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The intensity of keeping up with the Joneses: evidence from neighbour effects in car purchases

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

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Abstract

We show that status-driven behaviour 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 neighbours 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 makes, and is particularly apparent in higher price segments. We argue that, in connected communities, the signalling of income or wealth through the public display of consumption has a substantial effect on the behaviour of neighbours.

Keywords: conspicuous consumption, neighbour effects, population density, community

JEL codes: A14, D12

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1 Introduction

We show that status-driven consumption is stronger in suburban communities than in urban, more densely populated, areas. In particular, we study, for a large area of Southern California, the effect of the purchases of luxury make cars on car purchase decisions of immediate neighbours. Our sample includes three counties with large and diverse populations mostly living in metropolitan areas with different degrees of density, from low (suburban communities) to high (urban neighbourhoods). We find that the social influence of neighbours buying a luxury car increases as the population density decreases, and is highest in suburban communities, in which neighbours are likely to know each other well. In order to distinguish the status effect from a clustering of tastes or sheer word of mouth, our main result concerns the spillover across different car makes. In particular, we examine how the purchase of a given luxury car make affects subsequent purchases of *other* luxury makes by immediate neighbours.

The notion that individual agents are influenced in their economic decisions by the consumption or wealth of some comparison group (such as neighbours, 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 behaviour has been labelled "keeping up with the Joneses" and, arguably, it is at least partially motivated by the objective of signalling 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.[1] A related line of research has provided strong macroeconomic evidence of investment in conspicuous goods. Hirsch (1976) calls this type of activity the "positional economy."[2] Duesenberry (1949) postulated that the utility of con-

[1]According to the Longman Dictionary of Contemporary English, 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." (http://www.ldoceonline.com/dictionary/conspicuous-consumption)

[2]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.

sumers 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 signalling wealth through conspicuous consumption. More recently, Moav and Neeman (2012) show that a signalling equilibrium in which poor individuals tend to spend a large fraction of their income on conspicuous consumption can emerge. The recent availability of data on individual consumption permits to study how individual purchase decisions affect the consumption decisions of neighbours. Ravina (2007) finds that household consumption choices are influenced by both household past consumption and the consumption level of the city in which the household resides. 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 consumer in question.

While peer pressure can come from several reference groups, such as family and co-workers, our focus is on neighbours. Luttmer (2005) finds that, controlling for an individual's own income, higher earnings of neighbours are associated with lower levels of self-reported happiness. Results are stronger for people who socialise more with neighbours but not for those who socialise more with friends outside the neighbourhood, which further suggests that the mechanism mediating this effect is most likely caused by interpersonal preferences. Following this insight, we want to move a step forward and study the effect of community on status-driven behaviour. 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 on social networks and "social capital." Social capital typically refers to social, economic, and political effects of a social network. The sociology literature provides several reasons why it appears to decline with population density. Jacobs (1961) was the first to argue that strangers are far more common in big cities than acquaintances. In towns or communities that are smaller and simpler than big cities, controls on acceptable public behaviour 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, and the frequency of getting together with, one's local personal network. He also finds that social ties with nonrelatives who live nearby decrease with population density. Putnam (2001) shows that organizational forms of social capital—such as membership and participation in civic, social and fraternal clubs and societies—collapse with urbanization as well.

This paper bridges the two lines of literature—namely conspicuous consumption and social capital—with a new finding. 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—neighbours are more likely to influence each other's conspicuous consumption decisions. We document that purchases of luxury make cars have an effect on the neighbours' luxury make purchase decisions, and the effect is stronger in areas with lower population density—which represent suburban communities in our sample. In high density areas, it is more difficult to keep track of neighbours, and social interactions are more transitory and impersonal. Bumping regularly into the same people is also less likely, so there are fewer opportunities to form relationships. Neighbours 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 gardening.[3] Neighbours 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 places, attending the same churches, and even working for the same employers. In his seminal analysis of social networks, Granovetter (1973) argues that the degree of overlap of two individuals' networks varies directly with the strength of their tie to one another. According to this argument, suburban neighbours, who routinely interact in multiple ways with a relatively unchanging peer group, become a "connected" community. Such community provides an obvious reference for its members, and the lack of "anonymity" gives more strength to the visibility and attribution of conspicuous consumption.

In this paper, we focus on car purchases as status-signalling decisions. As documented by Heffetz (2011), cars are the single most visible expenditure category among 31 items that altogether cover 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) in that set. Choo and Mokhtarian (2004) provide more evidence of purchase of luxury cars as status-signalling devices. Kuhn et al. (2011) identify 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 effects of lottery prizes on neighbours of winners, but only for one good—car consumption—which is likely to be easily, and repeatedly, visible to a household's neighbours.[4] 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:

[3]In our sample, "lower population density" refers to areas in which neighbours 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.

[4]For example, having an immediate neighbour 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.

"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).[5]

Our data includes all car purchases, new and used, during the years 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—census block groups (BG). Our objective is to compare purchase patterns across different 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 neighbourhood or a small community, usually with relatively high household incomes.

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 neighbouring 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 neighbouring BGs allows us to use them as the level of analysis. The next element of our empirical strategy is a focus on temporal patterns within the BGs. This allows us to mitigate any cross-sectional differences between different areas and car types, which may explain the relation between population density and concentration in specific makes. We show that people in low density areas tend to react faster to their immediate neighbours. This is consistent with 'hot periods,' during which car purchases are lumped together in time, being more prevalent in connected communities. After controlling for the average interval within each BG-make pair, we find that intervals between car purchases are shorter in lower-density areas, and the magnitude of the effect is stronger in luxury cars. We then directly examine whether the decision to buy a car is affected by recent decisions made by neighbours. We

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

focus on higher price segments, as the behavioural effect is expected to be stronger in luxury makes, which are clearly more conspicuous. Our 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.

A major empirical challenge for our analysis is the existence of several potential 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. Grinblatt, Keloharju, and Ikaheimo (2008) find social effects, which occur immediately (within days), of car purchases among Finnish neighbours. 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 Scandinavian countries, pay is confidential and considered a very private and sensitive matter. As information on income and wealth becomes less transparent, status signalling 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 signalling plays an important role. We distinguish between the two channels, namely information transmission and status signalling, in several ways. First, 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 (Alesina and La Ferrara (2000)). For that reason, we control for income dispersion as the main source of heterogeneity.

We verify that homogeneity influences car purchases of neighbours across all makes, including luxury makes. In order to differentiate the effects of the information channel from the peer pressure on conspicuous consumption, which is the focus of our study, we turn to spillover effects across different makes. 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 signalling. We find that the density effect is strong even if the previous transaction involves a different luxury make. That is, if your neighbour 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 signalling.

By documenting a crucial determinant of status-driven behaviour, this paper offers a better understanding of the underlying forces in economic decision making. The empirical research on social influence is divided as for why consumers appear to keep up with the Joneses. Our evidence shows that social influence results from status-signalling behaviour, yet to a varying degree. The effectiveness of status-signalling behaviour depends on the extent to which a community is connected. To the best of our knowledge, this has not been directly studied before, although Hong, Kubik, and Stein (2008) and Gómez, Priestley, and Zapatero (2015) provide some indirect evidence of the effect of population density on relative wealth concerns through the equilibrium properties of security prices. Our analysis has implications for different social sciences such as sociology and psychology, managerial subfields like marketing and organization science (for example, 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. If poor families spend a large fraction of their income on conspicuous consumption, then the increasing marginal propensity to save can generate a poverty trap.

The paper is structured as follows. In section 2, we describe the data, and discuss how we address alternative explanations. In section 3 we present and discuss the results. Section 4 concludes.

2 Data and Methodology

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 comprises a household's immediate neighbours. 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. 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, which means that BGs with different population density will only differ in geographic size, while having similar population levels. This provides the statistical uniformity required for small area demographic and economic analysis. 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 to the 2000 census. While downtown Los Angeles is not very densely populated, the neighbourhoods 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 neighbourhood 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 neighbourhood, usually with relatively high household incomes. Therefore, in what we call "low population density," neighbours are likely to know one another and have the opportunity of communicating with one another easily (as opposed to areas in which neighbours 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.

2.1 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.[6] 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 neighbours. 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 neighbours.

[6] Population density is measured per dunam (1,000 square meters), however one can easily convert this density metric into population per square mile by multiplying by 2590.

[Table I about here.]

[Figure I about here.]

[Figure II about here.]

[Figure III about here.]

2.2 Methodology

We first want to establish that block groups present an adequate level of analysis for our purposes. We examine whether there is crowding in specific car makes at the expense of other makes within a BG. 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. We match each BG with the 10 nearest block groups. 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. This allows us to control for general market trends and general local characteristics.

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 this, 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 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. This two-stage methodology, first using preliminary regressions and next working with the residuals of those regressions, echoes the methodology used by Glaeser, Sacerdote and Scheinkman (1996) to examine the effect of social interactions on crime. It enables us to measure the extent to which the proportion of car makes is constant across neighbouring BGs. 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 neighbouring 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 which it is located. Spatial independence is also important to establish because it mitigates econometrical concerns associated with spatial autocorrelation.

We next focus purely on temporal patterns within the BGs. This allows us to examine whether population density translates into concentration in specific makes, without having to worry about cross-sectional differences between different areas and car types. We examine whether the crowding in specific makes in BGs with lower density is also concentrated in time. We test whether "hot" periods are more prevalent in areas with low population density. To proxy for hot periods, 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 the same BG. 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. If the timing of the decision to buy a car is unaffected by others, purchases will be spread out evenly over the entire sample period. If some people buy a car earlier because of others, the intervals within hot subperiods will be shorter than the average interval representing the no-peer-effect case. The expected interval also captures most cross-sectional variation between BGs and makes. For example, if low density is associated with higher car turnover, this will be captured by the expected interval. A more subtle concern is that specific ethnic groups tend to buy specific car brands and also tend to gravitate to neighbourhoods with particular type of dwelling (e.g. single family homes or apartments). The expected interval is essentially a BG-make fixed effect capturing any correlated unobservables and endogenous selection into neighbourhoods.

Finally, we examine whether the decision to buy a car is affected by recent decisions made by neighbours. Our logit model estimates the extent to which the likelihood of buying a luxury car is affected by previous transactions involving luxury cars within the same BG. 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). The independent variables include indicators for purchases of either the same make or a different luxury make within the same block group within the previous quarter. More interestingly, we include an interaction between recent transactions and 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.

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 arguably 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 neighbours and influence their choice of brand on purely consumer satisfaction grounds. In our empirical analysis, we control for this "information" effect in three 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 distinguish between different price segments, as the behavioural effect is expected to be stronger in luxury makes, which are clearly more conspicuous; (3) we study the effect across different makes—i.e., how purchases of one luxury make affects purchases of other luxury makes different from the original.

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 neighbour 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. Alesina and La Ferrara (2000) use survey data on group membership and data on U. S. localities, and find that participation in social activities is significantly lower in more unequal and heterogeneous communities. For that reason, we control for income dispersion as the main source of heterogeneity and use the Herfindahl index (HI) of family income based on 16 income groups within each BG. 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 neighbour effects in car purchases, it cannot distinguish between the two channels at play, namely information transmission and status signalling. 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 signalling 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 focus on luxury cars, and examine spillover effects across different luxury makes. 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, and some of the price is related to car attributes "that are not necessary." We then study whether and how the purchase of a car of a given luxury make is followed by purchases of a different luxury 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 signalling. In particular, our tests are designed to examine whether the magnitude of such status-driven behaviour depends on population density.

3 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 behavioural effects: good word of mouth from neighbours 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.

3.1 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-signalling 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.[7]

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. This two-stage methodology, of first using preliminary regressions and working with the residuals of those regressions, echoes the methodology used by Glaeser, Sacerdote and Scheinkman (1996) to examine the effect of social interactions on crime. It enables us to measure the extent to which the proportion of car makes is constant across neighbouring BGs. 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

[7]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.

from the original regression model onto the original regressors. As we explain in section 2, 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. We thus test how these residuals are spread rather than focus on their mean. We reiterate that BGs are defined by population, not by area. BGs with low population density do not have fewer people, and so the variance in car purchases is not expected to vary with density for pure mechanical reasons.

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.]

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. The more homogenous a BG is, the higher its HI. When income is more heterogeneous within the BG, each income group would have a lower weight, and the HI would be closer to zero. 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 centre block.

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 use either a linear regression or a dummy variable approach to control for density and income distribution. Note that in the categorical dummy estimation, the baseline is the highest rank, which represents dense inner-city neighbourhoods. The Low Density tertile represents small communities, while the Medium Density represents urban sprawl. The linear model we estimate is

$$Count_{i,j} = \alpha + ExpectedCount_{i,j} + Density_i + IncomeHI_i + \varepsilon_{i,j},$$

while the dummy variable approach yields

$$\begin{aligned} Count_{i,j} &= \alpha + ExpectedCount_{i,j} + I_{Density_i=Low} + I_{Density_i=Mid} + \\ &\quad I_{IncomeHI_i=Low} + I_{IncomeHI_i=Mid} + \varepsilon_{i,j}, \end{aligned}$$

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.

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 neighbourhood profile) in areas with low population density. The negative relation between the variance in the number of transactions and the population density cannot just be a statistical artefact, because BGs are defined by population rather than by area.

One may argue that BGs may be very homogenous, which would explain the BG-level effect that we find. We note that if we only had small pockets of highly homogenous populations in our sample, they should also be homogenous in income, and then income dispersion would be low (and HI would be high) throughout the sample, and HI would lack any explanatory power. Income dispersion, however, is highly significant. We find that more homogenous (higher HI) BGs exhibit higher crowding in specific makes (at the expense of other makes that fit the neighbourhood profile), consistent with stronger peer effects in more homogeneous populations.

It is possible that some of the clustering that we observe in car purchases is driven by local shocks. One 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.

Another potential local shock may be housing prices, but shocks to housing prices tend to spill over neighbouring 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—i.e., 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 effect of local shocks is not an alternative explanation because it goes against our results.

Still, there may be other correlated unobservables, such as ethnicity, occupation, and age which may drive the results. To address some of these concerns, we present a novel estimation approach in the following analysis. We focus purely on temporal patterns within each BG, which are clean from any cross-sectional effects. Specifically, we focus on recent transactions within the same BG. This allows us to explore the possible channels through which population density translates into concentration in specific makes.

3.2 Intervals

In our next exercise, we examine whether the crowding in specific makes in BGs with lower density is also concentrated in time. We test whether "hot" periods are more prevalent in areas with low population density. To proxy for hot periods, 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 the same 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. If the timing of the decision to buy a car is unaffected by others, purchases will be spread out evenly over the entire sample period. If some people buy a car earlier because of others, the intervals within hot subperiods will be shorter than the average interval representing the no-peer-effect case. As we explain in section 2, the expected interval also captures most cross-sectional variation between BGs and makes. For example, if low density is associated with higher car turnover, this will be captured by the expected interval. A more subtle concern is that specific ethnic groups tend to buy specific car brands and also tend to gravitate to neighbourhoods with particular type of dwelling (e.g. single family homes or apartments). The expected interval is essentially a BG-make fixed effect capturing any correlated unobservables and endogenous selection into neighbourhoods.

We start by plotting the distribution of excess days between transactions, defined as the deviation of the interval between transactions from the expected interval in the 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.

[Figure IV about here.]

[Figure V about here.]

[Figure VI about here.]

Table III is aimed to test whether the time between purchases is less smooth in areas with low population density. Specifically, it tests whether purchases of a specific car make within a specific BG tend to cluster in hot subperiods. If hot periods are more prevalent in lower-density areas and/or areas of lower income dispersion, then the shorter intervals during hot periods will result in a shorter average interval between car purchases in such BGs. The linear model we estimate is

$$Interval_{t,i,j} = \alpha + ExpectedInterval_{i,j} + Density_i + IncomeHI_i + \varepsilon_{t,i,j},$$

while the categorical model is

$$\begin{aligned} Interval_{t,i,j} &= \alpha + ExpectedInterval_{i,j} + I_{Density_i=Low} + I_{Density_i=Mid} + \\ & I_{IncomeHI_i=Low} + I_{IncomeHI_i=Mid} + \varepsilon_{t,i,j}, \end{aligned}$$

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 about here.]

Table III shows that people in low density areas tend to react faster to their immediate neighbours. Lower population density increases the influence of the purchase of a given make on the decisions of the neighbours, and the magnitude of the effect is stronger for luxury cars of a different make, which provides support for the relevance of status signalling 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 signalling 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 signalling.

3.3 The Decision to Buy a Luxury Car

Our next exercise examines the interaction between density and a recent nearby purchase. Our results in Table II show crowding in specific makes (at the expense of other makes that fit the neighbourhood profile) in areas with low population density. One concern is that crowding is a result a common local shock, which will affect neighbours similarly even if no peer effect is present. We address the simultaneity issue by examining whether the decision to buy a car is affected by past decisions made by neighbours.

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 behavioural 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 neighbours to purchase a different luxury make. 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. 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 signalling. The model we estimate is

$$\begin{aligned} I_{i,j,q} \quad = \quad & \alpha + Income_i + Density_i + SameMake_{i,j,q-1} + DifferentMake_{i,j,q-1} + \\ & SameMake_{i,j,q-1} Density_i + DifferentMake_{i,j,q-1} Density_i + \\ & I_{q=1} + I_{q=2} + I_{q=3} + \varepsilon_{i,j,q}, \end{aligned}$$

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 signalling 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.

4 Conclusion

In this paper, we show that the extent to which a community is 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 neighbours, and that this effect is stronger in suburban communities in which neighbours are likely to know each other well. More importantly, we show that the purchase of luxury cars—identified in the literature as the quintessential conspicuous good—has a strong effect on neighbours' purchases of luxury cars *even across different makes*. The effect is significantly stronger in suburban areas than in urban areas. Suburban communities in our sample are characterized by a high degree of "connectedness", which has been widely studied in the sociology literature.

In principle, our evidence is consistent with two possible channels of influence: information transmission and status signalling. To distinguish between the two, we use income disparity as a proxy for heterogeneity: low income dispersion (i.e., homogeneous population) is associated with more information exchange. We also control for seasonality, which can be very important in car sales patterns. The strong statistical significance of the effect of population density survives all these controls. Spillover across different luxury makes, which is more likely driven by status signalling than by good word of mouth, is also significantly stronger in suburban areas than in urban areas. Accordingly, we argue that the stronger effect of peer pressure on conspicuous consumption in areas with lower population density is driven mainly by status signalling behaviour. The "connectedness" and lack of "anonymity" in suburban communities gives more strength to the visibility and attribution of conspicuous consumption.

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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

	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
Area in acres	2,598,957	505,219	4,612,716	7,716,892
		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
Area in dunam	318	455	1,354
Area in acres	79	112	335
Population density per dunam	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

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 categorical models the highest tertile is the baseline.

	Count (population adjusted)		Count (household unit adjusted)	
Model	Linear	Categorical	Linear	Categorical
Intercept	11.40338***	5.38450***	13.13196***	6.94765***
Expected count	0.50214***	0.50128***	0.39833***	0.39767***
Population density	-0.29935***		-0.24561***	
Family income HI	-7.31151*		-9.44962**	
Low density (Tertile 0)		6.15713***		5.92586***
Medium Density (Tertile 1)		-0.85209		-1.10987
Low income HI (Tertile 0)		5.04348***		5.68326***
Medium income HI (Tertile 1)		1.01223		1.20981

Panel B: heteroscedasticity test

The dependent variable is the absolute residual from the models in Panel A.

	Count (population adjusted)		Count (household unit adjusted)	
Model	Linear	Categorical	Linear	Categorical
Intercept	5.08142***	0.88247	8.91940***	4.08308***
Expected count	0.47455***	0.47275***	0.35941***	0.35803***
Population density	-0.52244***		-0.42659***	
Family income HI	12.30069***		6.75790*	
Low density (Tertile 0)		9.04715***		8.63821***
Medium Density (Tertile 1)		0.16688		-0.52084
Low income HI (Tertile 0)		2.60507***		4.10363***
Medium income HI (Tertile 1)		-1.00446		-0.48131

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 categorical models, the highest tertile is the baseline.

	Interval (same make)		Interval (any luxury)		Interval (different luxury)	
Observations Used	6,141,309		613,261		395,163	
Model	Linear	Dummy	Linear	Dummy	Linear	Dummy
Intercept	4.63***	6.30***	2.79***	3.32***	3.83***	4.36***
Expected interval	0.76***	0.76***	0.78***	0.77***	0.47***	0.47***
Population density	0.01**		0.11***		0.14***	
Family income HI	7.08***		-3.04***		-5.96***	
Low density (Tertile 0)		-0.60***		-1.33***		-1.83***
Medium Density (Tertile 1)		0.45***		0.04		-0.19**
Low income HI (Tertile 0)		-1.18***		0.14**		0.13
Medium income HI (Tertile 1)		-0.43***		0.34***		0.43***

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.

Parameter	Estimate	Standard Error	Wald Chi-Square
Intercept	-1.5780***	0.0201	6,189.28
Family income	0.000021***	1.97E-07	10,989.06
Population density	0.0252***	0.00255	97.97
SameMake$_{t-1}$	1.5051***	0.0202	5,550.68
DifferentMake$_{t-1}$	0.6777***	0.0218	965.16
Same$_{t-1}\times$ Density	-0.0182***	0.00291	39.06
Different$_{t-1}\times$ Density	-0.0092***	0.00319	8.24
Quarter fixed-effects	Yes		
R-Square	0.1324		
Observations Used	295,020		

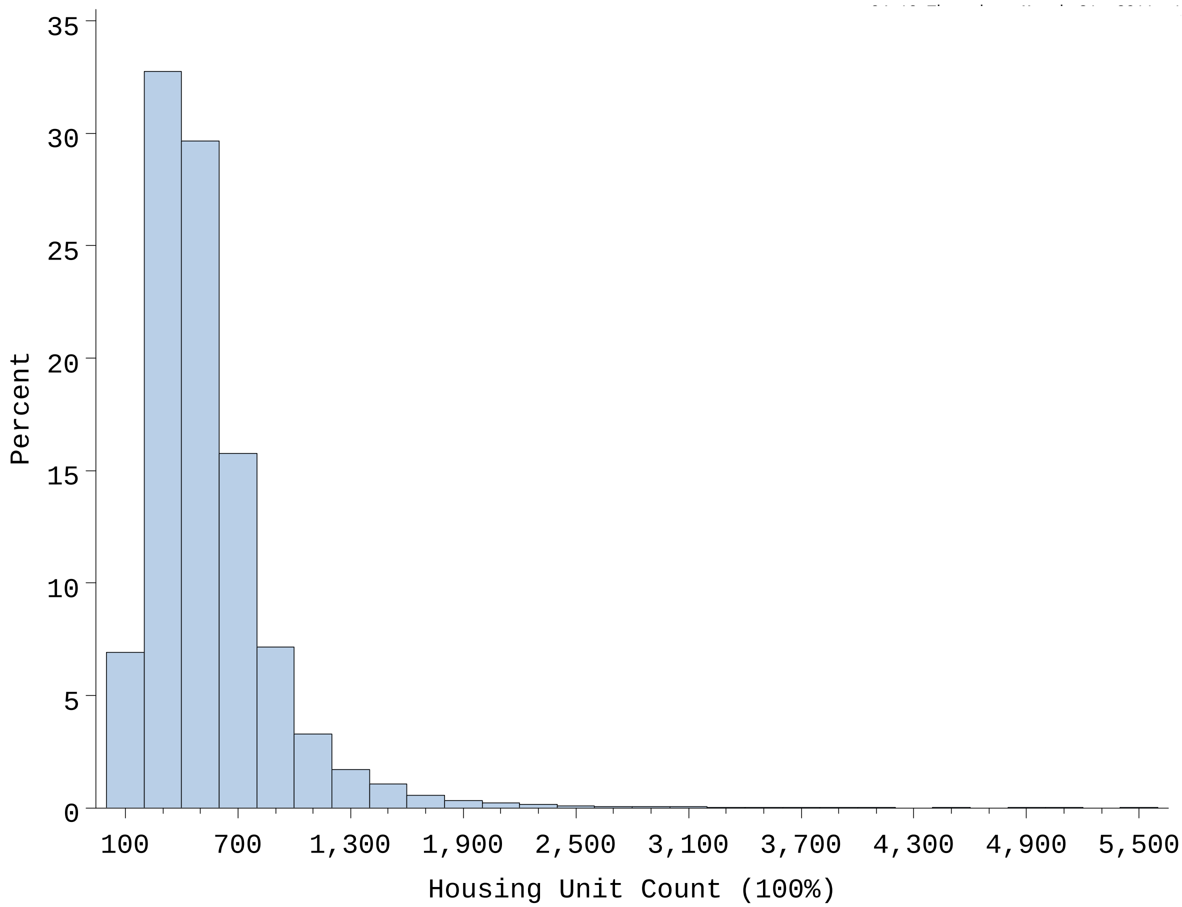

Figure I: Household Units per Block Group

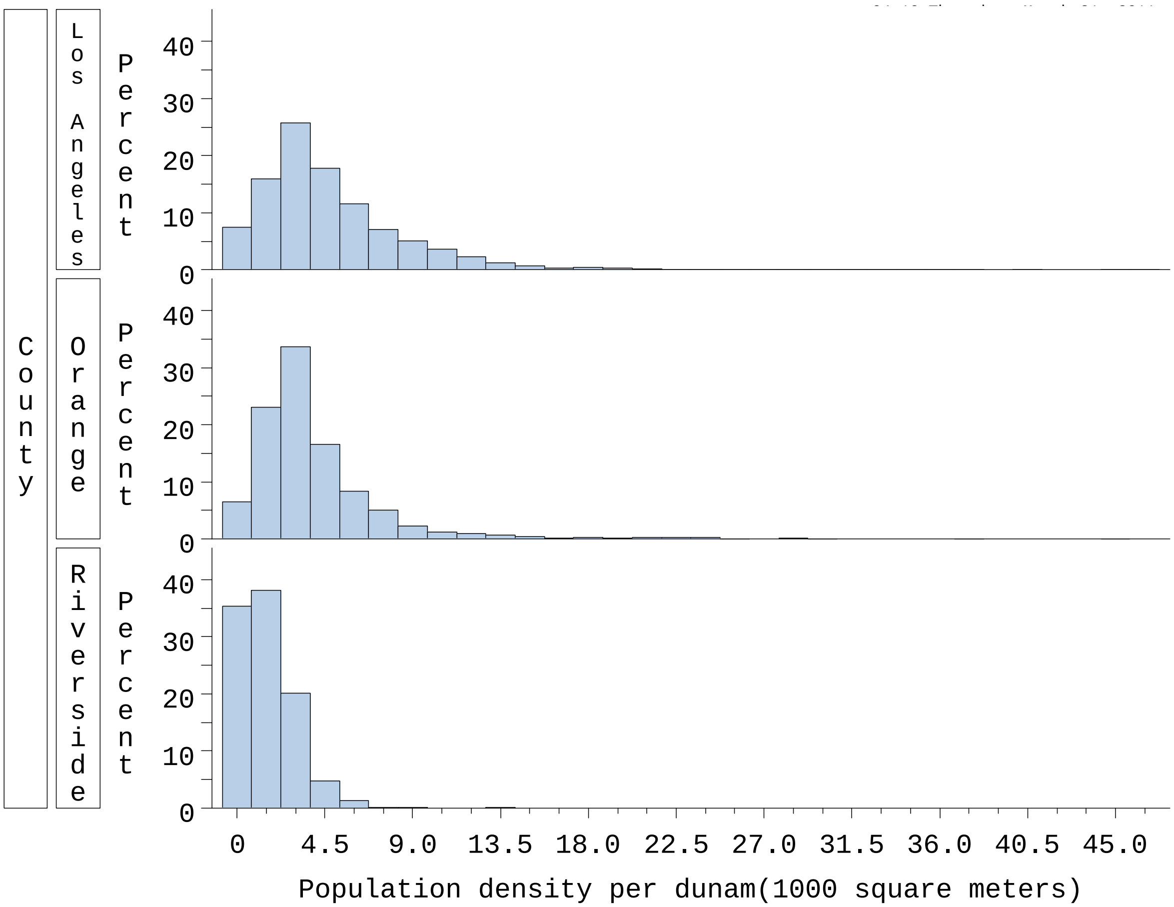

Figure II: Population Density per Block Group, by County

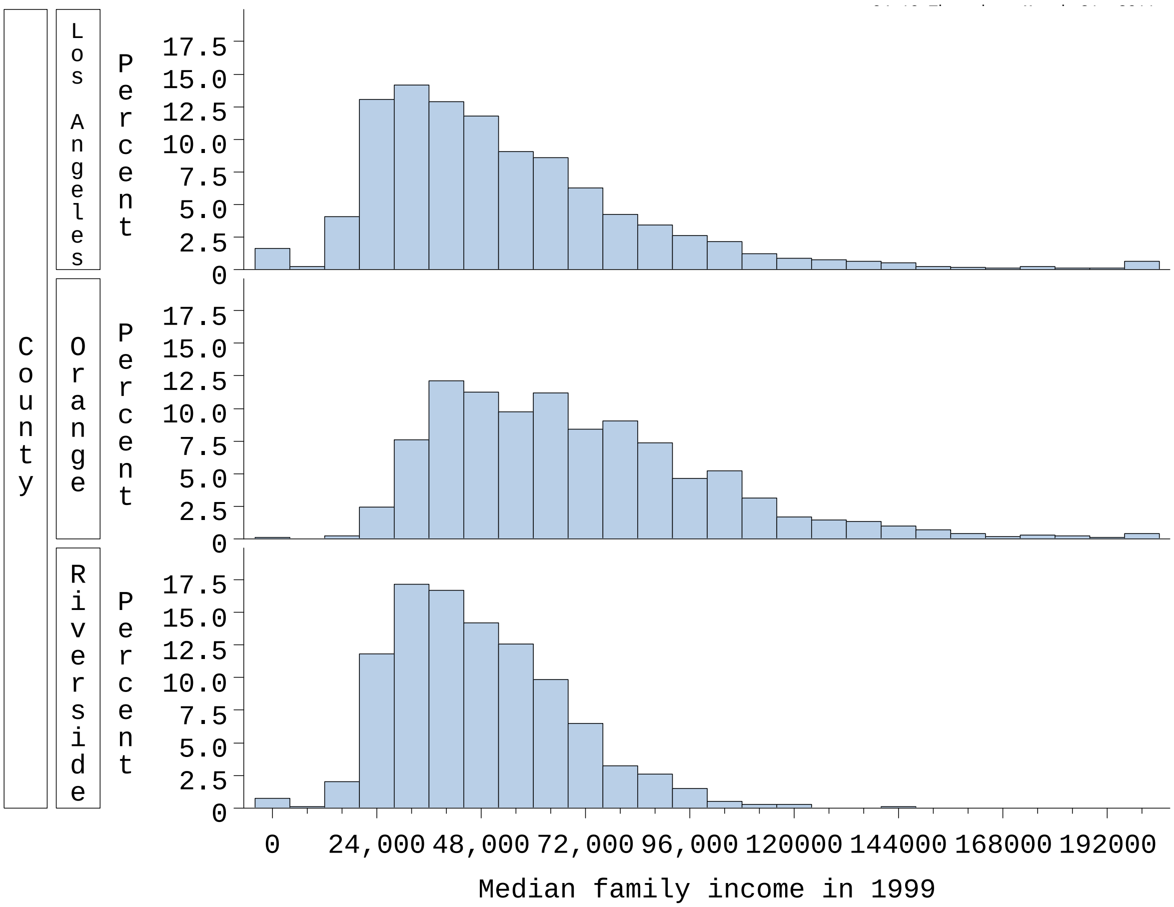

Figure III: Median Family Income per Block Group, by County

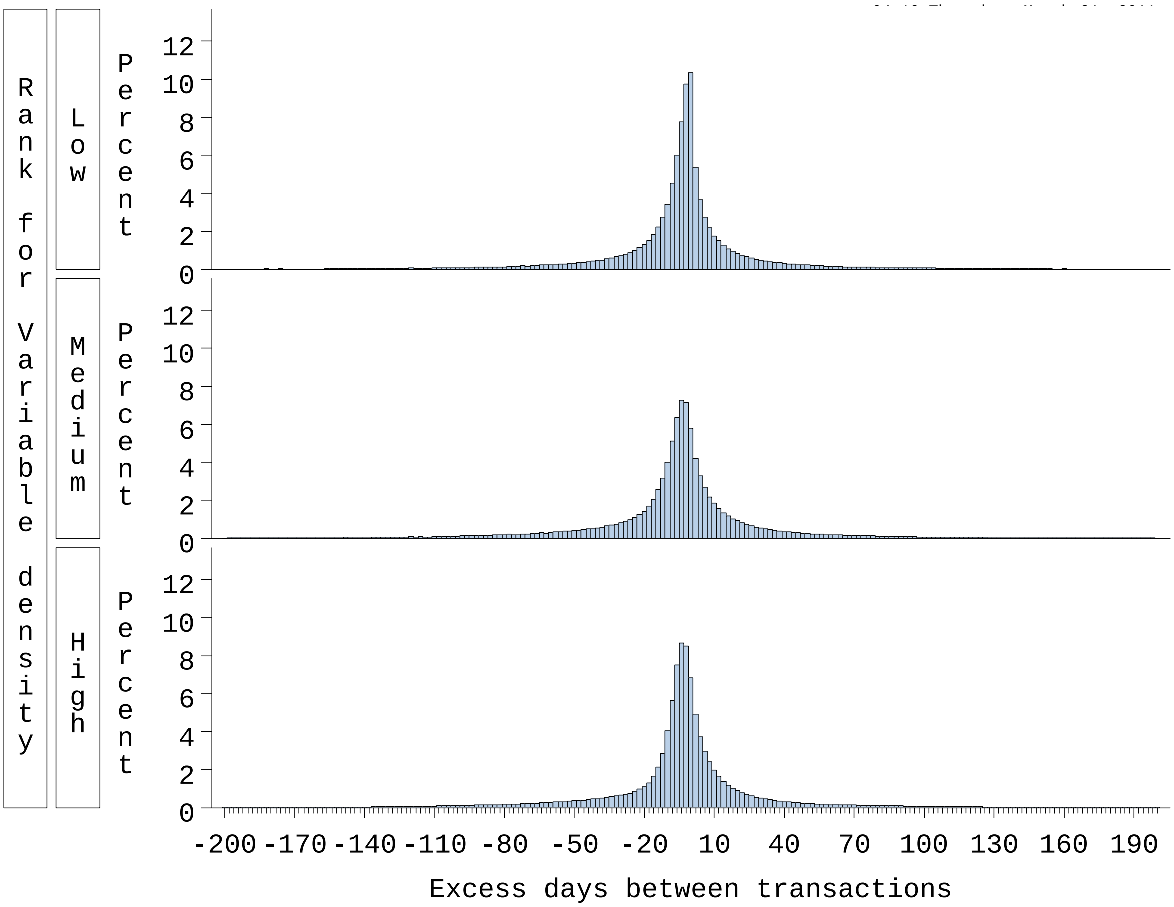

Figure IV: Days between Transactions of the Same Make, by Density.

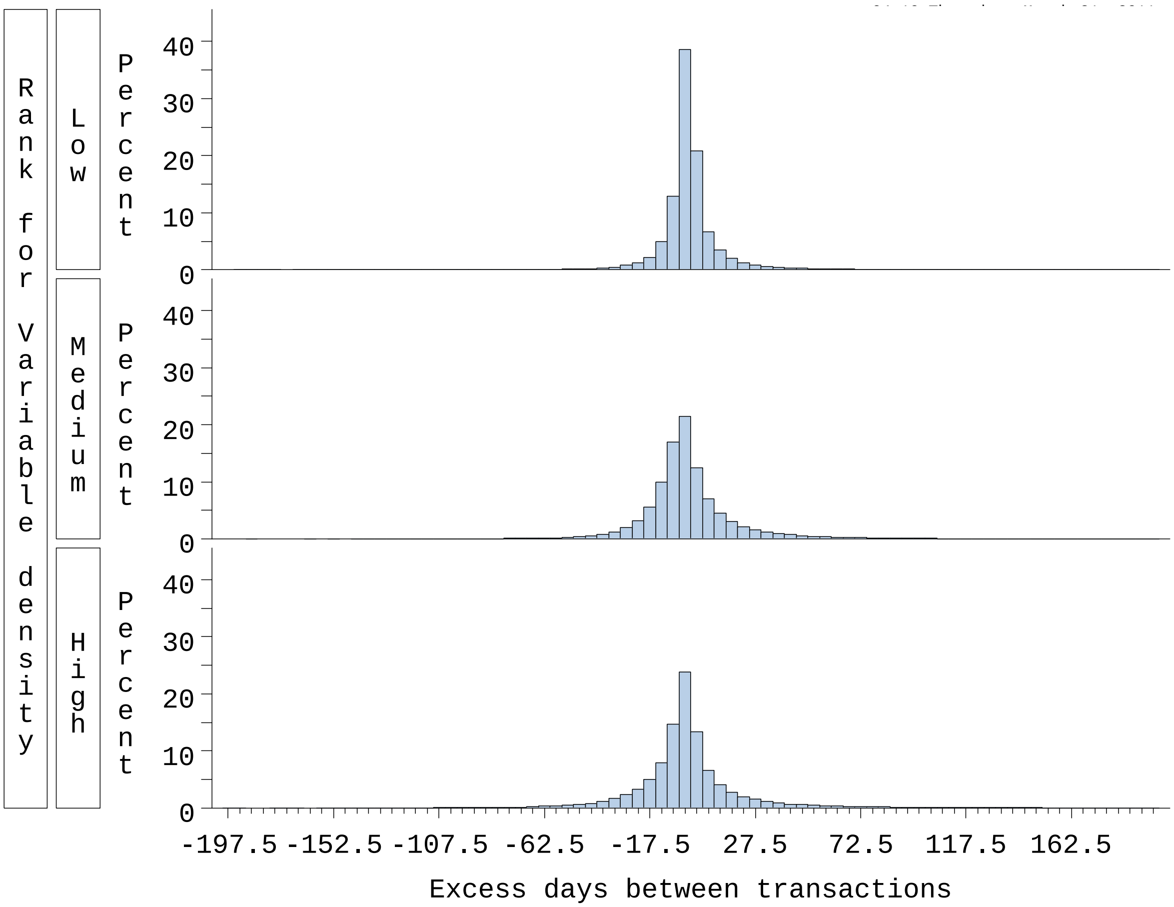

Figure V: Days between Transactions of Any Luxury Make, by Density.

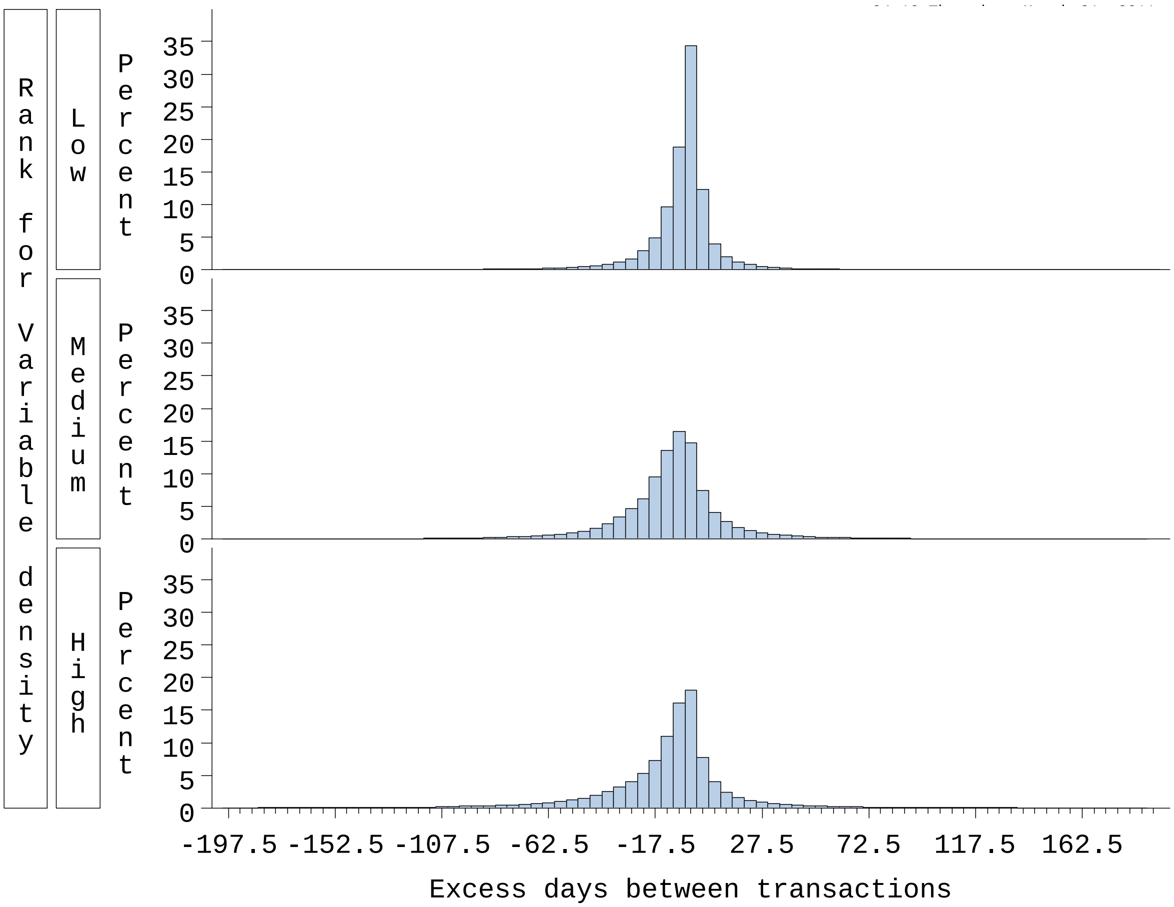

Figure VI: Days between Transactions of Different Luxury Makes, by Density.