The Intensity of Keeping Up with the Joneses Behavior:
Evidence from Neighbor Effects in Car Purchases *

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Abstract

We show that status-driven behavior is largely determined by how connected a community is. Using a unique dataset on car purchases in Southern California, we show that social influence intensifies in suburban communities in which neighbors are likely to know each other well. The effect of connected communities cannot be fully explained by word of mouth, as it spills over across different brands, and is particularly apparent in higher price segments. We argue that, in connected communities, the signaling of income or wealth through the public display of consumption has a substantial effect on the behavior of neighbors.

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1 Introduction

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 “keeping up with the Joneses,” and, arguably, it is motivated by the objective of signaling a certain level of economic status. In this paper, we study and find evidence that population density affects the intensity of the “keeping up with the Joneses” effects. In particular, in suburban communities, in which neighbors are likely to know each other well, there is stronger peer pressure in conspicuous consumption decisions. We use car purchases in Southern California, where the car is, at least in part, a conspicuous good.

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. Duesenberry (1949) postulates that the utility of a consumer depends on the ratio of her own consumption to a weighted average of a reference group. He further argues that people with whom the consumer has social contacts will have more weight than those with whom the consumer only has casual contacts. There seems to be strong macroeconomic evidence of investment in conspicuous goods. Hirsch (1976) calls this type of activity the “positional economy.” In an influential paper, Frank (1984) argues that income comparison effects explain why the dispersion in wages is lower than the dispersion in marginal productivity. 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. The recent availability of data on individual consumption has permitted the study of how individual purchase decisions affect the consumption decisions of neighbors. Ravina (2007) finds that household consumption choices are affected by both household past consumption and the consumption level of the city in which the household resides. Grinblatt, Keloharju, and Ikaheimo (2008)
study the purchase of cars in two Finnish provinces and find evidence of the effect of individual purchases on the decisions of neighbors. 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 as others of the same race living in the same state as the consumer in question. The negative relation between visible spending and the mean income of the reference group is consistent with status signaling and with the premise that being associated with a poorer reference group has negative informational consequences.

This paper is part of the growing literature on “keeping up with the Joneses” preferences and its economic effects, like conspicuous consumption. More explicitly, we study a straightforward peer group and the channel through which it regulates peer pressure. We document that in areas of relatively low population density, representing 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 consumption decisions. In suburban communities, neighbors know each other: their children go to the same school, they shop in the same store, attend the same church, work for the same employer etc. This lack of “anonymity” in suburban areas gives more strength to the visibility and attribution of conspicuous consumption.

Our analysis follows the notion of Hong, Kubik, and Stein (2008), and Gómez, Priestley, and Zapatero (2015), who provide some evidence of the effect of population density through the equilibrium properties of security prices. We choose to focus on car purchases because, as documented by Heffetz (2011), cars are the single most visible expenditure category among 31 items that together cover almost the entire range of consumer expenditures in the U.S. economy. Grinblatt et al. (2008) study the purchase of cars in two Finnish provinces and find evidence of the effect of individual purchases on the decisions of neighbors. The authors argue that their results are consistent with information transmission as the primary source of the social influence on consumption. We are interested in the extent to which car purchases can be used to signal wealth. In the U.S., unlike the Nordic model, 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. In fact, Kuhn et al. (2011) find robust evidence for 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. Our evidence shows that social influence is driven by status-signaling behavior, yet to a varying degree. The intensity of status-signaling behavior depends on the extent in which a community is connected.

Our data include all car purchases, new and used, during the years 2004–2006, in three large adjacent counties in Southern California. While we are unable to obtain the exact street address of each buyer, our data are broken down into small geographical units—census block groups (BG). Our objective is to compare purchase patterns across different areas with different population densities within these three counties. Our data offer enough dispersion in density for such an analysis. In particular, we study whether there is more clustering of car purchases of higher price segments in areas of lower population density than in areas of higher population density.

Our empirical analysis documents a strong effect of population density on the intensity of neighbor effects in car purchases. We first match each BG with the 10 nearest block groups, and then we show that the profile of car purchases in a BG generally deviates from that in its neighboring BGs. That is, controlling for general market trends and general local characteristics, there is crowding in specific car makes at the expense of other makes within a BG. Such independence across neighboring BGs allows us to use block groups as the level of analysis—the smallest level of analysis one can use in studying car purchases with U.S. data. We also show that the interval between transactions (the number of days between consecutive transactions of the same car make within the same BG) is correlated with population density. Intervals between car purchases are shorter in lower-density areas, and the magnitude of the effect is stronger in luxury cars. Finally, logit results show that the likelihood of buying a luxury car is affected by previous transactions involving luxury cars within the same BG.
More interestingly, the magnitude of this relation depends on its interaction with population density. We also control for seasonal effects that tend to lump car purchases around certain times of the year since this might give the false impression of influence in purchase decisions. While we cannot refute that at least some of the clustering that we observe in car purchases is driven by local shocks (for example, housing prices or car dealerships), we discuss later why such local shocks may not provide an alternative explanation to our results.

A major empirical challenge for our analysis is the existence of several reasons other than “keeping up with the Joneses” that might influence the purchase of a car. Arguably, one of the most important is the information channel, or word of mouth. 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 signaling plays an important role. We try to distinguish between the two channels, namely information transmission and status signaling, in several ways. First, we control for an important source of heterogeneity because we conjecture that information exchange is stronger in more homogeneous populations, where there is more interaction, and thus more information exchange through direct communication, leading to stronger peer effects. We use the Herfindahl index (HI) of family income (based on 16 income groups within each BG) as a proxy for heterogeneity.

Homogeneity, however, may also be correlated with social comparisons, and so controlling for homogeneity may not enable us to distinguish between the two channels at play. We therefore turn to spillover effects across different makes, in order to minimize the possibility of information exchange as the sole driver of our results. While it is possible that purchases of cars of the same model or even the same make are induced by good word of mouth, effects across different makes are more likely driven by status signaling. We find that the density effect is strong even if the previous transaction involves a different luxury make. That is, if your neighbor buys a BMW, you are more likely to buy a Mercedes. We also find that while homogeneity is associated with more clustering in specific car makes, it is negatively
correlated with spillover effects across different makes. This is consistent with homogeneity being associated more with communication than with status signaling. While people in more homogeneous groups are expected to exchange information in general—and about cars in particular—it is difficult to see how such information can create spillover effects across different car makes. Our results therefore cannot be fully explained by information exchange.

The paper is structured as follows. In section 2, we articulate the idea in the context of the related literature on social comparisons. In section 3, we describe the data, and in section 4 we present and discuss the results. Section 5 concludes.

2 Hypothesis

Since ancient times, there is ample evidence of consumption in conspicuous goods whose main purpose is to denote status. As Mason (2000) points out, “Sumptuary laws were often introduced to suppress excessive levels of ostentatious display,” (see Hunt, 1996, for a history of sumptuary laws). However, standard models of utility maximization in the past few decades ignore the quest for status and the value of investing in conspicuous consumption. Some authors, starting with Veblen (1899), Frank (1985), and Robson (2001) argue that status seeking has an evolutionary basis. In particular, the rate of success in finding mates in many species is higher for individuals endowed with characteristics associated with higher probability of survival. Arguably, wealth is, and has been for centuries, a predictor of survival (or longevity) in the human race. The quest for status as an indicator of wealth and, therefore, as a survival predictor, is hard-wired in the human brain, according to these authors. Frank (1985) postulates that status should be part of the utility function. Luttmer (2005) offers suggestive evidence for utility functions that depend on relative position. He 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 preferences. In fact, 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. However, these are standard asset-pricing models, based on a single consumption good, which rules out the possibility of considering dedicated investment in conspicuous goods.

In this paper, we do not postulate (or need) any particular rationalization for the consumption of conspicuous goods. However, based on the overwhelming empirical evidence, we take it as given that economic agents signal status by engaging in conspicuous consumption. According to the Longman Dictionary of Contemporary English\(^1\), conspicuous consumption is: “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.”

In particular, we focus on car purchases as status-signaling decisions. Of course, cars do not necessarily fit the definition of conspicuous goods that we just provided: for many people a car is just 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 (there is a category labeled “luxury cars”), and some of the price is related to car attributes “that are not necessary.” See, for example, Choo and Mokhtarian (2004) for evidence of purchase of luxury cars as status-signaling devices. Heffetz (2011) shows that car expenditures are not only the most visible but also the most luxurious (i.e., have the highest income elasticity) of such devices. In addition, the literature has documented a peer effect in the car purchase decision. Grinblatt et al. (2008), in a careful empirical analysis using data from Finland, show that a car-purchase decision influences future car-purchase decisions of neighbors. Kuhn et al. (2011) detect substantial social effects of the Dutch Postcode Lottery,

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\(^1\)http://www.ldoceonline.com/dictionary/conspicuous-consumption
in which one participating household in a randomly selected postcode receives a new BMW. The authors find robust evidence for 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 households neighbors. For example, having an immediate neighbor win the lottery raises the probability that a household will buy a car in the next six months by close to 7 percentage points and reduces the mean age of its main car by half a year (about a 7 percent decline) within six months after the lottery date. The following quote from the *New York Times*, explaining why someone had decided to buy a $190,000 fully electric Tesla sports car, provides some anecdotal evidence of the peer influence in the decision to buy a car:

“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).

In this paper, we want to move a step forward and study the effect of community on the neighbor’s effect we just discussed. As we discussed earlier, Duesenberry (1949) supports the inclusion of other people’s consumption in the utility function of economic agents. Furthermore, he 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.” Following this insight, we postulate that in areas of lower population density neighbors are on average likely to have more intense interaction than in areas of high population density. In high density areas, it is more difficult to keep track of neighbors, and social interactions are more transitory and impersonal. It is also less likely to bump into the same people with all the possibilities that a more urban area has to offer and so there are fewer opportunities to form relationships. Neighbors in suburban communities, on the other hand, have the opportunity to chat or wave hello when stepping out of their residences, playing in the lawn or doing some gardening. They also are likely to interact in multiple ways

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2“Cities Prepare for Life With the Electric Car” by Todd Woody and Clifford Krauss

3In our sample, “lower population density” refers to area in which neighbors live close enough to each other to interact, rather than to 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.
as a result of possibly having children who attend the same schools, shopping in the same places, attending the same churches, and even working for the same employers. These things can create a sense of belonging to a community that provides an obvious reference for their members. Of course, there might be other reference groups that are also influential, such as family and co-workers. However, there does not seem to be a reason why the peer pressure should come from just one reference group. In this paper, we will focus on neighbors, but we do not rule out other possible sources of influence.

The main empirical challenge for our analysis is the existence of several factors other than “keeping up with the Joneses” that might influence the purchase of a car. The most obvious is possibly the information channel: buyers who are happy with their decision after driving the car for a few days or weeks might express their satisfaction to their neighbors and influence their choice of brand on purely consumer satisfaction grounds. In our empirical analysis, we control for this “information” effect in two ways: (1) we use income dispersion as a control variable in our analysis, as lower dispersion is associated with more homogeneous groups and facilitates communication; (2) we study the effect across different brands—i.e., how purchases of luxury brands affect purchases of other luxury brands different from the original. Of course, there will also be an income effect in the purchase decision, especially for luxury cars, and so we control for the level of income, along with the dispersion. Finally, there are seasonal effects that tend to lump car purchases around certain times of the year, which might give the false impression of influence in purchase decisions. For that reason we also control for seasonality in purchases.

Still, it is possible that some of the clustering that we observe in car purchases is driven by local shocks (for example, housing prices or car dealerships, which are discussed in more detail below). We note that BGs are defined on the basis of population and not area, which means that BGs have similar population sizes but differ in area. Therefore, if such local shocks are indeed local—i.e., confined to a very small geographical area—they should 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 results.

When estimating the effect of population density on car purchasing patterns, it is important to control for other factors that may be correlated with both the dependent variable, namely neighbor effects measured by clustering in car purchasing patterns, and the independent variables, specifically density. In particular, we focus on the heterogeneity within the population, using the dispersion of income within each BG as a proxy. More homogeneous populations will involve more interaction, and thus more information exchange through direct communication, leading to stronger peer effects. It also seems reasonable that groups in less-dense areas tend to be more homogeneous. In Southern California at least, low-density areas typically represent wealthier small communities. Under these assumptions, namely that homogeneity is positively correlated with both density and clustering in car purchases, our analysis would have overestimated the effect of density had we failed to control for homogeneity.

While controlling for homogeneity is important for an unbiased estimation of the effect of population density on neighbor effects in car purchases, it cannot distinguish between the two channels at play, namely information transmission and status signaling. As mentioned earlier, more homogeneous populations will be characterized by more interaction, and thus there will be more information exchange through direct communication, leading to stronger peer effects. Homogeneity, however, may also be correlated with social comparisons. When agents have similar income or wealth, social comparisons may become more important. That is, when people are closer in absolute terms, their relative standing becomes more valuable. In more heterogeneous BGs, on the other hand, status signaling becomes less important since status classes are already clearly defined. In more heterogeneous BGs, members of the middle class are less concerned about being mistaken for the very poor, but on the other hand are also less able to compete with the very rich. It is possible, then, that homogeneity is a proxy not only for communication but also for the value of relative concerns.
To further assist in distinguishing between the two channels at play, we turn to spillover effects across different makes. We study whether and how the purchase of a car of a given make is followed by purchases of a different make within the same block group. While it is possible that purchases of cars of the same model or even the same make are induced by good word of mouth, effects across different makes are more likely driven by status signaling. In next section we describe our data in detail.

3 Data

We use information from a data set from R. L. Polk & Co. that records all car purchases, new and used, from most Departments of Motor Vehicles (DMVs) in the U.S. For each purchase, we have the model, make, and year of the car, price, and date of purchase. For privacy reasons, it is not possible to obtain the exact address of the buyer, but we get the census block group (BG), which is more detailed than ZIP codes. BGs are delimited by the U.S. Census Bureau, and contain between 600 and 3,000 people, with an average size of 1,500 people. This seems precise enough for our purposes. We merge the Polk data set with data from the 2000 U.S. census, which includes demographical information at the BG level.

In particular, 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 the most heavily populated areas in Southern California, with nearly 14 million inhabitants according the 2000 census. While downtown Los Angeles is not very densely populated, the neighborhoods west of downtown (e.g., Koreatown, Westlake, etc.) 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). The Los Angeles metropolitan area is surrounded by numerous smaller cities and communities, which 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 so population density can be diverse within a relatively small neighborhood and 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 one another and have the possibility of communicating with one another easily (as opposed to areas in which neighbors are so far apart that direct communication might require an extra effort). Our objective is to compare purchase patterns across different areas with different population densities within these three counties.

3.1 Descriptive Statistics

Table I includes descriptive statistics on all three counties. In total, we have over 7 million observations, and our population unit is a block group. In Fig. I, we show that the delimitation of the BGs is based on population, not area. In that histogram, we have used the number of households per BG, but population per BG yields a similar graph. Figure II provides a histogram of the distribution of population density across BGs, summarized in panel B of Table I for each of the three counties.\(^4\) Clearly, we have enough dispersion of density across our sample to test whether population density affects how purchase decisions of agents influence the purchase decisions of their neighbors. Similarly, Fig. III shows that we have enough dispersion in the distribution of household income across the BGs. We need dispersion, first, so that controlling for income (a main factor in the types of cars people buy) is meaningful but also in order to generate a proxy for homogeneity: areas of low dispersion of household income tend to be more homogeneous and, arguably, will show more communication among neighbors.

\(^4\)Population density is measured per dunam (1,000 square metres), however one can easily convert this density metric into population per square mile by multiplying by 2590.
4 Results

Our data allow us to study the time series of purchases and to empirically compare different patterns across different areas, especially areas with different population densities. The main challenge of our analysis is the need to control for a number of variables that are possibly relevant in purchase decisions, such as dispersion of household income. For this purpose, we merge the information of our database with data from the 2000 U.S. Census to control for other variables.

In addition, we need to establish that population density explains a given purchase pattern in a BG, as opposed to alternative explanations. In particular, we need to distinguish between informational and behavioral effects: good word of mouth from neighbors who bought a car might explain why some people decide to buy the same model. We address this problem in our empirical tests. We perform several tests, which we explain next.

4.1 Transaction Counts

In our first exercise, we want to establish that BGs are a relevant unit of analysis and that some of the effects we have discussed before are present in our data. At this stage, we do not try to establish the source of the effects—that is, whether they are due to status-signaling or communication—but whether the factors we are going to use—population density and dispersion of income—are relevant at the BG level.
In this test, we do not distinguish between different car segments. We proceed as follows. First we count the number of car registrations within each BG by car make (i.e. Honda, Toyota, etc.) during our sample period. Since we want to verify that the BG is a relevant unit for our analysis, we match each BG with the 10 nearest block groups. This allows us to control for general market trends and general local characteristics. The total number of car purchases in the 10 closest BGs divided by 10 gives us the “expected count” of car purchases of a given make if the BG is a perfect replica of the area in which it is located.\(^5\)

Cars of different makes are often considered to be imperfect substitutes because different makes may replace each other in use, and yet many consumers prefer one car make over other makes regardless of the relative price. Therefore, when there is crowding in specific car makes at the expense of other makes, the variance of the residuals of the regression on expected counts should increase. To demonstrate, if a BG exhibits more purchases of brand A at the expense of a substitute Brand B, the residual count of brand A will be positive while the residual count of B will be negative. The mean count doesn’t have to be affected, as in the case of a mean-preserving spread. We should thus test how these residuals are spread rather than focus on their mean.

We employ the Breusch-Pagan test (Breusch and Pagan, 1979) to test for heteroscedasticity in our linear regression framework. This exercise is designed to test whether the estimated variance of the residuals from a regression is dependent on the values of the independent variables. Specifically, we are interested in whether crowding in specific makes is correlated with our factors and in particular with density. We therefore regress the absolute residuals from the original regression model onto the original regressors. Our heteroscedasticity test also helps to establish that sufficient spatial independence exists between neighboring BGs in terms of car-purchasing patterns. If the BG is an adequate unit of analysis, the profile of the car purchases in a BG will deviate from the profile of purchases in the area in

\(^5\)Since the population may be different across the BGs (1,500 people in a BG only on average), the expected counts based on the 10 nearest block groups are adjusted both by population and by the number of household units.
which it is located. Spatial independence is also important to establish because it mitigates econometrical concerns associated with spatial autocorrelation.

We run a test for heteroscedasticity in Table II: we test whether transaction counts, controlling for the expected count based on the 10 nearest BGs, are more dispersed in areas with low population density—i.e., we test whether the residuals increase in absolute size with our factors.

[Table II about here.]

Panel A of Table II shows the first-step regression, which is used to estimate the differences in transaction counts between each BG and its 10 nearest BGs. The absolute residuals from this first-step regression are then used as the dependent variable in Panel B. Each column corresponds to a different model specification. We employ both a linear regression and a density fixed-effect model (note that in the fixed-effect model the highest rank is the baseline). The linear model we estimate is

\[ Count_{i,j} = \alpha + Expected\text{Count}_{i,j} + Density_i + IncomeHI_i + \varepsilon_{i,j}, \]

while the fixed-effects model is

\[ Count_{i,j} = \alpha + Expected\text{Count}_{i,j} + I_{Density_i=\text{Low}} + I_{Density_i=\text{Mid}} + I_{IncomeHI_i=\text{Low}} + I_{IncomeHI_i=\text{Mid}} + \varepsilon_{i,j}, \]

where \( i \) is a Block Group, and \( j \) is a car make. In columns 1 and 2, the “expected count” is defined as the total number of car purchases in the 10 closest BGs, adjusted by (the population in BG \( i \))/(the total population in the 10 nearest block groups), and in columns 3 and 4 the “expected count” is adjusted using the number of household units. Although we do not differentiate across different models within a given car maker, we also control for dispersion of income, as an important source of heterogeneity, which might affect the
transmission of information. We use the Herfindahl index (HI) of family income (based on 16 income groups within each BG) as a proxy for heterogeneity. We also use both linear regression and a fixed-effects model for income distribution (with the highest value of the index being the baseline). Note that we do not directly control for the level of income since it is indirectly controlled through the match with the 10 closest blocks, which are assumed to have similar income to the center block. We do control for the distribution of income as a proxy for information exchange. The results in Panel B show that transaction counts of different makes are more dispersed in areas with low population density. This evidence is consistent with higher crowding in specific makes (at the expense of other makes that fit the neighborhood profile) in areas with low population density.

It is possible that some of the clustering that we observe in car purchases is driven by local shocks. One potential local shock may be housing prices, but shocks to housing prices tend to spill over neighboring BGs and are thus accounted for by matching with the nearest BGs. If other local shocks are more restricted or are confined in a very small geographical area, then they would have a stronger effect on narrower BGs, or BGs that are more densely populated. Let us reiterate that BGs are defined on the basis of population and not area, and as such all BGs have similar population size and differ only in area. Since we report higher clustering in low-density areas, the effects of local shocks are not an alternative explanation because this goes against our results.

Another potential source of clustering is car dealerships since their presence may create a local effect by offering either specific brands or special promotions. The sample, however, includes mostly secondary sales, or used cars, which are in most cases sold directly by the owners. That said, some BGs in our sample include car dealerships, which may have an effect on the sales patterns of new cars. One concern is that in suburban areas there would be fewer dealerships, and thus fewer makes available, which could mechanically create clustering in specific car makes. Another concern is that promotions could mechanically create clustering in specific car makes during the sale period. These concerns, however, are not expected to
play a significant role in Southern California because even in the most suburban areas in our sample the nearest dealership is not more than 30 minutes’ drive away. Dealerships are thus not expected to have a local effect since the average consumer would have to put in minimal effort in order to buy a specific brand or act in response to a sales promotion. We next explore the possible channels through which population density translates into concentration in these makes.

4.2 Intervals

In our next exercise, we examine the intervals between transactions within a BG during our sample period. For each transaction, we compute the number of days between consecutive transactions of the same car make within a BG. 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. In testing whether the interval between transactions is correlated with population density, we control for the expected interval, which is defined as the total number of days in the sample divided by the total number of transactions of the same car make within the same block group.

The results for cars of the same make are collected in Fig. IV. In Fig. V, we focus only on luxury car makes (BMW, LEXUS, and MERCEDES-BENZ), for which the effect is expected to be stronger. Since even make-level effects may be driven by information exchange, we also explore only transactions that follow a luxury car (BMW, LEXUS, and MERCEDES-BENZ) of a different make in Fig. VI, that is, purchases of a car of a given make in this group followed by purchases of a different make within the same group.
Table III tests the significance of the results collected in the previous plots, particularly if intervals between car purchases are shorter in lower-density areas and/or areas of lower income dispersion. The linear model we estimate is

\[ \text{Interval}_{t,i,j} = \alpha + \text{ExpectedInterval}_{i,j} + \text{Density}_{i} + \text{IncomeHI}_{i} + \varepsilon_{t,i,j}, \]

while the fixed-effects model is

\[ \text{Interval}_{t,i,j} = \alpha + \text{ExpectedInterval}_{i,j} + I_{\text{Density}_{i} = \text{Low}} + I_{\text{Density}_{i} = \text{Mid}} + I_{\text{IncomeHI}_{i} = \text{Low}} + I_{\text{IncomeHI}_{i} = \text{Mid}} + \varepsilon_{t,i,j}, \]

where \( t \) is a transaction, \( i \) is a Block Group, and \( j \) is a car make. In column 1 and 2, the interval is the number of days since the last transaction within the same block group of the same car maker, and the “expected count” is the total number of days in the sample divided by the total number of transactions of the same car make within the same block group in our sample. In columns 3 and 4, the dependent variable is the interval (in days) between each transaction involving a luxury make and the previous transaction involving one of the luxury makes within the same BG. The “expected count” in this case is the total number of days in the sample divided by the total number of transactions involving a luxury make within the same block group in our sample. In columns 5 and 6, the dependent variable is the interval (in days) between each transaction involving a luxury make and the previous transaction involving a different luxury make within the same BG. The “expected count” in this case is the total number of days in the sample divided by the total number of transactions of a luxury make that follow a different luxury make within the same block group in our sample. Table III shows a strong effect of population density: lower population density increases the influence of the purchase of a given make on the decisions of the neighbors, and the magnitude of the effect is stronger for luxury cars of a different make, which provides support for the relevance of status signaling effects.
In the context of spillover effects across different makes, homogeneity becomes less correlated with information exchange. While people in more homogeneous groups are expected to exchange information in general, and about cars in particular, it is difficult to see how such information can create spillover effects across different car makes. Arguably, effects across different makes are driven by status signaling rather than by information exchange. Table III shows that low income dispersion is positively correlated with the expected number of days to purchase any car of the same make. This is consistent with more information exchange through direct communication in more homogeneous populations. People will tend to purchase the same make—sometimes even the same model—after receiving positive comments from their peers. Such crowding in specific car makes is expected to come at the expense of other makes since cars of different makes are often considered to be imperfect substitutes. Consistent with this observation, low income dispersion becomes negatively correlated with the expected number of days to purchase a different make. The higher demand for a specific make driven by word of mouth (column 1) comes at the expense of other makes (columns 2 and 3). The sign switch in the coefficient of income dispersion is therefore consistent with homogeneity being more associated with communication than with status signaling.

4.3 The Decision to Buy a Luxury Car

We use a logistic regression to study the decision to buy a luxury car or not. In this test, we focus on luxury cars, for which the behavioral effect is expected to be stronger because such cars are clearly more conspicuous. As in the previous test, we also study whether a decision to purchase a luxury car (of the class we defined earlier) has an effect on the decisions of neighbors to purchase a different luxury make. The logit model includes quarter fixed effects in order to control for within-year seasonality since it is widely known that there are times of the year that are more popular for car purchases (right before summer, for vacation traveling, and at the beginning of fall, when the new models are rolled out). This can produce some
lumping of purchases of luxury cars independent of communication and/or status signaling. The model we estimate is

\[ I_{i,j,q} = \alpha + \text{Income}_i + \text{Density}_i + \text{SameMake}_{i,j,q-1} + \text{DifferentMake}_{i,j,q-1} + \]

\[ \text{SameMake}_{i,j,q-1}\text{Density}_i + \text{DifferentMake}_{i,j,q-1}\text{Density}_i + \]

\[ I_{q=1} + I_{q=2} + I_{q=3} + \varepsilon_{i,j,q}, \]

where \( i \) is a block group, \( j \) is a luxury car make, and \( q \) is a calendar quarter. The dependent variable equals 1 if at least one luxury car of a specific make was purchased in a specific block group within a period of 3 months (calendar quarters). “SameMake” equals 1 if at least one luxury car of the same make was purchased within the same block group within the previous quarter, while “DifferentMake” equals 1 if at least one luxury car of a different luxury make was purchased within the same block group within the previous quarter.

[Table IV about here.]

Table IV shows that the likelihood of buying a luxury car is affected by previous transactions involving luxury cars within the same BG. The magnitude of this relation depends on its interaction with population density. More interestingly, the effect is strong even if the previous transaction involves a different luxury make. Arguably, effects across different makes are driven by status signaling rather than information exchange. Notably, this effect is present after controlling for seasonal effects, which might lump car purchases around certain times of the year and give the false impression of influence in purchase decisions.

5 Conclusion

In this paper, we explore whether the extent to which a community is connected has an effect on “keeping up with the Joneses” preferences. We use a unique database of car purchases for areas with different population densities, and we find strong evidence that car purchases
influence the purchase decisions of neighbors, and that this effect is stronger in suburban communities in which neighbors are likely to know each other well. More importantly, we show that the purchase of a luxury car has a strong effect on neighbors’ purchases of a luxury car *even across different brands*, and that population density makes this effect stronger in a statistically significant way.

The evidence is consistent with two possible channels of influence: information transmission and status signaling. We find evidence supporting both channels because our results cannot be fully explained by either information exchange or word of mouth. We control for household income, and we use income disparity as a proxy for heterogeneity: low income dispersion (i.e., homogeneous population) will be associated with more information exchange. The effect of population density persists even after we control for income distribution (as a proxy for homogeneity) and for seasonality. Accordingly, we argue that the stronger effect in areas with lower population density is mostly driven by status signaling behavior. The lack of “anonymity” in suburban communities gives more strength to the visibility and attribution of conspicuous consumption.
References


Table I: Descriptive Statistics

Panel A: Counties
The sample includes all car purchases, new and used, for the period 2004–2006 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.

<table>
<thead>
<tr>
<th>Census 2000</th>
<th>Los Angeles</th>
<th>Orange</th>
<th>Riverside</th>
<th>All counties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Block Groups</td>
<td>6,351</td>
<td>1,826</td>
<td>804</td>
<td>8,981</td>
</tr>
<tr>
<td>Total population</td>
<td>9,519,338</td>
<td>2,846,289</td>
<td>1,545,387</td>
<td>13,911,014</td>
</tr>
<tr>
<td>Total household units</td>
<td>3,270,909</td>
<td>969,484</td>
<td>584,674</td>
<td>4,825,067</td>
</tr>
<tr>
<td>Area in sq. meters (millions)</td>
<td>10,517</td>
<td>2,044</td>
<td>18,667</td>
<td>31,229</td>
</tr>
<tr>
<td>Area in acres</td>
<td>2,598,957</td>
<td>505,219</td>
<td>4,612,716</td>
<td>7,716,892</td>
</tr>
<tr>
<td>Car registrations in 2004-2006</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used</td>
<td>2,720,491</td>
<td>787,919</td>
<td>554,287</td>
<td>4,062,697</td>
</tr>
<tr>
<td>New</td>
<td>2,038,502</td>
<td>610,846</td>
<td>362,885</td>
<td>3,012,233</td>
</tr>
<tr>
<td>All</td>
<td>4,758,993</td>
<td>1,398,765</td>
<td>917,172</td>
<td>7,074,930</td>
</tr>
</tbody>
</table>

Panel B: Block Group medians

<table>
<thead>
<tr>
<th>Los Angeles</th>
<th>Orange</th>
<th>Riverside</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area in sq. meters</td>
<td>318,407</td>
<td>454,918</td>
</tr>
<tr>
<td>Area in dunam</td>
<td>318</td>
<td>455</td>
</tr>
<tr>
<td>Area in acres</td>
<td>79</td>
<td>112</td>
</tr>
<tr>
<td>Population density per dunam</td>
<td>3.81</td>
<td>3.08</td>
</tr>
<tr>
<td>Per capita income in 1999</td>
<td>17,296</td>
<td>25,738</td>
</tr>
<tr>
<td>Median family income in 1999</td>
<td>46,685</td>
<td>64,710</td>
</tr>
</tbody>
</table>
Table II: Car-Purchase Counts, Population Density, and Income Distribution

Panel A: 1st stage
The sample includes all car purchases, new and used, for the years 2004–2006, 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 the dependent variable is the number of cars per make and BG during the sample period. Expected count is the count for the same make in the 10 nearest block groups, adjusted by either population or by the number of household units. Demographical information at the BG level is from the 2000 U.S. census. Family income HI is the Herfindahl index (HI) of family income (based on 16 income groups within each BG). Note that in the fixed-effect models the highest tertile is the baseline.

<table>
<thead>
<tr>
<th>Model</th>
<th>Count (population adjusted)</th>
<th>Count (household unit adjusted)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>11.40338***</td>
<td>13.13196***</td>
</tr>
<tr>
<td>Expected count</td>
<td>0.50214***</td>
<td>0.39833***</td>
</tr>
<tr>
<td>Population density</td>
<td>-0.29935***</td>
<td>-0.24561***</td>
</tr>
<tr>
<td>Family income HI</td>
<td>-7.31151*</td>
<td>-9.44962**</td>
</tr>
<tr>
<td>Low density (Tertile 0)</td>
<td>6.15713***</td>
<td>5.92586***</td>
</tr>
<tr>
<td>Medium Density (Tertile 1)</td>
<td>-0.85209</td>
<td>-1.10987</td>
</tr>
<tr>
<td>Low income HI (Tertile 0)</td>
<td>5.04348***</td>
<td>5.68326***</td>
</tr>
<tr>
<td>Medium income HI (Tertile 1)</td>
<td>1.01223</td>
<td>1.20981</td>
</tr>
</tbody>
</table>

Panel B: heteroscedasticity test
The dependent variable is the absolute residual from the models in Panel A.

<table>
<thead>
<tr>
<th>Model</th>
<th>Count (population adjusted)</th>
<th>Count (household unit adjusted)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>5.08142***</td>
<td>8.91940***</td>
</tr>
<tr>
<td>Expected count</td>
<td>0.47455***</td>
<td>0.35941***</td>
</tr>
<tr>
<td>Population density</td>
<td>-0.52244***</td>
<td>-0.42659***</td>
</tr>
<tr>
<td>Family income HI</td>
<td>12.30069***</td>
<td>6.75790*</td>
</tr>
<tr>
<td>Low density (Tertile 0)</td>
<td>9.04715***</td>
<td>8.63821***</td>
</tr>
<tr>
<td>Medium Density (Tertile 1)</td>
<td>0.16868</td>
<td>-0.52084</td>
</tr>
<tr>
<td>Low income HI (Tertile 0)</td>
<td>2.60507***</td>
<td>4.10363***</td>
</tr>
<tr>
<td>Medium income HI (Tertile 1)</td>
<td>-1.00446</td>
<td>-0.48131</td>
</tr>
</tbody>
</table>
Table III: Car Purchase Intervals, Population Density, and Income Distribution

The sample includes all car purchases, new and used, for the three-year period 2004–2006 in three large adjacent counties in Southern California: Los Angeles, Orange and Riverside. The dependent variable is the interval (in days) between each transaction and the previous one of the same type within the same BG. Transaction type is defined by make, by any luxury make, or by a different luxury make. Luxury car makes include BMW, LEXUS and MERCEDES-BENZ, and the expected interval is defined as the total number of days in the sample divided by the total number of transactions of each transaction type within the same block group. Family income HI is the Herfindahl index (HI) of family income (based on 16 income groups within each BG). Note that in the fixed-effect models, the highest tertile is the baseline.

<table>
<thead>
<tr>
<th>Model</th>
<th>Interval (same make)</th>
<th>Interval (any luxury)</th>
<th>Interval (different luxury)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Linear</td>
<td>FE</td>
<td>Linear</td>
</tr>
<tr>
<td>Intercept</td>
<td>4.63***</td>
<td>6.30***</td>
<td>2.79***</td>
</tr>
<tr>
<td>Expected interval</td>
<td>0.76***</td>
<td>0.76***</td>
<td>0.78***</td>
</tr>
<tr>
<td>Population density</td>
<td>0.01**</td>
<td>0.11***</td>
<td></td>
</tr>
<tr>
<td>Family income HI</td>
<td>7.08***</td>
<td>-3.04***</td>
<td>-5.96***</td>
</tr>
<tr>
<td>Low density (Tertile 0)</td>
<td>-0.60***</td>
<td>-1.33***</td>
<td>-1.83***</td>
</tr>
<tr>
<td>Medium Density (Tertile 1)</td>
<td>0.45***</td>
<td>0.04</td>
<td>-0.19**</td>
</tr>
<tr>
<td>Low income HI (Tertile 0)</td>
<td>-1.18***</td>
<td>0.14**</td>
<td>0.13</td>
</tr>
<tr>
<td>Medium income HI (Tertile 1)</td>
<td>-0.43***</td>
<td>0.34***</td>
<td>0.43***</td>
</tr>
</tbody>
</table>
Table IV: Logit Model per Make and Block Group, 3-Month Intervals, Luxury Cars

The sample includes luxury car purchases, new and used, for the period 2004–2006 in three large, adjacent counties in Southern California—Los Angeles, Orange, and Riverside—and the luxury car makes were BMW, LEXUS, and MERCEDES-BENZ. The dependent variable equals 1 if at least one luxury car of a specific make was purchased in a specific block group within a period of 3 months (calendar quarters). SameMake equals 1 if at least one luxury car of the same make was purchased within the same block group within the previous quarter. Different-Make equals 1 if at least one luxury car of a different luxury make was purchased within the same block group within the previous quarter. Quarter fixed-effects control for within-year seasonality. 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.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Wald Chi-Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-1.5780***</td>
<td>0.0201</td>
<td>6,189.28</td>
</tr>
<tr>
<td>Family income</td>
<td>0.000021***</td>
<td>1.97E-07</td>
<td>10,989.06</td>
</tr>
<tr>
<td>Population density</td>
<td>0.0252***</td>
<td>0.00255</td>
<td>97.97</td>
</tr>
<tr>
<td>SameMake_{t-1}</td>
<td>1.5051***</td>
<td>0.0202</td>
<td>5,550.68</td>
</tr>
<tr>
<td>DifferentMake_{t-1}</td>
<td>0.6777***</td>
<td>0.0218</td>
<td>965.16</td>
</tr>
<tr>
<td>Same_{t-1}× Density</td>
<td>-0.0182***</td>
<td>0.00291</td>
<td>39.06</td>
</tr>
<tr>
<td>Different_{t-1}× Density</td>
<td>-0.0092***</td>
<td>0.00319</td>
<td>8.24</td>
</tr>
</tbody>
</table>

Quarter fixed-effects: Yes
R-Square: 0.1324
Observations Used: 295,020
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
Figure IV: Days between Transactions of the Same Make, by Density.
Figure V: Days between Transactions of Any Luxury Make, by Density.
Figure VI: Days between Transactions of Different Luxury Makes, by Density.