income (100K)	0.023***	-0.098***	2.613***
	(0.007)	(0.007)	(0.048)
Quarter fixed-effects	Yes	Yes	Yes
Tract fixed-effects	Yes	Yes	Yes
Make fixed-effects	Yes	Yes	Yes
R-Square	0.639	0.671	0.372
Observations Used	6,511,494	6,215,517	295,977

Notes: The sample includes all car purchases, new and used, for the 2004–2006 period in three large, adjacent counties in Southern California—Los Angeles, Orange, and Riverside. The level of analysis in our panel data is the triplet BG-Date-Make. The dependent variable is the number of car-make transactions, divided by the overall number of transactions of all makes, in a BG during a calendar quarter, in percentage terms (i.e., multiplied by 100). *SameMake* equals 1 if at least one car of the same make was purchased within the same block group within the previous quarter. *DifferentMake* equals 1 if at least one car of a different make was purchased within the same block group within the previous quarter. Quarter fixed-effects control for within-year seasonality, while census tract fixed-effects control for neighborhood characteristics. Make fixed-effects control for the general prevalence of each make in our sample. Block Groups (BG) and Tracts are delimited by the U.S. Census Bureau, and demographic information at the BG level is from the 2000 U.S. census. Density is defined per square meter as in the U.S. census. Family Income is scaled to 100,000. In Models 4–5 we examine non-luxury and luxury makes respectively. Luxury makes are BMW, LEXUS, and MERCEDES-BENZ. In these subsamples, *DifferentMake* equals 1 if at least one car of a different make but *of the same type* (luxury/non-luxury) was purchased within the same block group within the previous quarter.

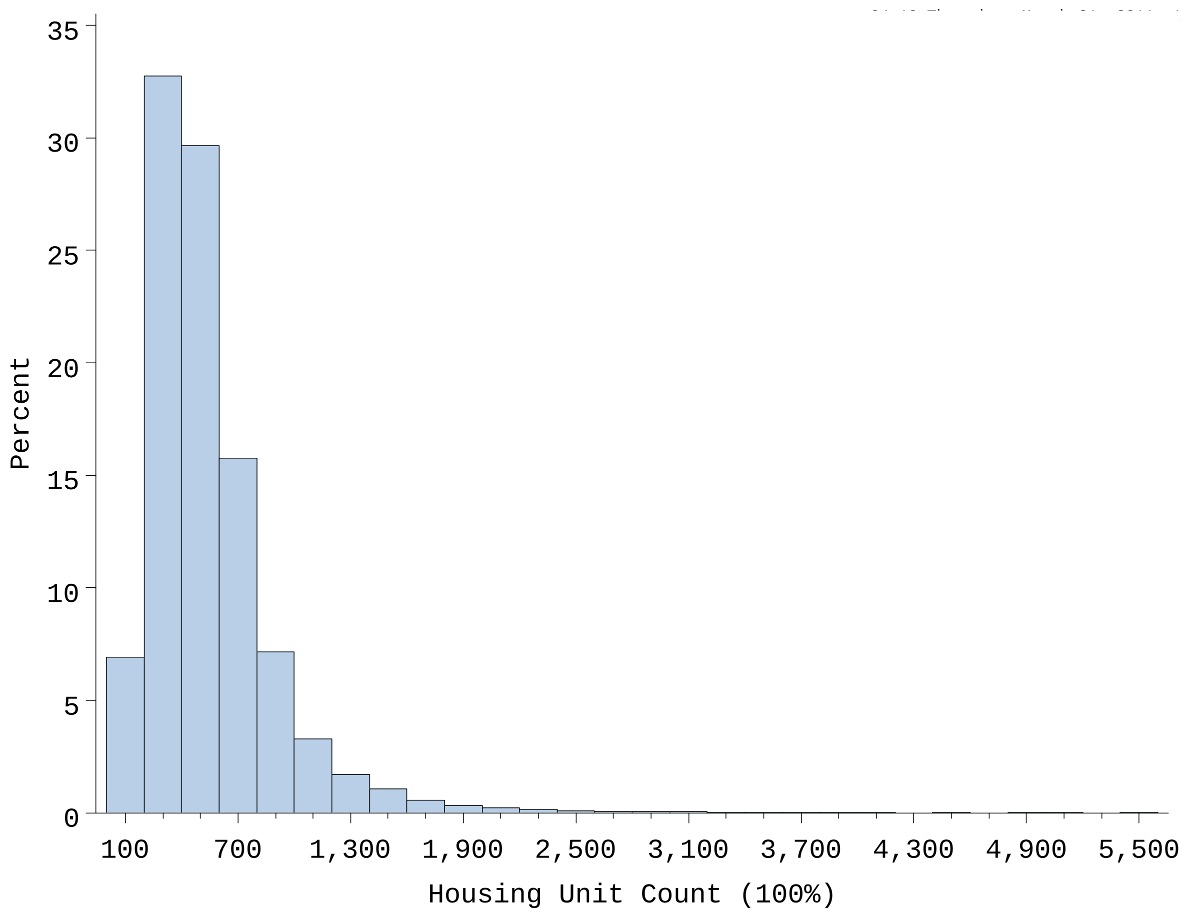

Figure I: Household Units per Block Group

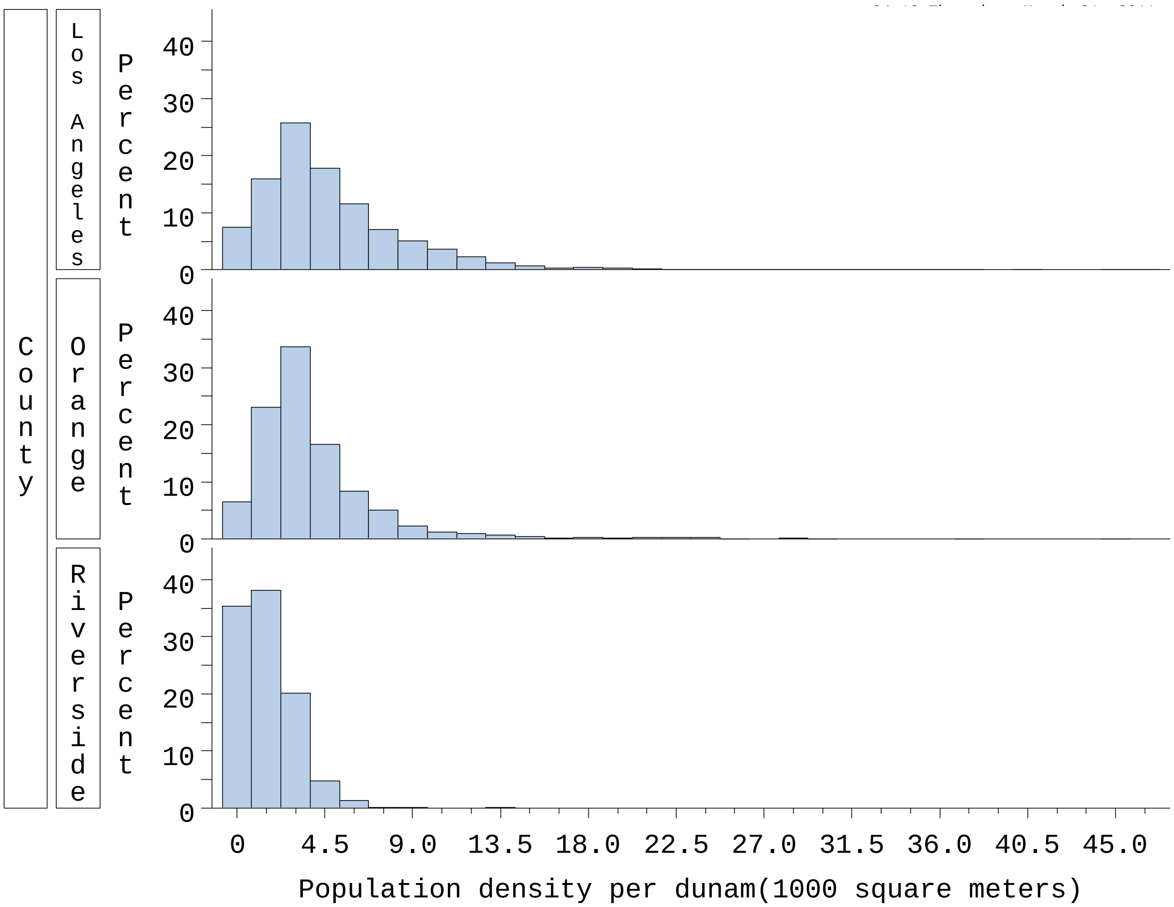

Figure II: Population Density per Block Group, by County

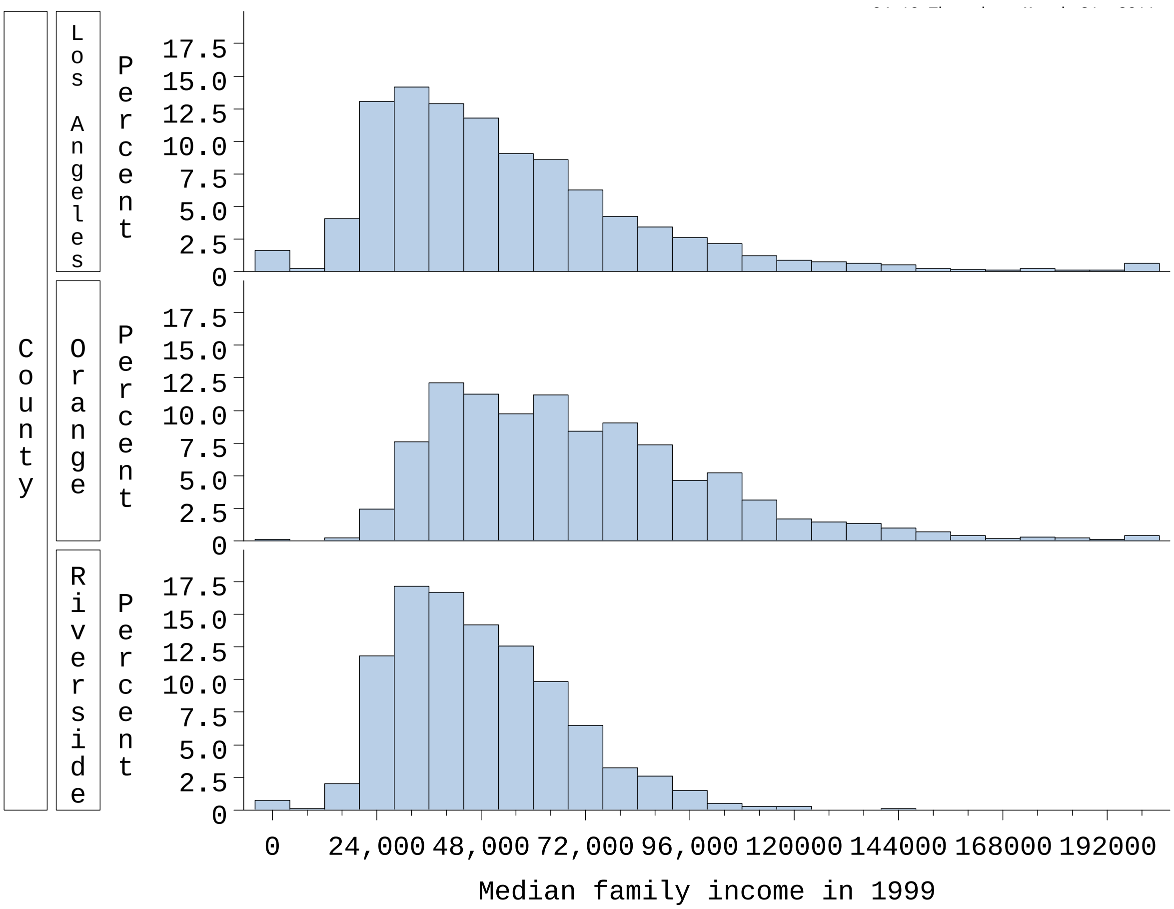

Figure III: Median Family Income per Block Group, by County